Peer-to-Peer Lenders versus Banks: Substitutes or Complements?

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ABSTRACT

This paper studies whether peer-to-peer (P2P) lending platforms operate as substitutes to banks or instead complement them in consumer credit markets. I develop a framework and derive testable predictions to distinguish between the two cases. Using a regulatory change as an exogenous shock to bank credit supply, I find that P2P lending is a substitute to bank lending in that it serves infra-marginal bank borrowers, but also complements bank lending for small-size loans. These findings suggest that the credit expansion P2P lending brings about is likely to occur only among borrowers with access to bank credit.

Keywords: peer-to-peer lending; access to credit; financial innovation.

JEL Classification: D14, E51, G2

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1 Introduction

The peer-to-peer lending (P2P) platforms, which have emerged since the 2008 financial crisis, allow individuals and small businesses to borrow without an traditional financial institution. Following several years of exponential growth, this sector is now a significant supplier of credit to consumers. For instance, in 2015, the three largest P2P platforms in the U.S. provided 7.3% (USD 17 billion) of total new consumer credit. Yet little is known about the market that P2P platforms address. Do P2P platforms serve demand otherwise unmet by banks? Or do they compete with banks for the same clientele? This issue is important for assessing the implications of the rise of P2P lending. If P2P platforms are complements to banks, they can improve financial inclusion by expanding access to credit to borrowers underserved by the banking system. If instead they compete directly with banks, the credit expansion they bring about is likely to occur only among borrowers with access to bank credit.

This paper investigates whether P2P platforms operate as substitutes or complements to banks in the consumer credit market. The empirical challenge is that whether P2P borrowers have access to similar bank loans is unobservable. For instance, a borrower's application for a P2P loan may be voluntary, i.e., she chooses P2P credit over bank credit, or forced, i.e., she was denied access to bank credit. Therefore, by simply looking at the characteristics of P2P borrowers, one cannot assess whether the main clientele of P2P platforms is borrowers underserved by banks or infra-marginal bank borrowers.

To address this problem, I develop a framework in which P2P platforms can operate as substitutes or complements to banks. I derive testable predictions about the impact of a negative shock to bank credit supply on the distribution of P2P borrower quality. The key assumption is that when banks experience a shock leading them to reduce credit supply, they tighten lending criteria, so that borrowers at the lower end of the bank borrower quality distribution are more likely to lose access to bank credit and migrate to P2P platforms, affecting the distribution of P2P borrower quality.

The predictions differ depending on whether banks and P2P platforms are substitutes or complements. Suppose first that P2P platforms and banks are substitutes. In that case, they serve the same clientele before the shock, with the same distribution of borrower quality. Following a negative shock to bank credit supply, low-quality bank borrowers will migrate to P2P platforms. As a result, the average P2P borrower quality should drop and the quantiles of the distribution of P2P borrower quality shift left.

Suppose instead that P2P platforms complement banks by addressing a low-quality borrower segment underserved by banks. In that case, the borrower pool of P2P platforms is of worse quality than banks. Upon the shock to bank credit supply, the borrowers switching from banks to P2P platforms will improve the quality of the P2P borrower pool. As a result, the average P2P borrower quality will increase, and the quantiles of the distribution of P2P borrower quality shift right.

To test these predictions empirically, I exploit a regulatory change that caused banks to tighten their lending criteria. In 2010, the Financial Accounting Standards Board (FASB) implemented a new regulation (FAS 166/167) requiring banks to consolidate securitized off-balance sheet assets onto their balance sheets and include them in the risk-weighted assets starting in 2011Q1. In aggregate, this caused banks to consolidate USD 399.9 billion of assets, over 80% of which were revolving consumer loans.[1] The change in accounting had a large effect on banks lending through its impact on regulatory capital. Different banks were affected differently depending on how much securitized assets qualifying for consolidation they held off-balance sheet. Affected banks reduced small business lending and mortgage approval rates (Dou 2016; Dou, Ryan, and Xie 2016), and increased the average quality of credit card loans (Tian and Zhang 2016).

I conjecture that the shock affect local credit markets differently depending on the exposure of local banks to the new regulation. I identify banks as being affected if they held off-balance sheet assets qualifying for the consolidation under FAS 166/167. Counties with at least one affected bank are defined as affected markets, other counties forming a control group. I then examine the change in the distribution of P2P borrower quality in affected markets. Hence, the bank credit supply shock's impact on the distribution of P2P borrower quality is identified by the variation in exposure to the shock across local markets.

[1] See the Board of Governors of the Federal Reserve System's "Notes on Data" of the data set "Assets and Liabilities of Commercial Banks in the United States - H.8", released on April 9, 2010, available at: https://www.federalreserve.gov/releases/h8/h8notes.htm.

I use information on asset consolidation from the annual Call Reports to identify affected banks. In total, 59 banks have consolidated assets under FAS 166/167. The data on P2P lending volume, loan application and borrower characteristics (FICO score, debt-to-income ratio, employment, etc.) as well as loan characteristics is obtained from LendingClub, a large P2P platform whose market share represents over 50% of P2P personal loans in the U.S. I construct county-level variables using the data on 880,346 loan applications and 93,159 loan originations during 2009-12. The final sample consists of 1,908 affected and 1,025 unaffected markets, defined at the county level. On average, per thousand inhabitants in a county, the number of P2P loan applications and the number of funded loans originated are 0.6 and 0.05 per year, respectively.

I start by examining the treatment effect of FAS 166/167 on P2P loan application and origination volumes. I find that compared to the control group, affected markets experience an increase in P2P loan applications. On average, per thousand inhabitants in the county, 0.07 more applications are made for an additional amount of USD 1,108, which represents a 27% increase in the number of applications and a 42% increase in the dollar amount. The results suggest that some borrowers who would otherwise have been served by banks turned to P2P platforms. Moreover, it appears that this additional demand was partially satisfied by P2P platforms. I find that compared to the control group, affected markets also saw an increase in the number and dollar amount of P2P loans. On average, per thousand inhabitants in the county, 0.016 more P2P loans were originated for an additional amount of USD 301. Compared to the pre-shock level of origination, the number of loans increases by 1.1 times and the dollar amount of loans increases by 1.5 times.

Second, I test the predictions regarding the shock's impact on the distribution of P2P borrower quality. Using FICO scores as a measure of borrower quality, I find that compared to the control group, affected markets experience a left shift of all quantiles of the distribution. These findings suggest that P2P loans are substitutes to bank loans.

Other tests on the frequency distribution of P2P borrower quality lend additional support to this interpretation. If bank borrowers migrating to P2P platforms are of worse quality than existing P2P borrowers, one should observe a higher frequency only in the low-FICO range of the P2P borrower quality distribution. This is indeed what I find. The number of originations increases by 1.6 times among borrowers with FICO scores below 690, which corresponds to the 45th percentile of the pre-shock distribution of P2P borrowers. In contrast, there is no significant change in the number of originations in the upper end of the borrower distribution.

FICO scores are a coarse measure of borrower quality, and banks often use additional information to assess default risk. For example, the primary reasons for mortgage application denials, as reported in the Home Mortgage Disclosure Act, include credit history, the debt-to-income ratio and length of employment. Therefore, I construct another measure of borrower quality combining FICO score, debt-to-income ratio, and length of employment. Specifically, I estimate an ordered probit model taking application outcomes (rejected, qualified but not funded, or qualified and funded) as the dependent variable and the three borrower characteristics as explanatory variables, and summarize all the information into a single cardinal measure, the predicted application quality.

Using the new measure in the quantile and frequency tests delivers similar results. First, compared to the control group, the predicted borrower quality distribution in affected markets experiences a left shift of all quantiles. The average predicted quality also decreases, although not significantly at the conventional levels. Second, the increase in the number of originations comes from borrowers with predicted quality below the 20th percentile. The overall number of originations among those low-quality borrowers increases by 1.3 times. Again, these results are consistent with P2P platforms operating as substitutes to banks.

Overall, these findings suggest that P2P platforms are substitutes to banks in that they serve the same borrower population. However, the technological advantage of P2P platforms may allow them to operate as complements to banks in the dimension of loan size. More specifically, due to a low fixed cost of originating loans, P2P platforms may focus on the small loan size segment compared to banks. I thus repeat the analysis for the distribution of loan size. I find that borrowers migrating from banks to P2P platforms apply for larger loans than pre-existing P2P borrowers. Compared to the control group, the average loan size in affected markets increases by 9.6% (USD 1,066) and the loan size distribution experiences a right shift of almost all quantiles. Frequency tests show that the number of originations quadrupled for loans larger than the 80th percentile of the pre-shock loan size distribution. In contrast, the number of loans of smaller size does not change significantly. This is consistent with P2P platforms operating as complements to banks by offering smaller loans.

To understand the implication of the expansion of P2P lending for P2P investors, I analyze loan performance before and after the shock. Controlling for borrower characteristics, I find that loans originated after the shock are not more likely to default or being late in payment. Therefore, loan performance does not deteriorate after the shock.

Taken together, the evidence suggests that P2P platforms operate as substitutes to banks by serving infra-marginal bank borrowers. The expansion of P2P lending is likely to mostly benefit this group of borrowers. P2P credit is fungible with bank credit for borrowers who could have been served by banks, though loans offered by P2P platforms tend to be smaller.

Much of the emerging literature on P2P lending focuses on investor behavior in relation to borrower characteristics, e.g., appearance, disclosures, and social networks (Herzenstein, Sonenshein, and Dholakia 2011; Michels 2012; Duarte, Siegel, and Young 2012; Lin, Prabhala, and Viswanathan 2013; Freedman and Jin 2017). Several papers document herding by online lenders (Kim and Viswanathan 2016; Chuprinin and Hu 2016; Zhang and Liu 2012). Another line of research studies the information production and efficiency in P2P market through auctions (Franks, Serrano-Velarde, and Sussman 2016), screening accuracy (Balyuk (2016)), and the use of non-standard information (Iyer et al. 2015).

The current study is among the first to investigate P2P lending in relation to bank lending. Previous papers show mixed evidence on the type of borrowers served by P2P platforms relative to banks. For example, Buchak et al. (2017) document complementarity between FinTech lenders and banks in the residential lending market. They find that shadow banks, including FinTech lenders, gain a larger share among less creditworthy borrowers. Similar results are also found in the consumer credit market in Germany and China (De Roure, Pelizzon, and Tasca 2016; Liao et al. 2017). However, some opposite results have been documents in the U.S. consumer credit market. Wolfe and Yoo (2017) provide evidence in line with P2P platforms being substitutes to banks as small (rural) commercial banks lose lending volume in response to P2P lending encroachment.

This study differs from the previous ones in several ways. First, I address explicitly the issue whether P2P borrowers could have obtained bank credit by considering a shock to bank credit supply. Second, I provide causal evidence that borrowers substitute bank credit with

P2P credit. Third, whereas most studies focus on the average borrower quality, I provide precise characterization of the borrowers who migrate from banks to P2P platforms.

The rest of the paper proceeds as follows. Section 2 outlines the conceptual framework. Sections 3 and 4 describe the institutional background of P2P lending and the data. Section 5 presents the empirical strategy. Section 6 reports main results on P2P lending volume and borrower composition, while some additional results on P2P loan size and performance are presented in Section 7. Finally, Section 8 concludes.

2 Conceptual Framework

To guide the empirical investigation of the P2P-bank relationship, I analyze a simple framework in which P2P lenders and banks coexist. In particular, I derive predictions about the impact of a negative shock to bank credit supply on the quantity and composition of P2P loans.

There is a population of potential borrowers with quality γ distributed according to certain distribution. They can borrow either from a bank or from a P2P platform. I make two simplifying assumptions on the supply side and the demand side of the lending market. First, bank credit supply and P2P credit supply to borrowers with quality above some threshold $\underline{\gamma}^i$ are perfectly elastic, and the elasticities are zero to borrowers with quality below $\underline{\gamma}^i$, for $i \in \{bank, P2P\}$. Second, for any level of borrower quality, a fraction $\alpha \in [0,1]$ of borrowers choose to borrow from P2P platforms if they can obtain credit from either banks or P2P platforms.

To streamline the discussion, I first consider two polar cases in which P2P platforms are either perfect substitutes or perfect complements to banks, and then discuss intermediate cases. Each case is characterized by the value of three parameters: $\underline{\gamma}^{bank}$, $\underline{\gamma}^{P2P}$ and α.

2.1 Perfect substitutes

The case in which P2P platforms operate as perfect substitutes to banks corresponds to $\underline{\gamma}^{bank} = \underline{\gamma}^{P2P}$ and $0 < \alpha < 1$. In this case, P2P platforms compete with banks at every level in the borrower quality distribution and do not serve the unbanked population as represented in Figure 1(a), which plots the distribution of the quality of borrowers receiving a loan from either a bank or a P2P platform (blue curve) and the part of this distribution served by P2P platforms (red curve).

(a) Before the shock (b) After the shock

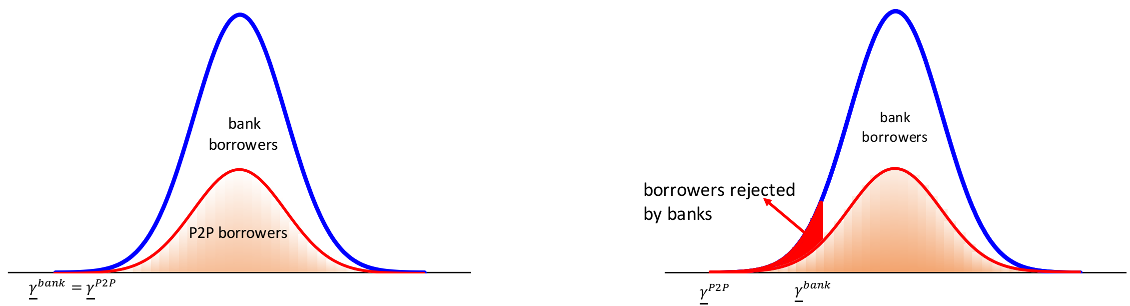

Figure 1: Borrower Quality Distribution: Perfect Substitutes

Notes: This figure shows the change in the P2P borrower quality distribution when banks tighten their lending criteria. The line at the top depicts the aggregate distribution of borrower quality; the area in orange represents the borrowers served by P2P platforms, while the area between the blue curve and the red curve are the borrowers served by banks. Panel (a) shows the initial distribution of P2P borrowers in the case of perfect substitutability (i.e., P2P platforms and banks serve the same population). Panel (b) shows the distributions after banks tighten their lending criteria; the borrowers in the red area switch to P2P platforms.

Consider now that the effect of a tightening of banks' lending criteria, i.e., an increase in $\underline{\gamma}^{bank}$, as illustrated in Figure 1(b). Borrowers with quality between $\underline{\gamma}^{P2P}$ and $\underline{\gamma}^{bank}$ previously borrowing from banks now obtain credit from P2P platforms. The quality of the borrowers migrating from banks to P2P platforms is at the low end of the pre-shock distribution of P2P borrower quality. It implies that the distribution of P2P borrower quality shifts to the left after the shock. More precisely, all the quantiles of the P2P borrower quality distribution decreases, while the increase in P2P lending volume is concentrated at the low end of the borrower quality distribution. To summarize:

Predictions from Substitutability: If P2P platforms and banks are perfect substitutes, a tightening of banks' lending criteria leads to the following predictions about P2P borrowers:

1. **Volume**: a higher P2P lending volume;

2. **Distribution**: a lower average P2P borrower quality and lower quantiles of the P2P borrower quality distribution;

3. **Frequency**: a higher P2P lending volume only in the low end of the pre-shock borrower quality distribution.

2.2 Perfect complements

P2P platforms are perfect complements to banks corresponds to $\underline{\gamma}^{P2P} < \underline{\gamma}^{bank}$ and $\alpha = 0$. In this case, P2P platforms and banks serve two non-overlapping segments of the market, with banks taking the high-quality borrowers and P2P platforms lending to individuals unable to obtain credit from banks, as represented in (Figure 2(a)).

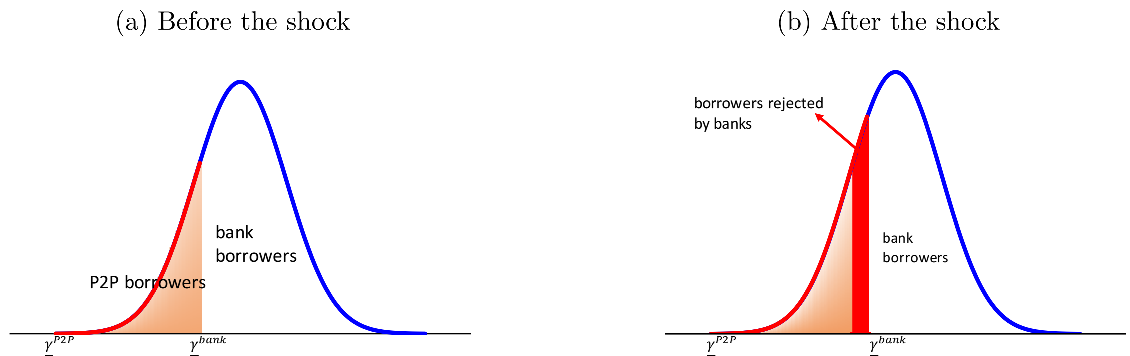

Figure 2: Borrower Quality Distribution: Perfect Complements

Notes: See the notes for Figure 1.

Again, consider a tightening of banks' lending criteria: $\underline{\gamma}^{bank}$ increases, as illustrated in (Figure 2(b)). Borrowers of quality between the pre-shock and post-shock values of $\underline{\gamma}^{bank}$ are denied access to bank credit and now borrow from P2P platforms. The quality of these new P2P borrowers is at the high end of the pre-shock distribution of P2P borrower quality. Therefore, the distribution of P2P borrower quality shifts to the right after the shock: all quantiles shift right. In addition, the increase in P2P lending volume is concentrated at the high end of the borrower quality distribution. To summarize:

Predictions from Complementarity: If P2P platforms and banks are perfect complements, a reduction in bank credit supply leads to the following predictions about P2P borrowers:

1. **Volume**: a higher P2P lending volume;

2. **Distribution**: a higher average P2P borrower quality and higher quantiles of the P2P borrower quality distribution;

3. **Frequency**: a higher P2P lending volume only in the high end of the pre-shock borrower quality distribution.

Comparing the predictions from substitutability with those from complementarity, one can notice that while the effect of the shock on P2P lending volume is the same whether P2P platforms substitute or complement banks, the effects on the distribution and frequency of P2P borrower quality are opposite. These opposite predictions will allow me to distinguish between the two cases in the empirical analysis.

As all the predictions are categorized into three groups (volume, distribution, and frequency), in the following, I use "Predictions on Volume" to refer to the predictions on volume from both substitutability and complementarity. "Predictions on Distribution" and "Predictions on Frequency" are similarly defined.

2.3 An intermediate case

My simple framework can also accommodate intermediate cases between perfect substitutability and perfect complementarity of banks and P2P platforms. For instance, P2P platforms may be substitutes to bank in the range of borrower quality served by banks while also complementing banks by lending to borrowers unserved by banks, i.e., $\underline{\gamma}^{P2P} < \underline{\gamma}^{bank}$ and $0 < \alpha < 1$, as represented in Figure 3(a). In this case, a tightening of banks' lending criteria will lead to an increase in P2P lending volume in the middle part of the P2P borrower quality distribution, as illustrated in Figure 3(b). Thus, analyzing changes in the frequency distribution of P2P borrower quality induced by the shock will also allow me to detect intermediate cases between perfect substitutability and perfect complementarity.[2] More specifically, the the tightening of lending criteria leads to a higher P2P lending volume in the middle of the distribution depending on the degree of substitution and complementarity.

[2]Another possibility not considered here is that P2P platforms cherry pick the highest-quality borrowers while banks lend to the rest of the population. In this case, a tightening of banks' lending criteria would have no effect on P2P lending volume, which I reject in the empirical analysis (see Section 6.1).

(a) Before the shock

(b) After the shock

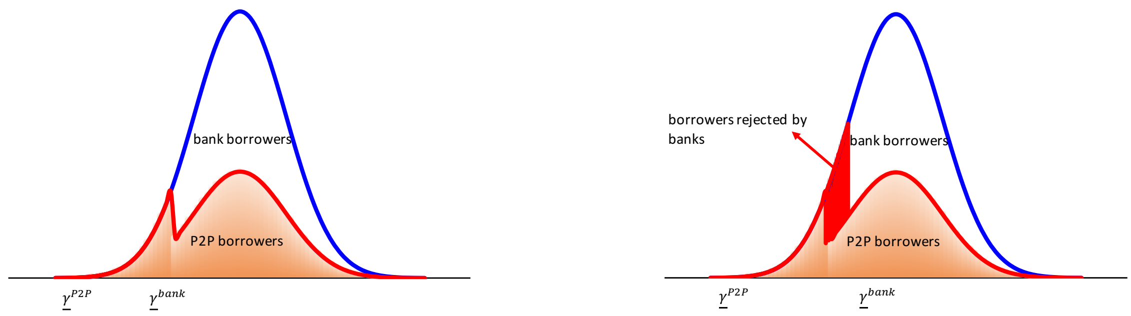

Figure 3: Borrower Quality in the Mixture Case

Notes: See the notes for Figure 1.

3 Institutional Background

3.1 LendingClub

This study uses a dataset from LendingClub, the largest online P2P lending platform in the U.S. To apply for a loan, an applicant reports her name, address, purpose of the requested fund, and the amount she wants to borrow on the platform. The platform uses the applicant's identity to acquire information on her credit report. It then filters out ineligible applicants based on the applicant's debt-to-income (DTI) ratio and FICO score. The cutoffs in terms of DTI ratio and FICO score are 0.35 and 660, respectively, during the sample period. If an applicant passes this screening process, LendingClub proposes to her a menu of loans with different amounts, maturities (either 36 or 60 months), and interest rates. Once an applicant has chosen a proposed loan from the menu, the loan request is listed on LendingClub's website and becomes accessible to investors .

Potential lenders, either institutions or individuals, compete to fund the loan on a first-come-first-serve basis based on the loan characteristics and a part of the borrower's credit report. Meanwhile, LendingClub also asks the applicant to report her income, profession, and employment length. For some applicants, LendingClub verifies the self-reported information. According to LendingClub's prospectus filed with SEC, 79% of the listed applicants in 2013 had their employment or income verified.[3] A listed loan can be unfunded for several reasons according to LendingClub: (i) the loan listing was removed based on "a credit decision or on a credit decision or the inability to verify certain borrower information", and (ii) the borrower withdrew her loan application. (iii) the listing is not fully funded. According to LendingClub, nearly all listed loans receive full investor funding, and many are fully funded in a few days.[4,5]

The applicants at LendingClub are located in 46 states and the District of Columbia. As of December 2016, LendingClub accounted for a 50% share in the U.S. market for P2P consumer loans, totaling USD 24.6 billion. On the investors side, during my sample period from 2009Q1 to 2012Q4, all loans are funded by individual investors.[6]

3.2 Pricing

To assess borrower credit risk, LendingClub assigns 35 credit grades from A1 to G5 based on a borrower's credit score, credit history, requested loan amount, and debt-to-income ratio. Interest rates are then determined based on the credit grades. Importantly, LendingClub's pricing policy is national, which means that the platform uses the same rule for loans from different locations.

This national pricing policy is in line with my assumption on the elastic supply of P2P credit. To show that indeed LendingClub's scoring model does not take into account the location of borrowers, I present LendingClub's prospectus filed with the SEC as well as my own empirical evidence in Section 7.2.1.

LendingClub's prospectus writes:

> *"Our interest rate committee sets the interest rates applicable to our loan grades. After a loan request's loan grade has been determined, we assign an interest rate to the loan request. For all loans, base interest rates will range between 5.32%*

[3] To verify income, LendingClub requests documents such as recent payrolls, tax returns, or bank statements. To verify employment, LendingClub may contact the employer or use other databases.

[4] Details on listing status can be found at https://help.lendingclub.com/hc/en-us/articles/213757368-Partially-funded-loans.

[5] For details on partially funded loans, see https://help.lendingclub.com/hc/en-us/articles/215488038-What-do-the-different-Note-statuses-mean-.

[6] After LendingClub opened the wholesale loan market to institutional investors in 2013, the share of loans funded by institutional investors increased up to 63% in 2015.

and 30.99%. We set the interest rates we assign to borrower loan grades in three steps. First, we determine Lending Club base rates. Second, we determine an assumed default rate that attempts to project loan default rates for each grade. Third, we use the assumed default rate to calculate an upward adjustment to the base rates (...) depending on the channel through which a borrower is sourced through, loan amount, term and other factors."[7]

To summarize, LendingClub takes two steps to establish the interest rate for each loan. A loan grade is first assigned, then the interest rate is calculated as the base rate in each loan grade plus an upward adjustment depending on the factors mentioned in the previous quote.

It is worth noting that no location-related factors are used in the pricing procedure. Recognizing the ambiguity in the textual description of the grading model and the platform's potential incentives to protect its private algorithm, I provide empirical evidence showing that the interest rates do not depend on borrower location in Section 7.2.1.

4 Data

P2P lending data I retrieve from LendingClub's website detailed information on all loan applications and funded loans between 2009 and 2012. For loan applications rejected by LendingClub in the initial screening process, the available information includes FICO score, DTI ratio, employment length, and city of applicants.[8] For funded loans, there is additional information on borrower's credit history, as well as loan performance if the loan has reached maturity. The final regression sample is constructed using 880,346 loan applications, of which 93,159 were funded.

Table 1 presents summary statistics of borrower and loan characteristics. An average

[7]According to the same prospectus, other factors include the general economic environment, taking into account economic slowdowns or expansions; the balance of funds and demand for credit through the platform, taking into account whether borrowing requests exceed investor commitments or vice versa; estimated default rates per loan type and competitive factors, taking into account the consumer credit rates set by other lending platforms and major financial institutions.

[8]LendingClub used to provide information on the city of borrowers, but recently this data entry has been replaced with three-digit ZIP codes. I thank Don Carmichael for sharing this previously-public dataset with me. The city names are then matched to county identifiers.

borrower has a FICO score of 711, a DTI ratio of 0.147, around 6 years of working experience, and applies for a loan of USD 13,224. The average interest rate is 13.3%, with the minimum being 5.4% and the maximum being 24.9%.

Bank data Banks that consolidate securitized assets under FAS 166/167 report the size of consolidated Variable Interest Entities (VIEs) in Schedule RC-V of the Call Reports starting in 2011Q1. I use the annual Call Reports to identify banks that consolidate securitized assets under FAS 166/167, and the Summary of Deposits to identify counties with presence of branches from those banks.

I also use use the Summary of Deposits to construct variables of the banking market structure at the county level: HHI, share of small banks, share of national banks, and the geographical diversity of local banks.

5 Empirical Strategy

In this section, I describe the main empirical strategy for testing the hypotheses generated by the conceptual framework in Section 2.

5.1 Identification strategy

Natural experiments in which banks cut lending for reasons unrelated to credit demand are rare. I circumvent this difficulty by exploiting an arguably exogenous shock to bank credit supply that was introduced by the implementation of the regulation FAS 166/167. In 2010, the Financial Accounting Standards Board (FASB) enacted a new regulation requiring banks to consolidate the assets held in VIEs (a) in their total assets when calculating leverage ratios and (b) in their risk-weighted assets when calculating risk-weighted capital ratios. The new regulation came with an optional four-quarter phase-in period.[9] I thus use 2011Q1 as the starting point of my post-shock period.

In total, 59 banks were subject to this regulation as they held off-balance sheet assets qualifying for consolidation. Dou, Ryan, and Xie (2016) report that at the end of 2010, assets held by the consolidated VIEs accounted for 5.3% of the banking industry's total

[9]For details, see https://www.federalreserve.gov/newsevents/pressreleases/bcreg20100121a.htm.

assets. Of these newly consolidated assets, about 10% were held by asset-backed commercial paper conduits, and 80% by other types of securitization entities, mostly credit card master trusts. Therefore, one expects to see a direct impact of FAS 166/167 on banks' choice of the quantity and quality of their credit card loans, because all credit card loans originated after the implementation of FAS 166/167 are treated as on-balance sheet assets.

Using data on small business lending at the bank-county level under the Community Reinvestment Act, I replicate the analysis in Dou (2016) and report the results in Appendix Table A2. I find that the regulation change leads affected banks to reduce small business lending by USD 3,097 per thousand inhabitants in the county, which represents 16% of the average small business lending volume before 2011. Moreover, the negative effect on credit supply is stronger for small businesses with annual revenues below USD one million than for those with annual revenue above. The reduction in lending for the two loan categories are USD 1,756 (20% of the pre-shock level) and USD 1,463 (14% of the pre-shock level), respectively. Due to the unavailability of personal loan data at the bank-county level, I cannot conduct the same exercise for consumer credit. However, it is plausible that the impact of FAS 166/167 on consumer credit is also negative.

In addition, Tian and Zhang (2016) show that after the implementation of FAS 166/167, the quality of credit card loans improves as the percentage of non-securitized credit card loans that are past due drops by 1.4 percentage points. This result provides empirical evidence that banks exhibit "fly-to-safety" behaviors by adjusting their loan portfolios away from risky borrowers.

The implementation of FAS 166/167 therefore provides me with an arguably exogenous shock inducing banks to cut lending at the bottom of their borrower quality distribution, which is in line with the type of bank credit shock in the conceptual framework outlined in Section 2. To identify the effects of this shock on P2P lending, I exploit variation in the presence of banks affected by FAS 166/167 across local markets.

5.2 Empirical specification

I identify the effect of FAS 166/167 on P2P lending by estimating regressions of the following form:

$$y_{c,t} = \beta \ Treated_c \times Post_t + Controls_{c,t} + \gamma_c + \sigma_t + \varepsilon_{c,t}, \tag{1}$$

where c denotes counties, and t indexes quarters or years, depending on the specifications. $Treated_c$ is a dummy variable equal to one for a county with at least one deposit branch of the banks affected by FAS 166/167, i.e., the banks required to consolidate off-balance sheet assets after the implementation of FAS 166/167. $Post_t$ takes value one from 2011 onwards and 0 before. γ_c represents a county fixed effect, and σ_t is a time fixed effect. $Controls_{c,t}$ denotes other control variables, including the banking market structure of county c at time t, as will be described below.

In terms of the dependent variable $y_{c,t}$, I use several measures to describe P2P lending. First, I measure the quarterly/annual P2P credit demand at the county level by the total volume of loan applications, which is either the dollar amount applied for or the number of applications, both normalized by county population. The quarterly/annual P2P lending volume is defined as the total loan amount or the number of funded loans, both normalized by county population. When either P2P application or origination volume is used as the dependent variable in Equation (1), I expect $\beta > 0$, no matter whether banks and P2P platforms are substitutes or complements (Predictions on Volume).

Second, to test the Predictions on Distribution and Frequency, I use two different measures for borrower quality. The first one is the FICO score, which is the most widely-used criterion in the loan underwriting process by financial institutions. However, borrower creditworthiness can be multidimensional. In this spirit, I develop an additional measure of borrower quality that combines information about FICO score, DTI ratio, and length of employment. More specifically, I first estimate an ordered probit model for the loan application outcome, which takes one of the three values — 0 if the application is rejected, 1 if it is qualified but not funded, and 2 if it is qualified and funded. The latent borrower quality determines the application outcome. With the model estimates, I then construct the predicted latent borrower quality, a continuous variable normalized to be between 0 and 1.

Details on the construction of this measure can be found in Appendix B.

To capture the statistical features of the distribution of P2P borrower quality, I construct the following measures: (i) the average quality of P2P borrowers; (ii) ten quantiles of the borrower quality distribution, the kth percentile with $k \in \{5, 15, \ldots, 95\}$; (iii) the number of borrowers in ten equal-width intervals of the P2P borrower quality distribution. For the FICO score, which ranges from 650 to 850, the ten intervals are 20-point wide. For predicted quality that takes value from 0 to 1, each of the ten intervals have a width of 0.1.

The Predictions on Distribution imply that $\beta < 0$ ($\beta > 0$) when the dependent variable is the average quality or quantiles if banks and P2P platforms are substitutes (complements). While the Predictions on Frequency imply that $\beta > 0$ when the dependent variable is borrower frequency of the low (high) end of the quality distribution, if banks and P2P platforms are substitutes (complements).

Lastly, banks and P2P platforms may be substitutes or complements along other dimensions of credit demand. One natural dimension is loan size, as P2P platforms may specialize in providing smaller-sized loans compared to banks. I therefore repeat the same exercises for loan size to obtain the average and the ten quantiles of the loan size distribution. In the sample period, loan size ranges from USD 1,700 to USD 35,000, I thus divide the support of loan size into ten intervals with a fixed width of 3,400 and calculate the number of loans in each loan size interval.

Following the banking competition literature, I construct various measures of the local banking market structure. I classify counties into three categories based on the value of the Herfindahl-Hirschman Index (HHI) of bank branches, with two conventional cutoffs at 1000 and 1800 (White 1987). Counties with lower HHI have more competitive markets. $Share(small\ banks)$ is the share of small banks with total assets below USD one billion. $Share(national\ banks)$ is the share of national banks. $Geo.\ diversification$, the median number of states that banks in each county operate in, captures the geographical diversification of local banks. *Deposit* is the dollar amount of total deposit in all local bank branches divided by county population. These variables control for local supply of bank credit, which may affect the demand for P2P credit.

I also control for county demographic and economic factors, including population, median personal income, and unemployment rate, as they may affect the size and composition of borrower pool.[10]

6 Main Results

6.1 Predictions on Volume

The first prediction of the simple framework outlined in Section 2 is that, regardless of the nature of the relationship between P2P platforms and banks, complements or substitutes, a tightening of banks' lending criteria induces an increase in the volume of P2P lending volume. To test this prediction, I estimate Equation (1) using P2P lending volume as the left-hand side variable. I use two measures of P2P lending volume: the total amount of loans and the number of loans, both normalized by county population (in thousands).

Table 2 lists statistics of county-level P2P lending volume. The average number of loan applications and qualified loans are 76 and 6, respectively. The largest local market, Los Angeles county, experiences 16,278 applications and 2,526 originations in 2012.

To visualize the timing of the effect of the bank credit shock, I start by replacing the $Post$ dummy in Equation (1) with year-quarter dummies and then plot the coefficients on the year-quarter dummies interacted with the $Treated$ dummy in Figure 4. P2P lending volume in the quarter preceding the policy change (2010Q4) is used as the reference level. Green dots represent loan applications and orange triangles represent funded loans. It shows that P2P application and origination volumes increase significantly in affected counties relative to control counties after the negative shock to bank credit supply, both in terms of the total loan amount (Panel a) and the number of loans (Panel b). In addition, there is no significant difference in P2P lending volume between treated counties and control counties before the shock. The absence of pre-shock trend reasures that the increase in demand for P2P credit is unlikely to be driven by unobservable differences between treated and control markets.

When I turn to predictions regarding the composition of borrowers in Sections 6.2 and 6.3, it will be preferable to work with annual data in order to obtain more precise measures of the statistical features (e.g., quantiles) of the borrower quality distribution at the county-

[10]The data on economic indices and demographics are from the Bureau of Economics Analysis.

time level. Thus, I re-estimate Equation (1) for P2P lending volume at the county-year level and tabulate the results in Table 3. Consistent with Figure 4, I find that, relative to control counties, affected counties experience an average increase in P2P loan application of USD 1,108 (column 1) or 0.070 additional loan applications (column 2) per thousand inhabitants. It represents 25.3% and 38.7% of the corresponding pre-shock levels (2,648 USD or 0.256 applications per thousand inhabitants). This higher demand is satisfied by the P2P platform. The lending volume increases by USD 301 (column 3) or 0.016 additional originations (column 4), representing 1.5 times the pre-shock level of the dollar amount originated and 1.1 times the pre-shock level of the number of originations.

To summarize, the results on P2P volume show that when banks cut lending in the consumer credit market, borrowers switch from traditional financial institutions to P2P platforms. This finding is consistent with P2P platforms and banks being either complements or substitutes (Predictions on Volume). I now turn to testing the Predictions on Distribution and Frequency of P2P borrowers where substitutability and complementarity lead to opposite predictions.

6.2 Predictions on Distribution

The Predictions on Distribution imply that if banks and P2P platforms are substitutes, the reduction in bank credit leads to a drop in the average quality of P2P borrowers and a decrease in the quantiles of the borrower quality distribution, whereas these predictions are reversed if banks and P2P platforms are complements.

To test these predictions, I estimate Equation (1) using the mean and quantiles of the borrower quality distribution as dependent variables. Table 4 reports the results when borrower quality is measured by the FICO score (Panel A) and by the predicted borrower quality (Panel B). A first look at the results reveals that, for both proxies of borrower quality, the quantiles (columns 1 to 10) as well as the mean (column 11) decrease simultaneously in treated counties relative to control counties, which is consistent with banks and P2P platforms being substitutes.

A closer look at the results allows me to make the interpretation more precise. First, the drop in the average borrower quality is not statistically significant at the conventional level (p-value equal to 0.12 in Panel A and 0.17 in Panel B). The reason can be grasped by inspecting more closely the effect on the quantiles. Using the FICO score to measure borrower quality, I find that while all quantiles decrease, the effect is statistically significant only above the 45th percentile. It suggests that the FICO scores of new borrowers are below the 45th percentile (equal to 690) of the pre-shock distribution of P2P borrowers' FICO scores. The frequency analysis in Section 6.3 will allow me to confirm and refine this conclusion.

Second, when using predicted borrower quality as a measure of quality, all the quantiles still decrease but the effect is now significant only at the 5th percentile. The interpretation is that while the borrowers rejected by banks who manage to obtain funding from the P2P platform belong to the bottom half of the FICO distribution, they belong to the very left tail of the quality distribution when the debt-to-income ratio and employment length are also taken into account. A possible explanation for this result is that the P2P platform imposes strict requirement on the FICO score but not on other borrower characteristics. It implies that the worsening of borrower quality is more visible on other dimensions than the FICO score.

The results on the change in the distribution of P2P borrower quality are thus consistent with banks and P2P platforms being substitutes. The analysis of quantiles has, however, one limitation when it comes to detect the range of the distribution in which new P2P borrowers rejected by banks are located. To see it, suppose for instance that all new P2P borrowers are between the 5th and the 45th percentiles. The regressions of quantiles will then show that all the quantiles from the 5th to the 95th decrease, failing to identify that the additional mass of borrowers stops at the 45th percentile. To overcome this limitation of the quantile analysis, I now analyze the frequency distribution of borrower quality.

6.3 Predictions on Frequency

The Predictions on Frequency are that, if banks and P2P platforms are substitutes, the increased demand for P2P credit will come from low-quality borrowers, leading to a higher number of borrowers only in the low-quality spectrum of the distribution. Instead, if P2P platforms operate as complements to banks, the increase in the number of borrowers will occur in the high-quality part of the distribution.

To test this prediction, I estimate Equation (1) using the number of P2P borrowers in each of the twenty-point-wide FICO score intervals between 650 and 850 as the dependent variable. The estimated coefficients are plotted in the top panel of Figure 5(a). I find that the increase in P2P lending volume is driven by the bottom two FICO score intervals, ranging from 650 to 690.

To interpret more precisely this result, I compare the estimated change in the frequency distribution (top panel) to the pre-shock distribution of P2P borrowers' FICO scores (bottom panel). The prediction is that, if banks and P2P borrowers are substitutes, the increase in the frequency distribution should be located in the left part of the support of the pre-shock distribution (see Figure 1), whereas if they are complements, the increase should be located to the right of the support of the pre-shock distribution (see Figure 2).

This is exactly what I find. More specifically, in the interval of FICO score between 650 and 690, which corresponds to FICO scores below the 45th percentile of the pre-shock distribution, the number of originations increases by 0.013 per thousand inhabitants (significant at 1% level), or 1.9 times of the pre-shock level. In contrast, the the number of originations does not increase significantly in other intervals where the FICO score is above 690. Thus, the increase in P2P lending induced by the shock to bank credit supply is located at the lower end of the P2P borrower quality distribution, consistent with P2P platforms and banks being substitutes.

I obtain similar results using predicted quality as the measure of borrower quality as reported in Figure 5(b). The top panel shows that the increase is located between 0.1 and 0.4, corresponding to the levels of predicted borrower quality below the 20th percentile of the pre-shock distribution. Comparing the top panel to the pre-shock distribution of predicted borrower quality in the bottom panel, we observe that the increase in the frequency distribution is indeed located in the left part of the pre-shock distribution. More specifically, the total number of originations in the bottom four intervals increases by 0.009 per thousand inhabitants (significant at 5% level), amounting to 1.3 times the pre-shock level. In contrast, the change in the other six intervals are not significant. These results suggest a disproportionally high growth in loan originations in low-quality intervals compared to in high-quality intervals.

Overall, the results in this section indicate that following the tightening of banks' lending criteria, P2P platforms experience an increase in originations among low-quality borrowers, in line with P2P platforms being substitutes to banks.

7 Additional Results

7.1 Complementarity in the loan size dimension

While I have shown that banks and P2P platforms are substitutes in the borrower quality dimension, they can still be complements along other dimensions of credit demand. With the internet-based loan underwriting process, P2P platforms may have a lower fixed cost in originating loans compared to banks, and thus specialize in providing smaller-sized loans.

To test this possibility, I follow the same approach as in Section 6 and apply the same analysis to the P2P loan-size distribution. As shown in Table 5, the average loan size increases by a statistically significant amount of US 1,066 (column 11). Moreover, the P2P loan-size distribution tilts towards the right end, as all percentiles except the 5th percentile move to the right (columns 1 to 10). The top two quantiles, the 85th and 95th, increase significantly by 1,563 USD and 3,870 USD, respectively. The interpretation is that the amount applied for by new borrowers is above the 85th percentile of the pre-shock loan size distribution. These results suggest that borrowers migrating to P2P platforms apply for larger loans than pre-existing P2P borrowers, in line with P2P platforms and banks being complements in the loan size dimension.

These results are also confirmed by frequency tests. As shown in the top panel of Figure 6, the increase in the number of originations only occurs in the top four intervals, where the loan size is between USD 21,400 and USD 35,000. This is in line with the results from the quantile analysis, because these new loans are larger than USD 19,750, the 90th percentile of the pre-shock loan-size distribution. Comparing the change in the distribution (top panel) to the pre-shock loan size distribution (bottom panel), one can observe a sizable increase in the right part of the distribution. In the top four intervals, the number of originations increases by 0.048 per thousand inhabitants, amounting to 4.3 times of the pre-shock level.

In contrast, none of the changes in other intervals is statistically significant at 5% level.

Taken together, the results on loan size suggest that P2P platforms complement banks by serving small-sized loans. This conclusion is subject to a caveat, however. The predictions generated by the simple framework in Section 2 rely on the assumption that banks curtail lending in the left part of the bank borrower distribution. This assumption is satisfied in the borrower quality dimension in my empirical setup, as FAS 166/167 leads banks to tighten credit standards, but it may not hold on the loan size dimension.

7.2 Plausibility of the assumption of elastic P2P credit supply

One of the assumptions in the framework presented in Section 2 is that the supply of P2P credit is elastic. It implies that an increase in the demand for P2P credit will not lead to a change in the interest rate. I now provide some empirical evidence to show the plausibility of this assumption.

If P2P credit supply is elastic, one should observe the following. First, at the platform level, P2P platforms do not adjust interest rates or screen borrowers based on local demand for P2P credit. Second, at the investor level, in response to the increased demand, P2P investors increase credit supply. In other words, the probability of loan listings being funded, after passing the initial screening by the platform, does not decrease.

I examine these two predictions one by one. I first show that interest rates set by the platform depend neither on the location of borrowers nor on the level of local demand for P2P credit following the negative shock to bank credit supply. Second, I present evidence that the probability of a loan listing being funded does not vary before and after the shock, conditional on loan characteristics.

7.2.1 LendingClub pricing policy

As explained in Section 3, according to LendingClub's prospectus, the interest rates on P2P loans do not depend on the location of borrowers. To verify whether this is actually the case, I test the joint significance of county fixed effects in the following regression:

$$y_{i,c,t} = \gamma_c + \beta Treated_c \times Post_t + \sigma_t + LoanControls_{i,c,t} + \varepsilon_{i,c,t},$$

where loans are indexed by i, counties by c, and quarters by t; $y_{i,c,t}$ is the loan grade or the interest rate of loan i; γ_c is the fixed effect for county c; $Treated \times Post$ is the interaction term used in the main specification; σ_t is quarter t's fixed effect; and $LoanControls_{i,c,t}$ includes loan and borrower characteristics.

I implement two sets of tests using the loan grade and the interest rate as dependent variables, because the platform sets the interest rate in two steps (see Section 3): it first assigns a loan grade based on borrower and loan characteristics, and then sets an interest rate based on loan grade and other factors. Hence, I first estimate the above equation using LendingClub's loan grade as the dependent variable. The loan grade takes 35 possible values, from A1 to G5. I assign 1 to 35 to each loan grade with lower numbers representing better grades. Second, I use the interest rate as the dependent variable, controlling for the loan grade.

If geography does not affect LendingClub's loan grade and interest rate, the county fixed effects should be zero in either regression. Similarly, if interest rates do not respond to local demand for P2P credit, the coefficient of the interaction term $Treated \times Post$ should also be zero.

Table 6 reports the regression results as well as F-statistics and p-values of the test on the joint significance of county fixed effects γ_c. As predicted, the county fixed effects are insignificant in all columns. The p-values of the test of the joint significance of county fixed effects are 0.188 (column 1) and 0.958 (column 3) when the dependent variable is loan grade and interest rate, respectively. Therefore, I fail to reject the null hypothesis that LendingClub's pricing policy is independent of borrower location. Moreover, as shown in columns 2 and 4, the estimated coefficients of $Treated \times Post$ is insignificant with t-statistics of -0.01 and -0.067. This implies that despite an increased demand for P2P credit in affected markets, interest rates do not adjust upwards for loans from those markets.

7.2.2 Investor funding behavior

Do P2P investors respond to an increased demand by raising credit supply, even though the interest rate does not increase? I show below that conditional on passing the initial screening by the platform, a loan listing has the same probability of being funded before and after the shock.

Using the data on loan listings, i.e., loan applications that have passed the initial screening procedure,[11] I estimate the following probit model:

$$
\begin{aligned}
&E(Funded_{i,c,t}|Treated, Post, Controls)\\
=&\Pr(Funded_{i,c,t} = 1|Treated, Post, Controls)\\
=&\beta Treated_c \times Post_t + \gamma_c + \sigma_t + Controls_{i,c,t},
\end{aligned}
$$

where $Funded_{i,c,t}$ is an indicator that takes value one if the listing received full funding and zero otherwise. If credit supply does not increase as much as the demand for credit, or if credit supply is even reduced, one will observe a negative β, i.e., a smaller fraction of loans will be funded after the shock.

Table 7 reports the results. In the first column, I do not include $Controls_{i,c,t}$. The county-level and loan-level control variables are gradually added to the regressions in the subsequent columns, while year and county fixed effects are always included. Across all specifications, the coefficient on $Treated \times Post$ is never significant. This result suggests that investors increase credit supply as a response to the increase in the demand for P2P credit even though the interest rate remains constant.

Overall, the evidence presented in this section is consistent with a perfectly elastic supply of P2P credit at the local market level, as assumed in the conceptual framework.

7.3 Implications for P2P Investors

The above results suggest that infra-marginal borrowers benefit from the expansion of P2P platforms, but remain silent about the effects on investors. I now examine the implications of the expansion of P2P lending on P2P investors. Specifically, I investigate whether the loan performance deteriorates when low-quality borrowers substitute bank credit with P2P credit. This would be true if the higher credit risk brought about by the worsening of the pool of P2P borrowers, following the negative shock to bank credit supply, is not or is imperfectly reflected in the interest rate.

[11] The data on loan listings are not available on LendingClub's website. I obtain this data from LendingClub's filings with SEC.

Since almost all loans originated no later than 2012 have reached maturity at the time of the data collection, I observe loan status. A loan can be fully paid, in grace period (late for 1-15 days), late for 16-120 days, charged off, or in default. I categorize a loan as non-performing if the loan is not paid in full, and test whether loan performance worsens in affected counties after the shock, controlling for interest rate. Now working at the loan level, I regress the non-performing loan dummy on the interest rate, the treated county dummy interacted with the post-FAS 166/167 dummy, as well as county and year fixed effects.

The results are reported in Table 8. In column 1, I check whether the interest rate predicts loan non-performance. Indeed, it does so with a high level of statistical significance (a t-statistic of 50). In column 2, I add the $Treated \times Post$ and find an insignificant coefficient. Adding the loan-level control variables (column 3) and the county-level control variables (column 4) yields similar results. To summarize, the worsening of the borrower pool is priced into interest rate, and therefore loan performance does not deteriorate after controlling for interest rate.

8 Concluding Remarks

The fast emergence of P2P lending after the 2008 financial crisis opens a hotly debated question about its consequences. The answer to the question crucially depends on whether the P2P industry merely displaces the incumbents or fills the gap in an under-served credit market. This paper provides insights on this debate by examining the relation between P2P platforms and banks. Exploiting a negative shock to bank credit supply, I show that P2P lending expands in the markets exposed to this shock. I also find evidence for substitution between banks and P2P platforms based on the fact that, when low-quality bank borrowers migrate to P2P platforms, P2P borrower pool worsens. This result suggests that the credit expansion opportunities brought by P2P lenders are likely to occur only for infra-marginal bank borrowers. On the other hand, P2P platforms complement banks by focusing on the market segment for small loans. The amount requested by borrowers migrating from banks to P2P platforms is larger than 90% of pre-existing P2P loans.

Although the empirical analysis carried out in the paper uses data from the largest P2P lending platform in the U.S., two caveats are in order. First, the empirical analysis focuses on the unsecured consumer loan market. The results may not generalize to other markets such as the residential lending market, or to other countries with a different banking market structure than the U.S. Second, the landscape of the FinTech industry is changing rapidly. Therefore, P2P platforms may not operate as substitutes to banks in the long run. That being said, it is noteworthy that notwithstanding the rapid growth of the sector, LendingClub was the dominant player in the P2P unsecured consumer loan market during my sample period 2019-12, and is still so in 2018, .

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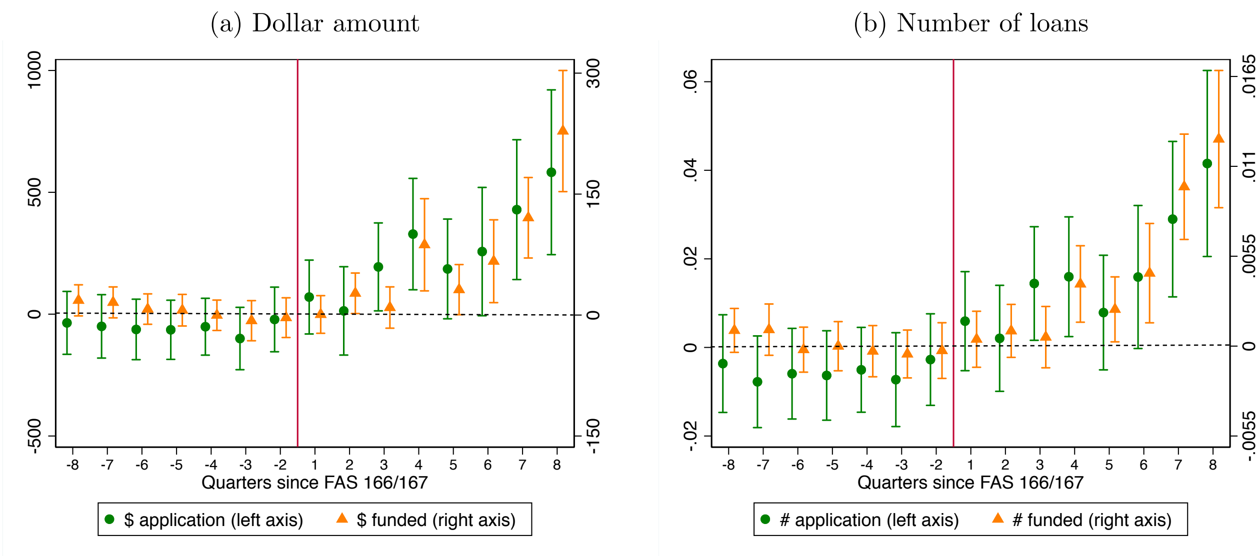
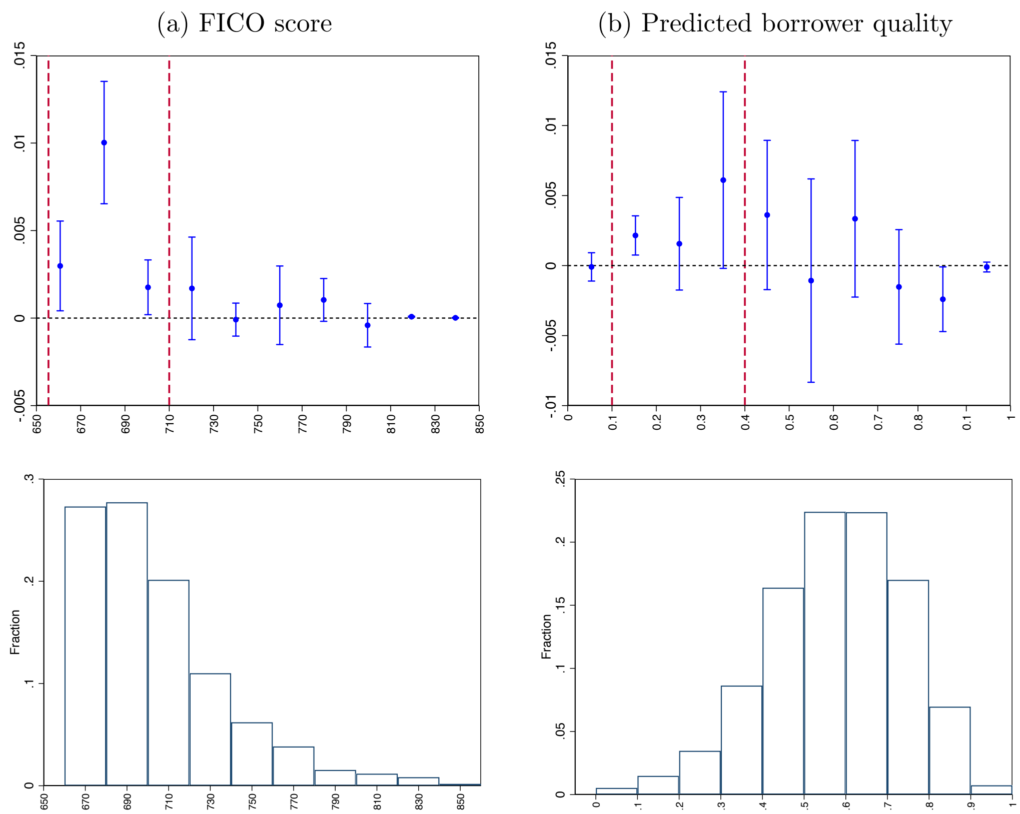
Figures and Tables

Figure 4: P2P Lending Volume around FAS 166/167



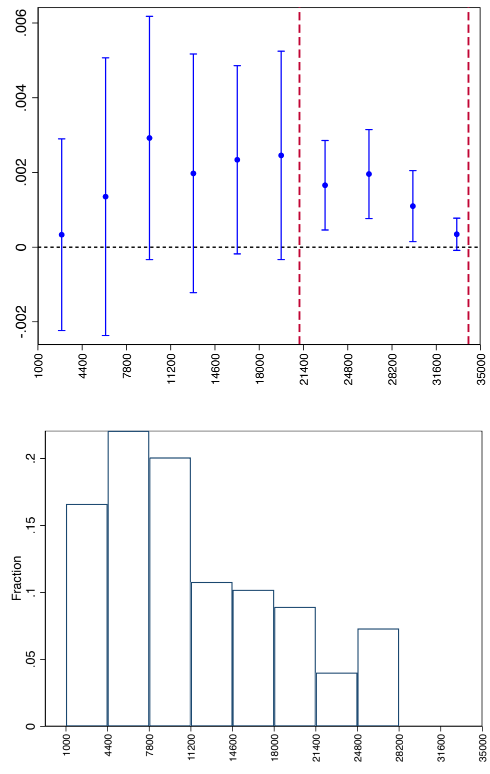
Notes: This figure reports the effects of FAS 166/167 on local P2P application volume (green dots) and origination volume (orange triangle), obtained from the estimates of Equation (1) at with the quarterly data. The left (right) vertical axis represents the magnitude of the green dots (orange triangle). P2P lending volume is measured in dollar amount per thousand inhabitants in panel (a) and by the number of loans per thousand inhabitants in panel (b). Quarter $t = -1$ denotes the last quarter of 2010 and is used as the reference point. Error bars show 95% confidence intervals. Standard errors are clustered at county level.

Figure 5: Frequency Change: Borrower Quality



Notes: This figure reports the effects of FAS 166/167 on the number of borrowers per thousand inhabitants in ten equal-width intervals of the P2P borrower quality. The coefficients plotted are obtained from Equation (1) with the annual data. In panel (a), borrower quality is measure by the FICO score and in panel (b) by the predicted borrower quality. The area between the two dashed vertical lines are where the number of borrowers increases significantly. The bottom part of each panel shows the pre-shock distribution of P2P borrower quality. Error bars depict 95% confidence intervals. Standard errors are clustered at county level.

Figure 6: Frequency Change: Loan Size



Notes: This figure reports the effects of FAS 166/167 on the number of borrowers per thousand inhabitants in ten equal-width intervals of P2P loan size. The coefficients plotted in the top part are obtained from Equation (1) with the annual data. The area between the two dashed vertical lines are where the number of borrowers increase significantly. The bottom part shows the pre-shock distribution of P2P loan size. Error bars show 95% confidence intervals. Standard errors are clustered at county level.

Table 1: Summary Statistics: LendingClub Loans

	Min	Mean	Max	Std. Dev.	Num. of observations
	Panel A. All applications				
Amount	1,000	1,3104	35,000	10,111	880,346
FICO score	457	666	815	82.988	880,346
DTI	0.000	0.188	1.000	0.162	880,346
LengthEmploy	0	2.053	11	3.553	880,346
	Panel B. Funded loans				
Interest rate	0.054	0.133	0.249	0.043	93,159
Amount	1,000	13,224	35,000	8,426	93,159
Maturity	0	0.135	1	0.342	93,159
DTI	0	0.147	0.332	0.079	93,159
FICO score	660	711	848	38	93,159
Predicted borrower quality	0	0.568	1	0.163	93,159
Mortgage	0	0.439	1	0.496	93,159
Home owner	0	0.106	1	0.308	93,159
Delinquency	0	0	1	0.016	93,159
Revolving balance	0	14,054	86,557	14,504	93,159
Total credit line	4	22.383	56	11.235	93,159
Open accounts	2	9.823	23	4.497	93,159
Revolver utilization	0	52.125	97.400	27.286	93,159
Inquiries last6m	0	0.953	5	1.151	93,159
Delinquency last2yers	0	0.174	3	0.506	93,159
LengthEmploy	0	5.703	11	3.929	93,159
LengthCredit	4	14.358	38	7.081	93,159

Notes: This table presents summary statistics of LendingClub loan characteristics for all loan applications (Panel A) and funded loans (Panel B). The definition of each variable is provided in Table A1 in Appendix A.

Table 2: Summary Statistics: County Characteristics

	Min	Mean	Max	Std. Dev.	Num. of observations
	Panel A. Lending Volume				
$ applications (in thousands)	0	776.090	240,235	4,012	15,180
# applications	0	76	16,278	288	15,180
$ funded loans (in thousands)	0	77.911	33,177	506.440	15,180
# funded loans	0	6	2,526	37	15,180
	Panel B. Normalized lending volume				
$ applications/(population/1000)	0	7,665	291,908	10,329	11,794
# applications/(population/1000)	0	0.585	18.935	0.701	11,794
$ funded loans/(population/1000)	0	604	50,457	1,387	11,794
# funded loans/(population/1000)	0	0.048	2.014	0.096	11,794
	Panel C. Other variables				
Treated	0	0.662	1	0.473	12,134
HHI	466	3,118	10,000	2041.191	12,058
Share(small banks)	0	0.389	1	0.402	12,058
Share(national banks)	0	0.154	1	0.271	12,058
Geo. diversification	1	3.037	40	4.642	12,058
Deposit	1,434	17809	1,795,294	24,379	11,728
Population	258	103,742	10,045,175	324,247	11,794
Personal income	14,360	35,298	176,046	9,681	11,794
Unemployment rate	1.600	8.922	28.900	3.026	11,795

Notes: This table shows the summary statistics of the county-level variables. Panels A and B report the overall P2P lending volume and the normalized P2P lending volume, respectively. Panel C presents other county-level variables. *Treated* is a binary dummy variable that takes value 1 if there is at least one bank affected by FAS 166/167 in the county. *HHI* measures market competition in the local banking industry. *Share(small banks)* is the share of banks with total assets below one billion; *Share(national banks)* is the share of national banks. *Geo. diversification* is a proxy for the geographical diversification of banks, measured by the median number of the states in which the banks in a given county operate. *Deposit* is the deposit per thousand inhabitants in a county. *Personal income* is the median annual personal income, in USD. *Unemployment* is the unemployment rate (in percentage points) in a given year in a county.

Table 3: The Impact of FAS 166/167 on LendingClub Demand and Supply

	Applications		Funded loans	
	Amount($)	Number(#)	Amount($)	Number(#)
	(1)	(2)	(3)	(4)
Treated × Post	1107.690***	0.070***	300.542***	0.016***
	(2.888)	(2.918)	(6.310)	(4.741)
$1000 \leqslant$ HHI < 1800	65.618	-0.019	-17.221	-0.000
	(0.130)	(-0.561)	(-0.191)	(-0.019)
HHI $\geqslant 1800$	151.585	-0.014	-36.821	0.000
	(0.242)	(-0.343)	(-0.348)	(0.024)
Share(small banks)	182.530	0.026	162.522	0.013
	(0.163)	(0.366)	(1.452)	(1.614)
Share(national banks)	-1159.254	-0.014	383.648	0.029*
	(-1.291)	(-0.236)	(1.473)	(1.794)
Geo. diversification	140.281**	0.013***	36.014	0.002*
	(2.167)	(3.055)	(1.481)	(1.696)
Population	-0.049***	-0.000***	-0.011***	-0.000***
	(-5.157)	(-5.225)	(-5.613)	(-5.651)
Deposit	0.004***	0.000***	0.001***	0.000***
	(3.098)	(2.953)	(2.617)	(4.038)
Personal income	0.013	0.000**	0.005	0.000
	(0.354)	(2.235)	(0.819)	(1.316)
Unemployment rate	747.445***	0.046***	79.788***	0.005***
	(6.339)	(6.521)	(3.792)	(4.885)
Year FE	Y	Y	Y	Y
County FE	Y	Y	Y	Y
Observations	11,726	11,726	11,726	11,726
R^2	0.710	0.756	0.532	0.557

Notes: This table reports the impact of the bank credit supply shock on P2P application and origination volumes, which is estimated from the following regression with the county-year data during 2009-12:

$$y_{c,t} = \beta Treated_c \times Post_t + Controls_{c,t} + \gamma_c + \sigma_t + \varepsilon_{c,t}.$$

The dependent variable is P2P application volume or P2P origination volume. Application volume is measured by either the total amount demanded in loan applications per thousand inhabitants (column 1) or the total number of loan applications per thousand inhabitants (column 2) in a given county. The same method is applied to the origination volume in columns 3 and 4. *Treated* is an indicator for whether there are affected banks in the county. *Post* takes value 1 from 2011 on and 1 before. Other county-level control variables are defined in Table A1. Year and county fixed effects are included in all regressions. t-statistics are in parentheses. Standard errors are clustered at county level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Changes in Post-shock Distributions of P2P Loans: Borrower Quality

	Percentile										Mean
	5th	15th	25th	35th	45th	55th	65th	75th	85th	95th	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
						Panel A. FICO score					
Treated×Post	-2.357	-0.317	-0.046	-2.402	-2.148	-8.675***	-7.996**	-8.790**	-6.716*	-1.175	-3.707
	(-0.744)	(-0.100)	(-0.015)	(-0.752)	(-0.680)	(-2.610)	(-2.311)	(-2.384)	(-1.710)	(-0.286)	(-1.562)
						Panel B. Predicted borrower quality					
Treated×Post	-0.053***	-0.021	-0.006	-0.013	-0.008	-0.023	-0.017	-0.024	-0.020	-0.007	-0.020
	(-3.060)	(-1.222)	(-0.396)	(-0.843)	(-0.532)	(-1.543)	(-1.124)	(-1.590)	(-1.352)	(-0.464)	(-1.396)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	5,059	5,059	5,059	5,059	5,059	5,059	5,059	5,059	5,059	5,059	5,059

Notes: This table reports the impact of the bank credit supply shock on the quantiles and the mean of the borrower quality distribution, which is estimated from the following regression with the county-year data during 2009-12:

$$y_{c,t} = \beta Treated_c \times Post_t + Controls_{c,t} + \gamma_c + \sigma_t + \varepsilon_{c,t}.$$

In each of columns 1-10, the dependent variable the k^{th} ($k \in \{5, 15, \ldots, 95\}$) percentile of the distribution of FICO scores (Panel A) and predicted borrower quality (Panel B). In column 11, the dependent variable is the average borrower quality. All columns include the same set of baseline controls as in Table 3 as well as county and year fixed effects. t-statistics are in parentheses. Standard errors are clustered at county level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Changes in Post-shock Distributions of P2P Loans: Loan Size

	Percentile										Mean
	5th	15th	25th	35th	45th	55th	65th	75th	85th	95th	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Treated×Post	-431.227	133.105	539.770	315.903	782.406	122.866	860.915	955.827	1562.936**	3869.708***	1066.046**
	(-0.774)	(0.240)	(1.003)	(0.559)	(1.360)	(0.209)	(1.456)	(1.433)	(2.049)	(4.819)	(2.043)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	5,059	5,059	5,059	5,059	5,059	5,059	5,059	5,059	5,059	5,059	5,059

Notes: This table reports the impact of the bank credit supply shock on the quantiles and the mean of the loan size distribution, which is estimated from the following regression with the county-year data during 2009-12:

$$y_{c,t} = \beta Treated_c \times Post_t + Controls_{c,t} + \gamma_c + \sigma_t + \varepsilon_{c,t}.$$

In each of columns 1-10, the dependent variable the k^{th} ($k \in \{5, 15, \ldots, 95\}$) percentile of the loan size distribution. In column 11, the dependent variable is the average loan size. All columns include the same set of baseline controls as in Table 3 as well as county and year fixed effects. t-statistics are in parentheses. Standard errors are clustered at county level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Testing the Elastic Supply of P2P Credit

	Loan grade		Interest rate	
	(1)	(2)	(3)	(4)
	Panel A: Test results			
Number of counties	1,925	1,925	1,925	1,925
F(1925, 89,839)	1.029	1.029	0.945	0.944
p-value	**0.188**	**0.186**	**0.958**	**0.958**
	Panel B: Estimated coefficients			
Treated × Post		-0.00186		-0.254
		(-0.010)		(-0.067)
Amount	0.000244***	0.000244***	0.000317***	0.000317***
	(157.750)	(157.745)	(9.133)	(9.136)
Loan term	6.185***	6.185***	10.38***	10.39***
	(225.074)	(225.080)	(15.139)	(15.152)
FICO score^2	0.000933***	0.000933***	0.00206***	0.00206***
	(147.587)	(147.582)	(14.582)	(14.583)
FICO score	-1.472***	-1.472***	-2.616***	-2.616***
	(-156.443)	(-156.439)	(-12.301)	(-12.304)
DTI	-13.42***	-13.44***	1804.2***	1803.8***
	(-4.360)	(-4.367)	(30.179)	(30.173)
FICO score × DTI	0.000583	0.000615	-2.507***	-2.506***
	(0.143)	(0.151)	(-31.670)	(-31.664)
DTI^2	33.11***	33.11***	-29.49	-29.60
	(20.739)	(20.733)	(-0.949)	(-0.952)
LengthEmploy	-0.0394***	-0.0393***	0.105	0.107
	(-3.696)	(-3.685)	(0.510)	(0.518)
LengthEmploy^2	0.00337***	0.00336***	-0.000775	-0.000965
	(3.910)	(3.895)	(-0.046)	(-0.058)
LengthCredit	-0.143***	-0.143***	0.874***	0.874***
	(-22.030)	(-22.026)	(6.934)	(6.936)
LengthCredit^2	0.00324***	0.00323***	-0.0223***	-0.0223***
	(18.995)	(18.993)	(-6.741)	(-6.741)
Mortgage	-0.354***	-0.355***	-3.703***	-3.707***
	(-14.391)	(-14.400)	(-7.735)	(-7.743)
Own	0.0133	0.0133	-1.109	-1.110
	(0.327)	(0.325)	(-1.399)	(-1.400)
Current delinquency	-1.804**	-1.805**	28.60*	28.59*
	(-2.161)	(-2.163)	(1.766)	(1.765)
Revolving balance	-0.0000135***	-0.0000135***	-0.000106***	-0.000106***
	(-14.588)	(-14.582)	(-5.899)	(-5.896)
Total credit lines	-0.00332**	-0.00329**	0.0980***	0.0984***
	(-2.356)	(-2.335)	(3.579)	(3.595)
Open accounts	-0.00694**	-0.00696**	0.285***	0.284***
	(-2.031)	(-2.038)	(4.292)	(4.287)
Revolver utilization	0.0299***	0.0299***	0.0184*	0.0184*
	(55.464)	(55.464)	(1.719)	(1.722)
Inquiries last6m	0.751***	0.751***	1.809***	1.810***
	(74.147)	(74.147)	(8.700)	(8.703)
Delinquency last2yrs	0.253***	0.253***	0.288	0.287
	(11.888)	(11.884)	(0.696)	(0.694)
Year-quarter FE	Y	Y	Y	Y
Loan grade FE	N	N	Y	Y
Observations	89,839	89,837	89,839	89,837
R^2	0.801	0.801	0.982	0.982

Notes: This table reports the test results of the elastic supply of P2P credit using the following regression equation, estimated at loan level during 2009-12:

$$y_{i,c,t} = \gamma_c + \beta Treated_c \times Post_t + LoanControls_{i,c,t} + \sigma_t + \varepsilon_{i,c,t}.$$

The dependent variable is either the loan grade assigned by LendingClub (columns 1-2) or the interest rate (in basis point) (columns 3-4). In all columns, loan and borrower characteristics are included. In columns 2 and 4, the interaction term $Treated \times Post$ is included. The F-statistic and p-value of the test on the joint significance of county fixed effects are reported in Panel A. Standard errors are clustered at county level. t statistics are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Probability of Loan Listings Being Funded

	Dependent variable = 1 if funded			
	(1)	(2)	(3)	(4)
Treated × Post	-0.016	-0.031	-0.098	-0.113
	(-0.252)	(-0.430)	(-1.303)	(-1.371)
Interest Rate			-13.427***	-13.337***
			(-45.898)	(-42.736)
Amount			4.6e-6**	4.8e-6**
			(2.259)	(2.154)
Amount × Interest rate			-0.000***	-0.000***
			(-10.498)	(-9.800)
FICO score			-0.086***	-0.086***
			(-22.276)	(-21.086)
FICO score^2			0.000***	0.000***
			(21.200)	(20.057)
DTI			16.972***	16.702***
			(12.996)	(12.002)
DTI^2			-18.921***	-18.711***
			(-31.131)	(-29.423)
FICO score × DTI			-0.015***	-0.015***
			(-8.683)	(-7.936)
LengthEmploy			0.014	0.014
			(0.802)	(0.657)
LengthEmploy^2			-0.001*	-0.001
			(-1.872)	(-1.489)
LengthCredit			0.014***	0.013***
			(4.886)	(4.255)
LengthCredit^2			-5.0e-4***	-4.8e-4***
			(-7.082)	(-6.318)
Mortgage			0.012	0.011
			(1.230)	(1.031)
Home owner			-0.295***	-0.302***
			(-20.097)	(-19.582)
Delinquency			-0.851***	-0.907***
			(-2.946)	(-2.983)
Revolving balance			-5.4e-6***	-5.5e-6***
			(-15.675)	(-15.649)
Total credit line			0.005***	0.006***
			(8.107)	(8.321)
Open accounts			0.009***	0.009***
			(6.323)	(5.628)
Revolver utilization			0.007***	0.007***
			(28.654)	(26.782)
Inquiries last6m			-0.079***	-0.077***
			(-17.014)	(-14.869)
Delinquency last2yrs			-0.010	-0.013
			(-1.186)	(-1.496)
County Controls	N	Y	N	Y
Year FE	Y	Y	Y	Y
County FE	Y	Y	Y	Y
# Observations	154,046	135,867	123,714	109,363
Pseudo R^2	0.018	0.018	0.152	0.151

Notes: This table reports the impact of the shock to the bank credit supply on the probability of P2P loans listings being funded. The estimates are from the following probit model with the loan level data during 2009-12:

$$
\begin{aligned}
&E(Funded_{i,c,t}|Treated, Post, Controls)\\
&= \Pr(Funded_{i,c,t} = 1|Treated, Post, Controls)\\
&= \beta Treated_c \times Post_t + \gamma_c + \sigma_t + Controls_{i,c,t},
\end{aligned}
$$

where the dependent variable is an indicator that takes value 1 if the loan listing is funded and 0 otherwise. In column 1, the interaction term is included as the explanatory variable. In columns 2 and 4, county level control variables are included. In columns 3 and 4, borrower characteristics and loan characteristics are included. Year and county fixed effects are always included. t-statistics are in parentheses. Standard errors are clustered at county level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Loan Performance

	Dependent variable = 1 if non-performing			
	(1)	(2)	(3)	(4)
Interest Rate	7.470***	7.470***	5.140***	5.120***
	(50.510)	(50.501)	(13.691)	(13.553)
Treated × Post		0.076	0.062	0.046
		(0.588)	(0.500)	(0.351)
Amount × Interest Rate			-0.000	-0.000
			(-0.885)	(-0.920)
Amount			0.000	0.000
			(0.749)	(0.745)
Maturity			0.293***	0.293***
			(16.781)	(16.771)
FICO score			0.020***	0.021***
			(3.326)	(3.423)
FICO score^2			-0.000***	-0.000***
			(-3.565)	(-3.655)
DTI			3.994**	4.410**
			(2.265)	(2.493)
DTI^2			0.857	0.809
			(0.934)	(0.875)
FICO score × DTI			-0.005**	-0.005**
			(-2.041)	-0.005**
LengthEmploy			-0.006	-0.007
			(-0.979)	(-1.066)
LengthEmploy^2			0.001	0.001
			(1.457)	(1.528)
LengthCredit			-0.001	-0.001
			(-0.330)	(-0.296)
LengthCredit^2			0.000	0.000
			(0.612)	(0.612)
Mortgage			-0.086***	-0.087***
			(-6.164)	(-6.131)
Home owner			-0.013	-0.011
			(-0.598)	(-0.505)
Revolving balance			-0.000***	-0.000***
			(-7.231)	(-7.084)
Total credit lines			-0.005***	
			(-6.618)	(-6.582)
Open accounts			0.006***	0.006***
			(3.083)	(3.026)
Revolver utilization			0.001***	0.001***
			(3.148)	(3.090)
Inquiries last6m			0.078***	0.078***
			(13.668)	(13.706)
Delinquency last2yrs			-0.023**	-0.024**
			(-2.054)	(-2.130)
County Controls	N	N	N	Y
Year FE	Y	Y	Y	Y
County FE	Y	Y	Y	Y
Observations	90,169	90,169	87,234	86,080
Pseudo R^2	0.065	0.065	0.078	0.077

Notes: This table reports the impact of the bank credit supply shock on loan performance. The estimates are obtained from the following probit model with the loan level data during 2009-12:

$$E(NPL_{i,c,t}|Treated, Post, Controls) = \Pr(NPL_{i,c,t} = 1|Treated, Post, Controls)$$
$$= \beta Treated_c \times Post_t + \gamma_c + \sigma_t + Controls_{i,c,t},$$

where the dependent variable is a dummy variable that takes value 1 if a loan is in default, charged off, in grace period, or late for 16-120 days. I add the following variables one by one: the interaction term $Treated_c \times Post_t$, borrower and loan characteristics, and county controls. County and year fixed effects are included in all specifications. t-statistics are in parentheses. Standard errors are clustered at county level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix

A Additional Tables

Table A1: Definition of Variables

Variable	Definition	Source
Credit supply shock		
Treated	An indicator for whether at least one bank is affected by FAS 166/167 in a given county.	Call Report, Schedule RC-V
Local market structure		
HHI	Herfindahl-Hirschman Index of banking market at county level based on deposit shares.	FDIC Summary of Deposits
Share(small banks)	Deposit share of small banks with total asset less than USD one billion.	FDIC Summary of Deposits
Share(national banks)	Deposit share of national banks at county level.	FDIC Summary of Deposits
Geo. diversification	The median number of states that banks at each county operate in.	FDIC Summary of Deposits
Deposit	Total deposits in all bank branches in the county, divided by population (in thousands).	FDIC Summary of Deposits
County demographics		
Population	Total population in the county.	Bureau of Economic Analysis
Personal income	Median annual personal income.	Bureau of Economic Analysis
Unemployment rate	Unemployment percentage.	Bureau of Economic Analysis

Definition of Variables, Continued

Variable	Definition	Source
Loan & borrower characteristics		
LendingClub interest rate	The interest rate proposed by LendingClub and accepted by borrowers and lenders.	LendingClub
Amount	The dollar amount requested by the borrower.	LendingClub
Maturity	The variable takes value 1 if the original maturity is 60 months, or 0 otherwise.	LendingClub
DTI	Debt-to-income ratio calculated using the borrower's total monthly debt payments on the total debt obligations, excluding mortgage and the requested LendingClub loan, divided by the borrower's self-reported monthly income.	LendingClub
LengthEmploy	Employment length reported by the borrower. It can take 10 values from less than 1 year, 2 years, 3 years...and equal or more than 10 years.	LendingClub
LengthCredit	The length of the borrower's credit history in years.	LendingClub
Homeowner	Home ownership status provided by the borrower during registration. It takes value 1 if the borrower owns his home completely.	LendingClub
Mortgage	Home ownership status provided by the borrower during registration. It takes value 1 if the borrower owns his/her home under mortgage.	LendingClub
Revolving balance	Total outstanding balance that the borrower owes on open credit cards or other revolving credit accounts reported by the credit bureau.	LendingClub
Total credit lines	The total number of credit lines currently in the borrower's credit file.	LendingClub
Open accounts	The number of open credit lines in the borrower's credit file.	LendingClub
Revolver utilization	Revolving line utilization rate, or the amount of credit that the borrower is using relative to all available revolving credit.	LendingClub
Inquiries last6m	The number of inquiries in past 6 months (excluding auto and mortgage inquiries) reported by the credit bureau.	LendingClub
Delinquency last2yrs	Number of delinquencies the borrower have had in the last two years.	LendingClub
Non-performing loan	The non-performing loan indicator takes value 1 if the current LendingClub loan status is default, charged off, late for 16-120 days, or in grace period.	LendingClub

Table A2: Effects of FAS 166/167 on Small Business Lending

	Total SBL volume ($) (1)	SBL volume ($) to borrowers w/ revenues < $1 million (2)	SBL volume ($) to borrowers w/ revenues < $1 million (3)
Treated	-3097.991**	-1756.203**	-1463.712*
	(-2.329)	(-2.274)	(-1.670)
Log(assets)	1349.621**	506.644**	834.959
	(2.068)	(1.547)	(1.547)
Tier-1 capital	573.676	4606.549	-4138.711
	(0.063)	(1.144)	(-0.595)
NPL ratio	-4536.097	-4989.639	110.879
	(-0.782)	(-0.938)	(0.025)
C&I loans	-269.005	-3003.313	2907.658
	(-0.060)	(-1.142)	(0.842)
Deposits	744.333	-416.897	1071.956
	(0.366)	(-0.359)	(0.675)
Securitization	-3201.790*	-2379.573**	-926.096
	(-1.783)	(-2.144)	(-0.864)
Year#County FE	Y	Y	Y
Bank FE	Y	Y	Y
N	277,426	270,404	270,404
R^2	0.208	0.210	0.184

Notes: This table reports the effects of FAS 166/167 on small business lending, which are estimated from the following regression with the bank-county-year level data during 2009-12:

$$SmallBusinessLending_{b,c,t} = Treated_{b,c,t} + BankControls_{b,t} + \sigma_{c,t} + \gamma_b + \varepsilon_{b,c,t}.$$

$Treated$ is a time varying variable and takes value one if bank b in county c consolidated assets under FAS 166/167 in year t. The dependent variable is the the dollar amount of small business loans per thousand inhabitants made by bank b in county c in year t. In column 1, the dependent variable is the total small business lending. In columns 2 and 3, the dependent variable is the lending volume made to small businesses with annual revenues below or above USD one million, respectively. Bank-level controls include size, measure by the logarithm of assets, tier-1 capital ratio, non-performing-loan ratio, commercial and industrial loans, deposits, and securitized asset, with the last three normalized by total assets. I also add $County \times Year$ and bank fixed effects to control for time-varying local economic conditions (e.g., credit demand) and bank unobservables. t-statistics are in parentheses. Standard errors are clustered at bank-level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B The construction of predicted borrower quality

This section describes the procedure for constructing the predicted borrower quality that combines information about FICO score, debt-to-income ratio and length of employment. These three variables are available for both rejected applications and qualified loans.

I estimate an order probit model for application outcomes with the following equation:

$$\begin{aligned} Quality_{i,c,t} = & \beta_1 FICO_{i,c,t} + \beta_2 DTI_{i,c,t} + \beta_3 LengthEmploy_{i,c,t} + \beta_4 FICO^2_{i,c,t} + \beta_5 DTI^2_{i,c,t} \\ & + \beta_6 LengthEmploy^2_{i,c,t} + \beta_7 FICO_{i,c,t} \times DTI_{i,c,t} \\ & + \beta_8 Amount_{i,c,t} + \beta_9 Amount^2_{i,c,t} + \gamma_{s,t} + \varepsilon_{i,c,t}, \end{aligned} \tag{2}$$

where $Quality_{i,c,t}$ is the latent quality of borrower i in county c at time t. Besides FICO score ($FICO_{i,c,t}$), debt-to-income ratio ($DTI_{i,c,t}$), length of employment ($LengthEmploy_{i,c,t}$), their squares, and some interaction, I also control for the amount applied for, as it may affect the application outcome; $\gamma_{t,s}$ is a state-year fixed effect, controlling for time-varying factors at state level; $\varepsilon_{i,c,t}$ has a standard normal distribution.

The latent borrower quality is unobservable but determines the application outcome in the following way:

$$Outcome_{i,c,t} = \begin{cases} 0 \text{ if } Quality_{i,c,t} < \underline{c}; \\ 1 \text{ if } \underline{c} \leqslant Quality_{i,c,t} < \overline{c}; \\ 2 \text{ if } Quality_{i,c,t} \geqslant \overline{c}. \end{cases}$$

The application outcome ($Outcome_{i,c,t}$), which is observable in the data, takes one of the three values: 0 if the application is *rejected*, 1 if it is *qualified but not funded*, and 2 if it is *qualified and funded*.

After estimating Equation (2), I use the estimated coefficients (β_1–β_7) for the three variables ($FICO_{i,c,t}$, $DTI_{i,c,t}$, and $LengthEmploy_{i,c,t}$), the squares of these variables, and the interaction to calculate the predicted value of $Quality_{i,c,t}$. When doing so, $Amount_{i,c,t}$ and $\gamma_{t,s}$ are set to be constant for all applicants, which amounts to filtering out their effects on the application outcome. In other words, the predicted value of $Quality_{i,c,t}$ only captures the contribution of the three variables of interest to $Quality_{i,c,t}$. A higher value of the predicted value of $Quality_{i,c,t}$ indicates a higher borrower quality and thus a higher probability of being qualified/funded.

The expression for the predicted borrower quality, denoted as $\widehat{Quality}_{i,c,t}$, is the following:

$$\begin{aligned}\widehat{Quality}_{i,c,t} =& 0.230FICO_{i,c,t} + 31.892DTI_{i,c,t} + 0.205LengthEmploy_{i,c,t} \\ & - 0.00015FICO^2_{i,c,t} + 36.745DTI^2_{i,c,t} - 0.007LengthEmploy^2_{i,c,t} \\ & - 0.0298 * FICO_{i,c,t} \times DTI_{i,c,t}.\end{aligned}$$

Not surprisingly, the predicted borrower quality is increasing in FICO scores and length of employment, and decreasing in debt-to-income ratio. All the seven coefficients are statistically significant at the 1% level. Furthermore, the pairwise correlations among the predicted borrower quality, FICO socre, DTI ratio, and employment length are shown in Table C1. All of them are significant at the 1% level.

Table C1: Pairwise correlation between predicted borrower quality and borrower characteristics

	Predicted borrower quality	*FICO Score*	*DTI*	*LengthEmploy*
FICO Score	0.7107***	1		
DTI	-0.3945***	0.0501***	1	
LengthEmploy	0.3676***	0.3129***	-0.0688***	1

I then normalize the predicted borrower quality with an affine transformation,

$$\frac{\widehat{Quality}_{i,c,t} - \min_{i,c,t}(\widehat{Quality}_{i,c,t})}{\max_{i,c,t}(\widehat{Quality}_{i,c,t}) - \min_{i,c,t}(\widehat{Quality}_{i,c,t})}.$$

The normalized predicted borrower quality is between 0 and 1 and is referred to as "the predicted borrower quality" in the main text.