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

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This paper studies whether, in the consumer credit market, peer-to-peer (P2P) lending platforms serve as substitutes for banks or instead as complements. I develop a conceptual framework and derive testable predictions to distinguish between these two possibilities. Using a regulatory change as an exogenous shock to bank credit supply, I find that P2P lending is a substitute for bank lending in terms of serving infra-marginal bank borrowers yet complements bank lending with respect to small loans. These results indicate that the credit expansion resulting from P2P lending likely occurs only among borrowers who already have access to bank credit. (*JEL* D14, E51, G2)

Peer-to-peer (P2P) lending platforms, which emerged after the 2008 financial crisis, allow individuals and small businesses to borrow without the presence of traditional financial institutions. Following several years of exponential growth, this sector is now a significant supplier of credit to consumers. According to TransUnion, a U.S. credit reporting agency, technology-based lenders have become the biggest lender type and account for 30% of the unsecured installment loan sector in 2016.[1]

Yet little is known about the borrower segments that P2P platforms serve. Do such platforms meet the credit demand that would otherwise be unmet by banks? Or do they compete with banks for the same clientele? This issue is important for assessing the implications of

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[1] For details, see https://newsroom.transunion.com/fintechs-taking-larger-share-of-personal-loan-market-while-increasing-portfolio-risk-return-performance/

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P2P lending expansion. If P2P platforms are complements to banks, they can make finance more inclusive by expanding credit access for borrowers who are underserved by the banking system. If instead they compete directly with banks, the credit expansion brought about by P2P platforms is probably limited to borrowers who have ready access to bank credit.

This paper investigates whether P2P platforms and banks are substitutes or complements in the consumer credit market. The empirical challenge is that the econometrician does not observe whether P2P borrowers have access to equivalent bank lending. For instance, borrowers may voluntarily choose P2P credit over bank credit, or they may be forced to seek P2P loans after being denied access to bank loans. It is therefore not sufficient—simply by looking at the characteristics of P2P borrowers—to determine whether most P2P borrowers are underserved by banks or instead are infra-marginal bank borrowers.

To address this problem, I develop a conceptual framework in which P2P platforms may operate as substitutes for banks or instead as complements. I derive testable predictions about the effect of a negative shock to bank credit supply on the distribution of P2P borrower quality. The key identification assumption is that, if banks experience a shock that leads them to reduce credit supply, they tighten lending criteria. Borrowers at the *lower* end of the bank borrower quality distribution are therefore more likely to lose access to bank credit and hence migrate to P2P platforms. This results in a potential shift in the distribution of P2P borrower quality.

The nature of the resulting change in the P2P borrower quality distribution depends on whether banks and P2P platforms are substitutes or complements. Suppose first that they are substitutes. In that case, the two types of lenders serve the same clientele before the shock and face the same distribution of borrower quality. Following a negative shock to bank credit supply, low-quality bank borrowers will migrate to P2P platforms. Hence the average P2P borrower quality should drop, and all the quantiles of the distribution of P2P borrower quality should decrease.

Now suppose that P2P platforms instead complement banks by serving a low-quality borrower segment that is underserved by banks. In this case, the borrower pool of P2P platforms is of worse quality than that of banks. Following the shock to bank credit supply, borrowers switching from banks to P2P platforms will be of higher quality than existing P2P borrowers. The average P2P borrower quality should then improve, and all the quantiles of the distribution of P2P borrower quality should increase.

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, that required banks to consolidate securitized off–balance sheet assets onto their balance sheets and, starting in the first quarter of 2011 (2011Q1), to include them in their risk-weighted assets. In aggregate, this caused banks to consolidate more than $600 billion of assets in 2011, over 80% of which were revolving consumer loans.[2] This accounting change had a considerable effect on bank lending through its impact on regulatory capital. Banks with different amounts of off–balance sheet securitized assets that were subject to consolidation were heterogeneously affected. Previous studies show that affected banks reduced their small business lending and mortgage approval rates (Dou 2017; Dou, Ryan, and Xie 2017), while increasing their mortgage sales rates (Dou, Ryan, and Xie 2017) and the average quality of credit card loans (Tian and Zhang 2018).

I conjecture that this shock affected local credit markets differently depending on the exposure of local banks to the regulation change. I classify banks as being treated if they held off–balance sheet assets subject to consolidation under FAS 166/167. Treated markets are defined as counties with at least one treated bank; other counties constitute the control group. I then examine the changes in the distribution of P2P borrower quality in treated markets. Thus the effect of the bank credit supply shock on the distribution of P2P borrower quality is identified by the variation in exposure to that shock across local markets.

Using asset consolidation data obtained from Call Reports, which are mandated by the Federal Deposit Insurance Corporation (FDIC), I identify a total of 59 banks that consolidated assets under FAS 166/167. Data on P2P lending volume, loan application, and borrower characteristics are obtained from LendingClub, a large P2P platform representing more than half of the US market share of P2P-based personal loans.[3] I construct county-level variables using data on 880,346 loan applications and 93,159 loan originations during the period 2009–2012. The final sample consists of 1,908 treated and 1,025 untreated markets, all defined at the county level.

The first step of my analysis is to examine the treatment effect of FAS 166/167 on P2P loan application and origination volumes. I find that, relative to the control group, treated markets experienced a disproportionate increase in P2P loan applications after 2011. Per thousand inhabitants in treated counties, an average of 0.07 more

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

[3] Source: https://www.statista.com/statistics/468469/market-share-of-lending-companies-by-loans/

applications were made for an additional \$1,108; this figure represents a 25% increase in the number of applications and a 39% increase in their respective dollar amounts. These 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 at least partially satisfied by P2P platforms. I find that treated markets also saw an increase (over the control group) in the total number and dollar amount of P2P loans. Again per thousand county inhabitants, an average of 0.016 more P2P loans were originated for an additional amount of \$301. In comparison with the pre-shock level of originations, the number (amount) of loans increased by a factor of 1.1 (1.5).

Next, I test predictions concerning the shock's effect on the distribution of P2P borrower quality. Toward that end, FICO scores are used as a measure of borrower quality. I find that, compared with the control group, treated markets experienced a decrease in all the quantiles of the distribution. On average, the ten deciles decreased by 4 points, that is, 2% of the difference between the maximum and the minimum of the FICO scores of LendingClub borrowers. Most prominently, the top four deciles decreased by an average of 8 points. According to this result, P2P platforms act as substitutes for banks.

Tests exploiting 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, then a higher frequency should be observed only in the low-FICO range of the P2P borrower quality distribution. This is indeed what I find. The number of originations increased by 1.9 times among borrowers with FICO scores below 710, or the 45th percentile of the pre-shock FICO scores of LendingClub borrowers; in contrast, there was no significant change in the number of originations at the upper end of the distribution.

The FICO score is a fairly coarse measure of borrower quality, so banks often use additional information to assess default risk. For example, data collected under the Home Mortgage Disclosure Act (HMDA) show that the primary reasons for mortgage application denials include credit history, debt-to-income ratio, and length of employment. I therefore construct another measure of borrower quality that combines FICO score, debt-to-income ratio, and length of employment. More specifically, I estimate an ordered probit model in which the dependent variable is the application outcome (rejected, qualified but not funded, or qualified and funded) and the explanatory variables are those three borrower characteristics. The model estimates allow me to construct a single-dimension cardinal measure: the predicted borrower quality, normalized to be between 0 and 1.

Using this new measure in the quantile and frequency tests delivers similar results as before. First, the predicted borrower quality distribution in treated markets experienced a decline, with respect to the control group, in all the quantiles. In particular, the average reduction in the ten deciles is 0.02, or 2% of the difference between the maximum and the minimum of the predicted borrower quality. Second, frequency tests show that the increase in the number of originations was driven by borrowers whose predicted quality is below the 20th percentile. The overall number of originations among those low-quality borrowers increased by a factor of 1.3. Once again, the results are consistent with the hypothesis that P2P platforms operate as substitutes for banks.

Overall, these findings indicate that P2P platforms are substitutes for 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 terms of loan size. That is, in light of their low fixed cost of originating loans, P2P platforms may be able to focus on providing smaller loans than banks, and therefore operate as complements in this segment of the market.

To test this hypothesis, I repeat the analysis for the distribution of P2P loan size. I find that borrowers migrating from banks to P2P platforms applied for larger loans than did pre-existing P2P borrowers. Relative to the control group, the average P2P loan size in treated markets increased by 9.6%, or $1,066, and almost all the quantiles of the loan size distribution exhibited an increase. In particular, the top two quantiles, the 85th and 95th, increased significantly by $1,563 and $3,870, respectively. Moreover, frequency tests show that the number of originations quadrupled for loans larger than the 80th percentile of the pre-shock loan size, whereas the number of smaller loans did not change significantly. This outcome is consistent with P2P platforms operating as complements to banks in the small loan market.

Taken together, the evidence suggests that P2P platforms operate as substitutes for banks by serving infra-marginal bank borrowers, who are thus the most likely to benefit from the expansion of P2P lending. On the one hand, peer-to-peer credit appears to be fungible with bank credit for borrowers who could have been served by banks, but on the other hand, the loans offered by P2P platforms tend to be relatively smaller.

Related literature. Much of the emerging literature on P2P lending focuses on investor behavior in relation to borrower characteristics such as appearance, disclosures, and social networks (Herzenstein, Sonenshein, and Dholakia 2011; Duarte, Siegel, and Young 2012; Michels 2012; Lin, Prabhala, and Viswanathan 2013; Freedman and Jin 2017). Several studies document herding by investors (Zhang and Liu 2012; Chuprinin and Hu 2016; Kim and Viswanathan 2016) or the adverse incentives of investors when there are rewards for loan originations

(Hildebrand, Puri, and Rocholl 2016). Other lines of research investigate information production and efficiency in the P2P lending market from the perspectives of investors' use of nonstandard information (Iyer et al. 2015), the efficiency of auction-based versus centralized pricing (Franks, Serrano-Velarde, and Sussman 2016), or information spillover from P2P lenders to traditional banks (Balyuk 2018). Vallee and Zeng (2018) examine, through the lens of optimal platform design, how the production of information is shared between platforms and investors.

This paper is among the first to investigate P2P lending in relation to bank lending. Previous studies have yielded mixed evidence on the type of borrowers served by P2P platforms—or, more broadly, FinTech lenders—as compared with those served by banks.[4] For instance, Buchak et al. (2018) document complementarity between FinTech lenders and banks in the residential lending market; they find that "shadow" banks garner a larger share of less creditworthy borrowers. However, Fuster et al. (2018) find no evidence that FinTech lenders target risky or marginal borrowers. A few studies also examine the consumer credit market. De Roure, Pelizzon, and Thakor (2018) develop a model with endogenous choices of bank versus P2P lending and then test their predictions using German consumer credit data. These authors find that P2P loans are on average riskier than bank loans but that risk-adjusted rates on P2P loans are actually lower than those on bank loans. Using survey data, Liao et al. (2017) similarly find that, in China, P2P platforms focus on underserved borrowers. Even so, contrary findings have been documented in the US consumer credit market: Wolfe and Yoo (2017) document that small (rural) commercial banks lose lending volume to encroachment by P2P lending, which accords with P2P platforms being substitutes for banks.

This study differs from those aforementioned in several ways. First, I develop a conceptual framework to study segmentation in the credit market—a framework that may be adapted for the study of other markets. Second, by considering a negative shock to bank credit supply, I explicitly address the issue of whether P2P borrowers could have obtained bank credit. Third, unlike other studies that focus on average P2P borrower quality, I infer the P2P–bank relation from a rich set of the distributional features of borrower quality, such as quantiles.

[4] P2P lending, as a form of FinTech lending, is mostly present in the consumer credit market. FinTech lenders are different from traditional banks, including online banks, in two major ways. First, FinTech lenders automate the loan origination process and require zero or minimum human interactions (see Buchak et al. (2018) and Fuster et al. (2018) for a more precise definition). Second, they are not subject to capital requirement constraints faced by deposit-taking institutions.

1. Conceptual Framework

To guide the empirical investigation of the P2P–bank relation in serving various borrower segments, I develop a simple framework in which P2P lenders and banks coexist. I then derive predictions about the effect of a negative shock to bank credit supply on the quantity and composition of P2P loans.

The conceptual framework considers a consumer credit market in which banks and P2P lenders compete with each other. For borrowers of a given quality, $\gamma \in \mathbb{R}_+$, each lender, either a bank or a P2P platform, offers a menu of price-quantity combinations specifying interest rates and the corresponding loan sizes. It is possible that a lender excludes borrowers with insufficient quality. That is, some borrowers cannot obtain loans from a lender at any possible interest rate. The market reaches an equilibrium when, given the menus offered by other lenders, each lender provides an optimal (profit-maximizing) menu given each level of borrower quality γ; in addition, on the borrower side, everyone chooses the optimal price-quantity combination offered to her.

The relation between banks and P2P lenders is defined by the clientele they serve in equilibrium. Considering the total number of quality-γ borrowers who are served by either type of lenders, I let $\alpha(\gamma) \in [0,1]$ be the fraction of borrowers who are served by P2P lenders.[5] For a given borrower quality γ, the two types of lenders are substitutes if $0 < \alpha(\gamma) < 1$; they are complements if $\alpha(\gamma)$ is either 0 or 1.

I derive the predictions about the effect of a shock to bank credit supply under the following assumptions. First, the market is in equilibrium before the shock, and it immediately reaches a new equilibrium after the shock. By investigating the differences between the pre-shock and post-shock equilibria, I infer the pre-shock P2P–bank relation.

The second assumption is that in equilibrium, both banks and P2P platforms set an optimal lender-specific threshold, $\underline{\gamma}^i$, $i \in \{\text{bank,P2P}\}$. Moreover, for borrowers whose quality is above the threshold, the respective credit supply is perfectly elastic, while borrowers whose quality is below $\underline{\gamma}^i$ cannot obtain loans from lender i. The lender-specific thresholds may stem from various sources such as risk-based capital requirement (faced by banks), statutory interest rate limits on consumer credit products, and the interaction between interest rate and

[5] $\alpha(\gamma)$ is not defined for borrowers with quality γ who are not served by any lender.

default probability.[6,7] The assumption of an elastic P2P credit supply at the local market level is also plausible given P2P platforms' national pricing policy (to be introduced in Section 2.2), and I formally test this assumption in Section 5.

To streamline the discussion, I first consider two polar cases—where banks and P2P platforms are either perfect substitutes or perfect complements—and then discuss an intermediate case. Under the assumptions just described, each case is fully characterized by the following parameters: $\underline{\gamma}^{\text{bank}}$, $\underline{\gamma}^{\text{P2P}}$, and $\alpha(\gamma)$.

1.1 Perfect Substitutes

P2P platforms operate as perfect substitutes for banks when the following conditions are satisfied:

$$\underline{\gamma}^{\text{bank}} = \underline{\gamma}^{\text{P2P}};\ 0 < \alpha(\gamma) < 1, \forall\ \gamma \geq \underline{\gamma}^{\text{bank}}.$$

That is, banks and P2P platforms employ the same lending threshold. Among all borrowers qualifying for both types of credit, some but not all choose P2P platforms over banks, potentially because of their preferences or borrower-specific costs. Without loss of generality, I assume that $\alpha(\gamma) = \alpha$, $\forall\ \gamma \geq \underline{\gamma}^{\text{bank}}$. In this case, P2P platforms provide all existing bank borrowers with a substitute loan product and do *not* serve the "unbanked" population; see Figure 1(a). The distribution of the quality of borrowers receiving a loan from either a bank or a P2P platform is represented by a solid curve, and the part of the borrowers served by P2P platforms is shaded under a dashed curve. The unshaded area under the dotted curve corresponds to unserved borrowers.[8]

Now consider the effect of tightened bank lending criteria, or an increase in the optimal lending threshold from $\underline{\gamma}^{\text{bank}}$ to $\underline{\hat{\gamma}}^{\text{bank}}$, induced by a negative shock to bank credit supply. As illustrated in Panel (b) of Figure 1, borrowers of quality between $\underline{\gamma}^{\text{bank}}$ and $\underline{\hat{\gamma}}^{\text{bank}}$ in the darker area, who previously borrowed from banks, now obtain credit only from

[6] For example, the interest rate restriction in California is 36% for loans in the range $2,550-$25,000. LendingClub caps the interest rate at 36% and thereby excludes most deep subprime borrowers from the platform. Rigbi (2013) finds that an increase in interest rate cap resulted in borrowers having greater access to credit through the P2P platform and also that the marginal borrowers benefited the most from the lifted interest rate cap.

[7] This interaction can be described as follows. A lender would prefer charging high interest to a low-quality borrower (who has high default probability); however, doing so adversely affects the borrower's capacity to repay the debt, thus increasing the default probability (Stiglitz and Weiss 1981). Hence charging high interest rates to low-quality borrowers hardly guarantees the profitability of such loans. This two-way interaction may give rise to a borrower quality threshold below which a loan is not expected to be profitable.

[8] The distribution is a beta distribution, *Beta*(3,2), which is similar to the empirical distributions of the FICO score documented in Keys et al. (2010) and Agarwal et al. (2014).

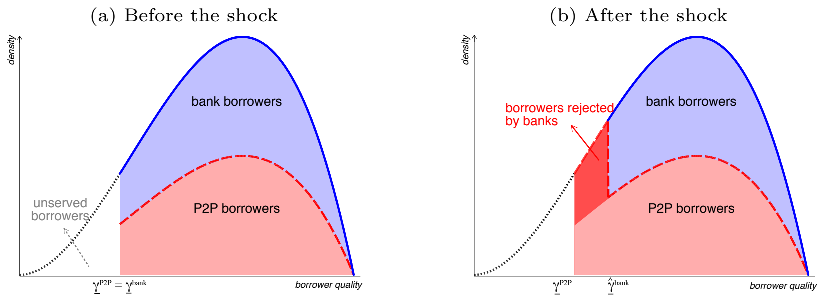

Figure 1
Borrower Quality Distribution: Perfect Substitutes
This figure shows the change in the P2P borrower quality distribution when banks tighten their lending criteria. The uppermost plotted line marks the aggregate distribution of borrower quality. Panel (a) shows the initial distribution of P2P borrowers (area under the dashed curve) in the case of perfect substitutability where P2P platforms and banks serve the same borrower segment. Panel (b) shows the distribution after banks tighten their lending criteria; borrowers in the darker area switch from banks to P2P platforms.

P2P platforms.[9] The quality of the borrowers migrating from banks to P2P platforms is thus at the low end of the pre-shock distribution of P2P borrower quality, which implies that the left tail of the P2P borrower quality distribution becomes denser after the shock. More precisely, following the shock, all the quantiles of the P2P borrower quality distribution decrease, and the increase in P2P lending volume is concentrated at the low end of the borrower quality distribution.

The predictions can therefore be summarized as follows. If P2P platforms and banks are perfect substitutes, then the tightening of bank lending criteria entails (i) a higher P2P lending volume; (ii) a lower average P2P borrower quality and lower quantiles of the P2P borrower quality distribution; (iii) an increased P2P lending volume only at the low end of the pre-shock borrower quality distribution.

1.2 Perfect Complements

In the second polar case, where P2P platforms operate as perfect complements to banks, the following conditions hold:

$$\underline{\gamma}^{\text{P2P}} < \underline{\gamma}^{\text{bank}};\ \alpha(\gamma) = 1,\ \forall \underline{\gamma}^{\text{P2P}} \leq \gamma < \underline{\gamma}^{\text{bank}};\ \alpha(\gamma) = 0,\ \forall \gamma \geq \underline{\gamma}^{\text{bank}}.$$

In other words, P2P platforms have a lower lending threshold than banks. The lower standard of P2P platforms could be explained by their lighter regulatory burden, P2P investors' tastes for risk, and the platforms' lower operational costs. In addition, borrowers of a

[9] The framework does not necessarily require *all* borrowers in the darker area between $\underline{\gamma}^{\text{bank}}$ and $\hat{\underline{\gamma}}^{\text{bank}}$ to switch to P2P lenders. As long as some of them do, the predictions derived below hold.

given level of quality are served by at most one lender type: those whose quality is between $\underline{\gamma}^{\text{P2P}}$ and $\underline{\gamma}^{\text{bank}}$ only obtain credit from P2P platforms; others with quality above $\underline{\gamma}^{\text{bank}}$, while qualifying for P2P loans, borrow exclusively from banks. There could be several reasons for this market segmentation. First, high-quality borrowers may derive some benefit from having their loans underwritten by banks. Second, banks may be able to offer more favorable loan terms to high-quality borrowers than P2P lenders. In this case, as shown in Figure 2(a), the credit market is characterized by two non-overlapping segments that are served, respectively, by P2P platforms (the area between $\underline{\gamma}^{\text{P2P}}$ and $\underline{\gamma}^{\text{bank}}$) and banks (the area above $\underline{\gamma}^{\text{bank}}$). Here banks serve the high-quality borrowers, while P2P platforms complement banks by serving borrowers who do not qualify for bank credit. Borrowers whose quality is lower than $\underline{\gamma}^{\text{P2P}}$ are denied access to both types of credit.

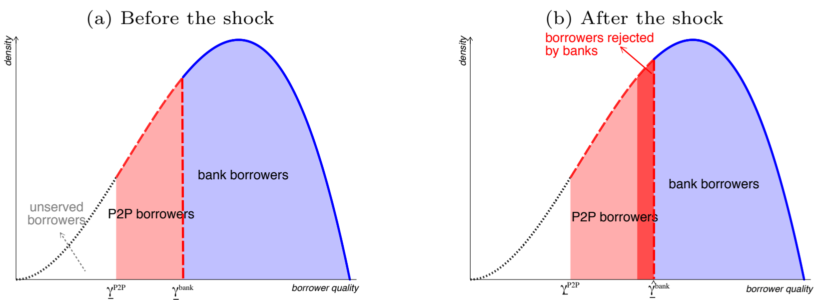

Figure 2
Borrower Quality Distribution: Perfect Complements
See the notes to Figure 1.

Again we may consider a tightening of banks' lending criteria, or an increases in the optimal lending threshold from $\underline{\gamma}^{\text{bank}}$ to $\hat{\underline{\gamma}}^{\text{bank}}$, as illustrated in Figure 2(b). Borrowers whose quality is between the $\underline{\gamma}^{\text{bank}}$ and $\hat{\underline{\gamma}}^{\text{bank}}$ are denied access to bank credit (the darker area) and so may migrate to P2P platforms. Since P2P platforms targeted low-quality borrowers before the shock, it follows that the quality of the switching borrowers is at the high end of the pre-shock distribution of P2P borrower quality. Hence the right tail of the P2P distribution shifts rightward after the shock. In fact, all the quantiles of the P2P distribution increase. Furthermore, the increase in P2P lending volume is concentrated at the high end of the borrower quality distribution. To more be precise, the right tail of the P2P distribution would extend further rightward.

Thus the next set of predictions are as follows: if P2P platforms and banks are perfect complements, a reduction in bank credit supply leads to (i) a higher P2P lending volume; (ii) a higher average P2P borrower quality and larger quantiles of the P2P borrower quality distribution; (iii) an increased P2P lending volume, concentrated around the right tail of the pre-shock borrower quality distribution.

It is clear from comparing the predictions under these two polar cases that the effect of the shock on P2P lending *volume* is the same whether P2P platforms substitute or complement banks. However, this shock has the opposite effects on both the *quantile* and *frequency distribution* of P2P borrower quality in these two cases. Those opposite predictions will allow me to distinguish between the two possible P2P-bank relations in the empirical analysis.

1.3 An Intermediate Case

This framework can also accommodate cases that are intermediate between the perfect substitutability and the perfect complementarity of banks and P2P platforms. For instance, P2P platforms may operate as substitutes for borrowers qualifying for bank credit while also catering to borrowers who are unserved by banks. Namely,

$$\underline{\gamma}^{\mathrm{P2P}} < \underline{\gamma}^{\mathrm{bank}};\ \alpha(\gamma) = 1,\ \forall \underline{\gamma}^{\mathrm{P2P}} \le \gamma < \underline{\gamma}^{\mathrm{bank}};\ 0 < \alpha(\gamma) < 1,\ \forall \gamma \ge \underline{\gamma}^{\mathrm{bank}}.$$

Figure 3(a) illustrates that, in this case, P2P platforms serve a larger range of borrowers (the area under the dashed curve) than do banks. 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 (the darker area). Although there is no clear implication for the average P2P borrower quality, analyzing shock-induced changes in the frequency distribution of P2P borrower quality enables the detection of such intermediate cases. In particular, a tightening of banks' lending criteria leads to a higher P2P lending volume in the *middle* of the distribution, and the precise location depends on the relative extent of substitution and complementarity.

Formally, if P2P platforms are a substitute for banks in the high-quality-borrower segment and yet complement banks in the low-quality-borrower segment, then a reduction in bank credit supply leads to (i) a higher P2P lending volume; (ii) *no* definitive predictions on the average P2P borrower quality and the quantiles of the P2P borrower quality distribution; (iii) an increased P2P lending volume, concentrated in the middle of the pre-shock borrower quality distribution.

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 that situation, a tightening of banks' lending criteria would have no effect on P2P lending volume—an outcome that is

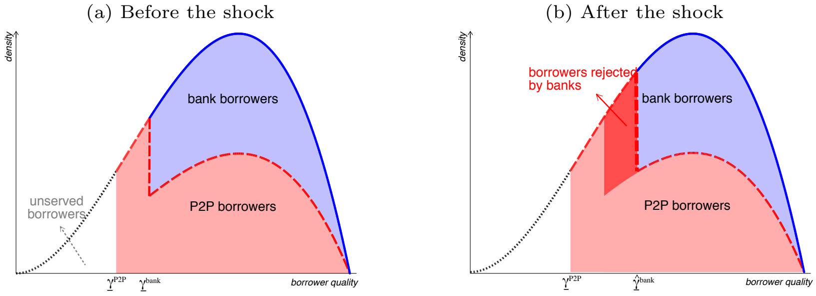

Figure 3
Borrower Quality Distribution: An Intermediate Case
See the notes to Figure 1.

rejected by the empirical analysis (see Section 4.1). It is also possible that banks lend to a broader pool of borrowers than do P2P lenders. Yet here the implication for borrowers would be much as in the case of perfect substitutes, where P2P lenders serve only infra-marginal borrowers and do not expand credit access to underserved borrowers.

To facilitate the discussion of the empirical results, all the predictions are categorized into three groups: predictions on volume, quantiles, and frequency. Hereafter, the phrase *predictions on volume* will be used to refer to volume-related predictions from both substitutability and complementarity. I shall make analogous use of the phrases *predictions on quantiles* and *predictions on frequency*.

2. Institutional Background

2.1 LendingClub

This study uses a data set from LendingClub, the largest online P2P lending platform in the United States. To apply for a loan, the applicant reports her name, address, purpose of the requested funds, and the amount to be borrowed. The platform uses the applicant's identity to acquire information on her credit report. It then deems ineligible any applicant whose debt-to-income (DTI) ratio is above 0.35 or whose FICO score is below 660. To applicants who pass this screening process, LendingClub proposes 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, which may be either institutions or individuals, compete to fund the loan on a first-come, first-served basis; they observe the loan characteristics and certain information from the borrower's credit report. Meanwhile, LendingClub asks the applicant to report her income, profession, and length of employment. For some applicants, LendingClub verifies this self-reported information. According to LendingClub's prospectus, filed with the Securities and Exchange Commission (SEC), in 2013, 79% of the borrowers had their employment or income verified.[10] LendingClub states that a listed loan can be unfunded for one of several possible reasons: (i) the loan listing was removed based on "a credit decision or the inability to verify certain borrower information"; (ii) the borrower withdrew her loan application; and (iii) the listing was not fully funded. According to this P2P platform, nearly all listed loans receive full investor funding and many are fully funded within a few days.[11]

The LendingClub applicants are located in 46 states and the District of Columbia. During the sample period (2009Q1–2012Q4), all loans were funded by individual investors.[12]

2.2 Pricing

LendingClub assesses borrower credit risk by assigning 35 credit grades—which range from A1 to G5—based on the borrower's credit score, DTI ratio, credit history, requested loan amount, and loan maturity. The applicable interest rate is then determined by the credit grade so assigned. It is worth noting that LendingClub's pricing policy is national, which means that the platform's rules do not differ from one location to the next. This national pricing policy is in line with the assumption that P2P credit supply is elastic, which I formally address in Section 5.1. To confirm that LendingClub's interest rates are independent of borrower location, I quote text from LendingClub's prospectus filed with the SEC, and also provide empirical evidence in Section 5.1.

The following text appears in LendingClub's prospectus:

> *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% and 30.99%. We set the interest rates we assign to borrower loan grades in three steps. First, we determine LendingClub 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*

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[10] To verify income, LendingClub requests documents such as recent paychecks, tax returns, or bank statements; to verify employment, it may contact the employer directly or reference other databases.

[11] Details on listing status are available at https://help.lendingclub.com/hc/en-us/articles/213757368-Partially-funded-loans. For details on partially funded loans, see https://help.lendingclub.com/hc/en-us/articles/215488038-What-do-the-different-Note-statuses-mean-.

[12] LendingClub opened the wholesale loan market to institutional investors in 2013, and by 2015 the share of loans funded by these investors stood at 63%.

upward adjustment to the base rates . . . depending on the channel through which a borrower is sourced . . ., [the] loan amount, term and other factors.[13]

Thus LendingClub follows a two-step process when establishing the interest rate for each loan: (1) assigning a loan grade; and (2) calculating the interest rate as the platform's base rate (for that grade) *plus* an upward adjustment reflecting the quoted factors.

2.3 Data

P2P lending data. From LendingClub's website I retrieve detailed information on all loan applications and funded loans between 2009 and 2012. Since not all applicants are successful, I use "borrowers" to refer to those whose loan applications are funded. For loan applications that LendingClub rejected during its initial screening process, the available information includes FICO score, DTI ratio, employment length, and city of residence.[14] For funded loans, there is additional information on the borrower's credit history and also on loan performance provided the loan has reached maturity. The final sample is based on 880,346 loan applications, of which 93,159 were funded.

[[Insert Table 1 about here]]

Table 1 presents summary statistics of borrower and loan characteristics. The average borrower receives $13,224, has a FICO score of 711, a DTI ratio of 0.147, and about six years' working experience. The average interest rate is 13.3%, ranging from 5.4% to 24.9%.

Bank data. Since 2011Q1, banks that consolidated securitized assets under FAS 166/167 have reported the size of consolidated variable interest entities (VIEs) on Schedule RC-V of their Call Reports. I use Call Reports to identify banks that consolidate securitized assets under FAS 166/167, and I use the Summary of Deposits to identify counties in which the branches of those banks are located. I use the Summary of Deposits also to construct variables characterizing banking market structure at the county level: market concentration, share of small banks, share of national banks, and geographical diversity of local banks.

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[13] According to this 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; and 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.

[14] For loans and rejected applications from 2009 to 2012, LendingClub used to publish information on the city of borrowers/applicants; however, that information has since been replaced by ZIP codes (first three digits). I thank Don Carmichael (University of Houston) for sharing a historical version of the dataset, which contains borrower city information, downloaded from LendingClub's website.

3. Empirical Strategy

In this section, I describe the main empirical strategy for testing the predictions generated by the conceptual framework presented in Section 1.

3.1 Identification Strategy

The conceptual framework requires a negative shock to bank credit supply that leads banks to tighten their lending criteria. In this regard, I consider an arguably exogenous shock to bank credit supply that was due to the implementation of the FAS 166/167 regulation. In 2010, the FASB enacted a new regulation requiring banks' assets held in VIEs to be consolidated into (a) their total assets when calculating leverage ratios and (b) their risk-weighted assets when calculating risk-weighted capital ratios. The new regulation came with an optional four-quarter phase-in period.[15] Thus, banks are required to report those consolidated assets in their Call Reports from 2011Q1, which is defined as the starting point of the post-shock period.

I define a bank as being treated if it held off–balance sheet assets subject to consolidation. In total, 59 banks have consolidated assets under this regulation. This treated group, consisting mostly of large banks, held more than half of the entire banking industry's assets. Dou, Ryan, and Xie (2017) report that, at the end of 2010, assets held by the consolidated VIEs accounted for 5.6% of the banking industry's total assets. Of these newly consolidated assets, about 10% were held by asset-backed commercial paper conduits and some 80% were held by other types of securitization entities (mostly credit card master trusts). One would therefore expect to see a direct impact of FAS 166/167 on banks' choice of the quantity and quality of their consumer credit loans, because all such loans that were originated subsequent to the implementation of FAS 166/167 had to be 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 of Dou (2017) and report the results in Online Appendix A. I find that treated banks reduced small business lending by \$3,097 per thousand county inhabitants, which represented 16% of the average small business lending volume before 2011. This negative effect on credit supply was greater for small businesses with annual revenues below \$1 million than for those with higher annual revenue. Moreover, additional tests in Dou (2017) reveal that the decline in credit supply by affected banks was not fully absorbed by other banks in the same area. The lack of data on consumer lending at the bank–county level precludes conducting the same exercise

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

for consumer credit, but it is likely that FAS 166/167 had a negative effect on consumer credit as well.

Besides its impact on bank credit supply, the new regulation may have affected the quality of loans originated by VIE-consolidating banks; Dou, Ryan, and Xie (2017) estimate that FAS 166/167 led to a 1% reduction in the risk-based capital ratio of such banks. This decrease, in turn, may lead banks to deny more high-risk loan applications, since such loans are more costly in terms of risk-based capital. Also, Tian and Zhang (2018) show that the quality of credit card loans of treated banks improved following the implementation of the new regulation: the percentage of non-securitized credit card loans that were past due dropped by 1.4 percentage points. In short, banks seem to exhibit "fly to safety" behavior in adjusting their loan portfolios so as to reduce the number of risky borrowers.

It is therefore reasonable to view the implementation of FAS 166/167 as an exogenous shock that induced banks to cut lending to borrowers at the bottom of their borrower quality distribution, which is in line with the type of bank credit shock posited in the conceptual framework.

The identification of the treatment effects on P2P lending relies on variation in the geographical "footprint" of treated banks. Treated banks are, of course, different from untreated banks with regard to the structure of their balance sheets and their securitization activities. However, multiple studies show that the negative effect of FAS 166/167 on bank credit supply is not driven by these differences (Dou 2017; Dou, Ryan, and Xie 2017; Tian and Zhang 2018). Note also that the exposure to FAS 166/167—as construed at the market level using the pre-shock presence of treated banks—is less subject to endogeneity concerns as opposed to the bank-level exposure to FAS 166/167. Markets with at least one branch of any treated bank are defined as treated. The final sample consists of 1,908 treated and 1,025 untreated markets, all defined at the county level. Finally, all the regression analyses control for market characteristics that might confound the effect of FAS 166/167 on the demand for P2P credit.

Admittedly, with the "difference-in-differences" approach, I cannot fully rule out the possibility that time-varying unobserved market characteristics simultaneously affected the growth of P2P lending and the location of treated banks before the shock. To address this concern, I present evidence in Section 4.1 that treated and untreated markets exhibit a similar P2P lending pattern prior to 2011. I also show that the treatment effects appear sharply in 2011Q1. Given the timing of FAS 166/167, this pattern is unlikely to be driven by other factors.[16]

One may also be concerned that banks did not use the four-quarter phase-in period so that they began to contract credit supply in 2010. If this were the case, using 2011Q1 as the starting point for the post-shock period will lead to an under-estimation of the positive treatment effect on P2P lending volume. Similarly, the estimated effects of FAS 166/167 on P2P borrower quality will also be diluted because P2P borrower quality would have deteriorated in 2010 already.

3.2 Empirical Specification

To identify the effects of this regulatory shock on P2P lending, I exploit variation in the presence of treated banks across local markets. The regression equation is specified as follows:

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

where c denotes counties and t indexes quarters or years depending on the specification. $Treated_c$ is a dummy variable set equal to 1 for counties with at least one branch of a treated bank, and set to 0 otherwise. The indicator $Post_t$ is set to 1 for years 2011 onward and set to 0 for previous years. γ_c represents a county fixed effect and σ_t is a time fixed effect. $Controls_{c,t}$ stands for other control variables, such as the banking market structure of county c at time t.

The dependent variables are those that describe P2P lending. The first set of dependent variables measures P2P lending volume and the second set concerns P2P borrower quality. The former is used for testing the predictions on volume, and the latter for testing the predictions on quantiles and frequency.

To measure P2P application and origination volumes at the county level, I calculate either the dollar amount or the number of applications and loans, respectively. Each of those dependent variables is normalized by county population. The advantage of using this normalization, rather than taking logarithms, is that the former preserves zero-value observations that appear frequently at the beginning of the sample period. However, results do not change qualitatively if instead the logarithm of loan volume (or of number of loans) is used as the dependent variables.

Table 2 reports summary statistics on county-level P2P lending volume. The average number of loan applications and funded loans are 74 and 8, respectively. In the largest local market, Los Angeles County,

[16] The aforementioned previous studies also show that the treatment effect of FAS 166/167 on bank credit supply is not explained by other concurrent shocks such as the 2007-2009 financial crisis, Dodd-Frank Act, stress tests, Troubled Asset Relief Program, etc.

there were 16,278 applications and 2,526 originations in 2012.

[[Insert Table 2 about here]]

When either P2P application volume or P2P origination volume is used as the dependent variable in Equation (1), I expect $\beta > 0$ irrespective of whether banks and P2P platforms are substitutes or complements (see predictions on volume in Section 1).

Next, to test predictions on quantiles and on frequency, I use two different measures of borrower quality. The first is the FICO score, the criterion most widely used by financial institutions in the loan underwriting process. However, the creditworthiness of a borrower may not be fully reflected in her FICO score. I therefore develop a second measure that combines information about FICO score, DTI ratio, and length of employment. With the loan application data from LendingClub, I 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 both qualified and funded. The outcome of an application is determined by a latent borrower quality. I then use the model estimates to predict this latent borrower quality and normalize it to be between 0 and 1. Details of this procedure are given in Online Appendix B.

To capture the statistical features of the distribution of P2P borrower quality, I construct the following dependent variables: (i) the average quality of P2P borrowers; (ii) ten quantiles of the borrower quality distribution, where $k \in \{5, 15, \ldots, 95\}$ for the kth percentile; and (iii) the number of borrowers in ten equal-width intervals of the P2P borrower quality distribution. For the FICO scores, which range from 650 to 850 in the sample, each such interval is 20 points wide. Because predicted quality ranges from 0 to 1, each of these ten intervals has a width of 0.1.

When the dependent variable is the average quality or a quantile of the borrower quality distribution, the predictions on quantiles imply that $\beta < 0$ if banks and P2P platforms are substitutes. The opposite holds if they are complements. When the dependent variable is borrower frequency in the ten intervals, the predictions on frequency imply that $\beta > 0$ only for intervals at the low (high) end of the quality distribution if P2P platforms and banks are substitutes (complements).

Finally, banks and P2P platforms may be substitutes or complements along other dimensions of credit supply. One natural dimension is loan size, as P2P platforms may specialize in providing smaller loans than those typically originated by banks. Hence, I repeat the same exercises for loan size to obtain additional dependent variables: the average and ten quantiles of P2P loan size. During the sample period, the loan size ranged from $1,700 to $35,000; I therefore divide the support of loan size into ten intervals with a fixed width of $3,400 and then calculate the number of loans within each loan size interval.

As for the control variables, following the literature on banking competition, 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 cut-off values at 1000 and 1800 (cf. White 1987); Markets with low HHI are more competitive. I use $Share(SmallBanks)$ to signify the deposit share of banks with total assets of less than $1 billion; $Share(NationalBanks)$ is the deposit share of national banks. The variable *Geo.Diversification* is the median number of states in which a county's banks operate and thus captures the geographical diversification of banks in that county. I use *Deposits* to represent the dollar amount of total deposits in all bank branches divided by county population. These variables measure the local supply of bank credit, which may affect demand for P2P credit.

Regression Equation (1) also controls for county demographic and economic factors—including population, median personal income, and unemployment rate—because they could affect the size and composition of the borrower pool. Data on those economic indices and demographics are retrieved from the US Bureau of Economic Analysis.

4. Main Results

In this section, I follow the above empirical strategy to test the predictions from the conceptual framework (Section 1). I estimate the effects of FAS 166/167 on P2P lending volume, borrower quality distribution, and loan size distribution in turn. Comparing the empirical results to the predictions, I conclude that P2P lenders and banks are substitutes in the borrower quality dimension, while being complements in the loan size dimension.

4.1 Testing Predictions on Volume

As discussed in Section 1, regardless of whether P2P platforms and banks are complements or substitutes, a tightening of banks' lending criteria induces an increase in P2P lending volume. To test this prediction, I estimate Equation (1) using P2P lending volume as its left-hand-side variable. For this test 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).

To visualize the timing of the shock's effect, I start by replacing the $Post_t$ dummy in Equation (1) with year-quarter dummies and then plot the coefficients of those dummies interacted with the indicator variable $Treated_c$. For the reference level, I use P2P lending volume in the quarter preceding the policy change (i.e., 2010Q4).

The results are presented in Figure 4, where dots represent loan applications and triangles represent funded loans. This figure establishes that relative to control counties, P2P application and origination volumes increased significantly in treated counties after 2010Q4, in terms of both the total loan amount (Panel a) and the number of loans (Panel b). Observe also that there was no significant difference, between treated and control counties, in P2P lending volume before the shock. This absence of a pre-shock trend confirms that the increase in demand for P2P credit is unlikely to be driven by unobservable differences between treated and control markets.

[[Insert Figure 4 about here]]

When assessing predictions about the composition of borrowers, in Sections 4.2.1 and 4.2.2, it will be preferable to work with annual data so as to obtain more precise measures of the statistical features (e.g., quantiles) of the borrower quality distribution at the county–time level. Hence I re-estimate Equation (1) for P2P lending volume at the county-year level and report the results in Table 3. Consistent with Figure 4, I find that relative to control counties, treated counties experienced an average increase in P2P loan applications of \$1,108 (column [1]), or of 0.070 additional loan applications (column [2]), per thousand inhabitants. These values amount to 25.3% and 38.7% of the corresponding pre-shock levels. This increased demand was at least partially satisfied by the P2P platform. Its lending volume increased by \$301 (column [3]) or 0.016 additional originations (column [4]), which are equivalent to 1.5 (1.1) times the pre-shock level of the dollar amount originated (number of originations).

[[Insert Table 3 about here]]

To summarize, the results on P2P volume show that, when banks cut lending in the consumer credit market, some borrowers do switch from traditional financial institutions to P2P platforms. This finding is consistent with P2P platforms and banks being complements *or* substitutes (predictions on volume). However, this analysis is necessary for validating FAS 166/167 as a negative shock to bank credit supply. I now turn to examine the changes in the quantiles and frequency distribution of P2P borrower quality, for which substitutability and complementarity entail opposite predictions.

4.2 Substitutability in the Borrower Quality Dimension

4.2.1 Testing predictions on quantiles. If banks and P2P platforms are substitutes, then the shock-induced reduction in bank credit should lead to declines in (a) the average quality of P2P borrowers and (b) the quantiles of the borrower quality distribution. These predictions are reversed if banks and P2P platforms are complements.

To test the 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 when it is measured 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]–[10]) and also the mean (column [11]) decreased simultaneously in treated counties relative to control counties, which is consistent with banks and P2P platforms being substitutes.

[[Insert Table 4 about here]]

A closer look at the results yields a more precise interpretation. First, average borrower quality decreased, although not statistically significantly at conventional levels (the p-value is 0.12 in Panel A and 0.14 in Panel B). Second, when FICO score is used to measure borrower quality, even though all quantiles decreased, the effect is statistically significant only for those above the 45th percentile. On average, the four quantiles between the 50th and 90th percentiles decreased by 8 points, or 4% of the difference between the minimum and maximum FICO scores in the sample.[17] By combining this result with the second line of Panel A, which shows the average value of each quantile across counties before the shock, one can infer that only quantiles corresponding to scores above 715 decreased after the shock. This outcome suggests that the FICO scores of new borrowers are lower than 715, or below the 45th percentile of the pre-shock distribution of P2P borrowers' FICO scores. This interpretation is confirmed in the frequency analysis in Section 4.2.2, where I find that the increase in P2P lending volume was driven by the lowest three FICO score intervals comprising scores between 650 and 710.

Moreover, when predicted borrower quality is used to measure borrower quality, all quantiles still decrease but the effect is significant at the 1% level only for the 5th percentile. The average reduction in the ten quantiles is 0.02 units, representing 2% of the difference between the minimum and maximum values of predicted borrower quality. By combining this result with the second line of Panel B, one can infer that only quantiles with corresponding values smaller than 0.415 experienced a significant decline. This outcome also is confirmed by the frequency analysis in Section 4.2.2, as the frequency distribution experienced an increase only in the three intervals between 0.1 and 0.4.

[17] The average reduction in the ten quantiles of FICO scores is 4 points, which represents 2% of the difference between the minimum and maximum FICO scores in the sample.

Comparing the results from FICO scores and with from predicted borrower quality, one may have the following interpretation. Although the borrowers who are rejected by banks arrive at the lower half of the FICO distribution of P2P borrowers, they are in the leftmost tail of the quality distribution when length of employment and the DTI ratio are also taken into account. A possible explanation of this result is that the P2P platform imposes a strict requirement on the FICO score but not on other borrower characteristics, which would mean that deteriorating borrower quality is more visible in non-FICO dimensions.

The results from quantile tests are thus consistent with banks and P2P platforms being substitutes. However, the analysis of quantiles has one limitation when it comes to interpreting the results. In particular, the magnitude of the change in a given quantile depends on several factors, such as the number of new borrowers, the quality range of new borrowers, and the shape of the pre-shock quality distribution.[18] It follows that the estimated change in the quantiles may not be significant everywhere in the distribution. To overcome this limitation of the quantile analysis, I next analyze the frequency distribution of borrower quality.

4.2.2 Testing predictions on frequency. Frequency tests generates results that can sometimes be easier to interpret than those from quantile tests. One reason is that frequency tests use the same ten fixed-width intervals to classify borrowers in all counties. In contrast, the value of a given quantile calculated for different counties may not be the same, which makes the results difficult to interpret in terms of the absolute value of borrower quality. Another advantage of frequency tests is that the changes in frequencies in various intervals are independent of each other; with quantile tests, the changes in different quantiles for a given county are (by definition) connected.

The predictions on frequency state that if banks and P2P platforms are substitutes, then the increased demand for P2P credit will come from low-quality borrowers and thus lead to a higher number of borrowers only in the low-quality part of the distribution. Yet if P2P platforms instead operate as complements to banks, then the increase in the number of borrowers will occur only in the high-quality part of that distribution.

I test the predictions on frequency by estimating Equation (1) using, as the dependent variable, the number of P2P borrowers in each of

[18] Suppose, for example, that new borrowers' FICO scores are below the pre-shock median value. The effect of new borrowers on the quantiles *below* the median (i.e., 5th, 15th,…, 45th percentiles in the analysis) will have different magnitudes, depending on whether the pre-shock distribution is denser in the left part or in the right part. In particular, it will be smaller in the former case. The opposite statement holds for quantiles *above* the median (i.e., the 55th, 65th,…, 95th percentiles).

the 20-point FICO score intervals between 650 and 850. The estimated coefficients are plotted in the upper part of Figure 5(a). I find that the increase in P2P lending volume was driven by the lowest three FICO score intervals, which encompass scores from 650 to 710. This result is in line with those from quantile tests, which show that the distribution of FICO scores became denser in the left part—that is, where the FICO score is below 715.

[[Insert Figure 5 about here]]

To interpret this outcome more precisely, I compare the estimated change in the frequency distribution of P2P borrowers' FICO scores (the upper part of Panel a) with their pre-shock distribution (the lower part). As the conceptual framework predicts, if banks and P2P borrowers are substitutes, the increase in the frequency distribution will be *disproportionately* located in the left part of the support of the pre-shock distribution (see Figure 1); if they are complements, then the increase will be disproportionately 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 containing FICO scores between 650 and 710, the number of originations increased by 0.013 per thousand inhabitants (significant at the 1% level), 1.9 times the pre-shock level. In contrast, the the number of originations did not increase significantly in other intervals when the FICO score exceeds 710. Thus, the increase in P2P lending induced by the shock to bank credit supply was located at the lower end of the P2P borrower quality distribution; this finding accords with P2P platforms and banks being substitutes.

I obtain similar results using predicted quality as the measure of borrower quality; see Figure 5(b). The upper part of this panel shows that the increase was located between 0.1 and 0.4. Comparing this subfigure with the pre-shock distribution of predicted borrower quality in the lower part of Panel (b), we can see that the increase in the frequency distribution is indeed disproportionately located in the left part of the pre-shock distribution. More specifically, the total number of originations in the four lowest intervals increases by 0.009 per thousand inhabitants (significant at the 5% level), amounting to 1.3 times the pre-shock level. In contrast, changes in the other six intervals are not significant. Even when the point estimates in those intervals are positive, the magnitudes are small relative to the pre-shock frequencies in the corresponding intervals. These results suggest a disproportionately high growth of loan originations in low-quality intervals as compared with high-quality intervals.

Overall, the results in this section indicate that the tightening of banks' lending criteria was followed by P2P platforms experiencing an increase in originations among low-quality borrowers. This outcome is in line with P2P platforms being substitutes for banks.

4.3 Complementarity in the Loan Size Dimension

The above analysis shows that banks and P2P platforms are substitutes in the borrower quality dimension, but they could still be complements along other dimensions of credit supply, in particular, loan size. In light of their Internet-based loan underwriting process, P2P platforms may have a lower fixed cost of originating loans than do banks and might therefore specialize in providing smaller loans.

4.3.1 Testing predictions on quantiles. I follow the same approach as in Section 4.2 and investigate the distribution of P2P loan size. The changes in the quantiles of the loan-size distribution are presented in Table 5. The average loan size increased by a statistically significant amount of $1,066 (column [11]). Moreover, the P2P loan-size distribution shifted toward the right end, as all quantiles except the 5th increased (columns [1]–[10]). The top two quantiles, the 85th and 95th, increased significantly by $1,563 and $3,870, respectively. Here the interpretation is that the amount for which new borrowers apply is above the 85th percentile of the pre-shock loan size distribution, or above $13,501, the average 85th percentile of the pre-shock county-level loan size distribution. These results indicate that borrowers migrating to P2P platforms apply for larger loans than do pre-existing P2P borrowers. One possible explanation is that the bank loans that would have been obtained by those borrowers are larger than P2P loans absent the regulatory shock. Hence we may conclude that P2P platforms and banks are complements in the loan size dimension.

[[Insert Table 5 about here]]

4.3.2 Testing predictions on frequency. The complementarity between banks and P2P lenders in the loan size dimension is also confirmed by frequency tests. The upper part of Figure 6 shows that the increase in the number of originations occurred only in the top four intervals, where the loan size is between $21,400 and $35,000. This result is in line with those from quantile tests, because new loans were larger than the 95th percentile of the pre-shock loan size distribution, and the arrival of these loans induced an increase in almost all the quantiles, especially the highest quantiles. When comparing the change in the loan size distribution (the upper part of Figure 6) with the pre-shock distribution (the lower part), we can see a sizable increase not only at the right tail of the distribution (i.e., between $21,400 and $28,200) but also *beyond* the right tail of the distribution (i.e., between $28,200 and

$35,000). In the top four intervals, the number of originations increased by 0.048 per thousand inhabitants, the equivalent of 4.3 times the pre-shock level. In contrast, none of the changes in other intervals are statistically significant at the 5% level. Even when some of these point estimates are marginally significant at the 10% level, the magnitudes of the increases are small relative to the pre-shock frequencies in the corresponding intervals—especially in the left part of the distribution.

[[Insert Figure 6 about here]]

Taken together, the results on loan size suggest that P2P platforms complement banks by serving borrowers seeking relatively small loans. Notice that this conclusion also relies on the assumption that the bank credit supply shock affects the left tail of the bank loan size distribution. However, this assumption is plausible because borrowers denied by banks after the shock are low-quality borrowers as show in Section 4.2, and they are therefore likely to be those who obtained smaller loans before the shock. Nevertheless, I discuss the limitations and validity of the results in Section 6.2.

5. Testing the Assumption of an Elastic P2P Credit Supply

One assumption of the framework presented in Section 1 is that the supply of P2P credit is elastic for creditworthy borrowers. This means that, in theory, an increase in P2P credit demand will not lead to a change in the interest rate. In an empirical setting, this assumption implies that a P2P applicant with a given set of observable characteristics who reside in a treated market should receive the same loan terms before and after the shock. If this assumption is violated, then the change in the composition of P2P borrowers may also reflect the pricing effect, besides the treatment effect of the negative bank credit supply shock.

Therefore, if P2P credit supply is elastic, we should observe the following. At the platform level, P2P platforms would neither adjust interest rates nor apply different screening criteria in response to increased local demand for P2P credit. At the investor level, P2P investors would respond to higher demand by increasing the credit supply. Hence the likelihood of loan listings being funded, once they pass the platform's initial screening, would not decrease.

I examine these two predictions and provide supporting evidence in turn. First, I demonstrate that interest rates set by the platform depended neither on borrower location nor on local demand for P2P credit. Second, I show that, conditional on loan characteristics, the probability of a loan listing being funded was much the same before as after the shock.

5.1 LendingClub pricing policy

Recall from Section 2 that, according to the LendingClub prospectus, interest rates on P2P loans do not depend on borrower location. One implication of this national pricing policy is that loan terms do not reflect *local* demand. To check the veracity of that claim, I test the joint significance of county fixed effects in the following regression:

$$y_{i,c,t} = \gamma_c + \beta\, Treated_c \times Post_t + LoanControls_{i,c,t} + \sigma_t + \varepsilon_{i,c,t}. \tag{2}$$

Here loans are indexed by i, counties by c, and quarters by t; $y_{i,c,t}$ is the assigned 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; $LoanControls_{i,c,t}$ includes loan and borrower characteristics; and σ_t is year-quarter t's fixed effect.

I implement two sets of tests, one each in which loan grade or interest rate is used as the dependent variable. I focus on these two variables because the platform sets the interest rate in two steps: it first assigns a loan grade based on borrower and loan characteristics, and then it sets an interest rate based on that loan grade and other factors. Therefore, I first estimate Equation (2) using LendingClub loan grade as the dependent variable. As described in Section 3.2, the loan grade takes one of 35 possible values, with better grades represented by lower numbers; hence I assign to each loan grade a value from 1 to 35. Second, I perform another estimation in which interest rate is the dependent variable, while controlling for loan grade.

If, as advertised, geography does *not* affect LendingClub loan grade and interest rate, then the county fixed effects should be jointly insignificant in both regressions. Similarly, if loan grade and interest rate do not vary as a function of local demand for P2P credit, then the coefficient β of the $Treated \times Post$ interaction term should also be zero.

[[Insert Table 6 about here]]

Table 6 reports the regression results, as well as F-statistics and p-values for the test on the joint significance of county fixed effects γ_c. As predicted, the county fixed effects are insignificant in all the columns of the table. The p-value for the test of the joint significance of county fixed effects is 0.188 (column [1]) and 0.958 (column [3]) when the dependent variable is loan grade and interest rate, respectively. Thus I fail to reject the null hypothesis that LendingClub's pricing policy is independent of borrower location. Furthermore, as shown in columns [2] and [4], the respective estimated coefficients of $Treated \times Post$ are insignificant; the t-statistics are -0.01 and -0.067. The implication is that, despite an increased demand for P2P credit in affected markets, interest rates exhibit no upward adjustment for loans in those markets.

5.2 Investor funding behavior

Do P2P investors respond to increased demand for loans by increasing the credit supply even when the interest rate remains stable? I show below that, conditional on passing the platform's initial screening process, a loan listing has the same probability of being funded before and after the shock.

Using the data on loan listings, I estimate the following probit model:

$$\begin{aligned}&E[\mathit{Funded}_{i,c,t} \mid \mathit{Treated}_{i,c,t}, \mathit{Post}_{i,c,t}, \mathit{Controls}_{i,c,t}]\\&\quad = \Pr(\mathit{Funded}_{i,c,t} = 1 \mid \mathit{Treated}_{i,c,t}, \mathit{Post}_{i,c,t}, \mathit{Controls}_{i,c,t})\\&\quad = \beta\, \mathit{Treated}_c \times \mathit{Post}_t + \gamma_c + \sigma_t + \mathit{Controls}_{i,c,t},\end{aligned}$$

where $\mathit{Funded}_{i,c,t}$ is an indicator variable set to 1 if the listing received full funding, and set to 0 otherwise.[19] If credit supply either is reduced or increases less than the demand for credit, then β will be negative; that is, a smaller fraction of loans will be funded after the shock.

Table 7 reports the regression results. Column [1] of the table excludes $\mathit{Controls}_{i,c,t}$. Columns [2] and [3] include the county-level and loan-level control variables, respectively, and column [4] includes both. Year and county fixed effects are included in all regressions. In all specifications, the coefficients of $\mathit{Treated} \times \mathit{Post}$ are insignificant. It seems therefore safe to conclude that investors increase the P2P credit supply in response to increased demand even though the interest rate remains constant.

[[Insert Table 7 about here]]

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

6. Validity of FAS 166/167 as a Negative Shock to Bank Credit Supply

A feature of the negative shock to bank credit supply considered in the conceptual framework is that it leads banks to exclude low-quality borrowers. If this is not the case, the validity of the results from FAS 166/167 may be in question.

The purpose of this section is twofold. First, I describe how the conceptual framework accommodates different types of shocks to bank credit supply, categorized by their impact on the bank borrower distribution; for each type, I derive predictions on P2P lending volume

[19] The data on unfunded loan listings, which are not available on LendingClub's website, were obtained from that platform's filings with the SEC.

and borrower composition. Second, I assess the validity of the results from FAS 166/167 by comparing them to those predictions.

Toward these ends, I explore two most plausible alternative types of shocks. The first type would make bank contract credit supply to all borrowers proportionately, and the second would make banks exclude borrowers at the high end of the distribution. In the following, I focus on the predictions on P2P borrower quality, while the same discussion applies to loan size. Also, I forgo stating the predictions on P2P loan volume because it increases regardless of the type of the negative shock.

Furthermore, I present results from an additional shock, bank branch closings, which can potentially be classified as the first alternative type. Lastly, I show that in the residential lending market, FinTech lenders and banks operate as *substitutes* in the loan size dimension.

6.1 Alternative Types of Shocks

6.1.1 Alternative Type I. The first alternative type of shocks considered here affects bank credit supply to all borrowers. By applying the same reasoning in Section 1, we can obtain the following predictions.

Predictions from substitutability. If P2P and bank lending are perfect substitutes, there should be no shift in the distribution of P2P borrower quality after the shock, because banks exclude borrowers at every quality level. In other words, the quantiles of P2P borrower quality distribution should remain unchanged, and P2P loan frequency should increase at all levels of borrower quality.

Predictions from complementarity. In the case of perfect complements, because all bank borrowers have higher quality than pre-shock P2P borrowers, the predictions will be largely the same as those in the conceptual framework. Specifically, all quantiles of the P2P borrower quality distribution increase. Moreover, the frequency increases only *beyond* the right tail of the pre-shock distribution, that is, the right tail extends further rightward.

6.1.2 Alternative Type II. Let us now consider shocks that would lead banks to exclude borrowers at the high end of the distribution. The predictions for this type are as follows.

Predictions from substitutability. In the case of perfect substitutes, borrowers rejected by banks are from the top part of the bank borrower distribution. These borrowers, if migrating to P2P platforms, would make the P2P borrower distribution become denser at the right tail. Thus, all quantiles increase and the frequency increases only *at* the right tail of the pre-shock distribution. Notice that in this case, the right tail becomes denser but it does not extend further rightward.

Predictions from complementarity. If P2P and bank lending are instead perfect complements, predictions are the same as those from complementarity for the first alternative type.

The predictions for these three types of shocks—the baseline type considered in the conceptual framework and the alternative types I and II—are summarized in Table 8.

[[Insert Table 8 about here]]

6.2 Validity of the Results from FAS 166/167

To assess the validity of the results from FAS 166/167, I compare the findings from FAS 166/167 in Section 4 to the predictions in Table 8. The objective is to verify whether the empirical findings on borrower quality (loan size) *only* correspond with the predictions from substitutability (complementarity), even if FAS 166/167 does not lead banks to exclude only low-quality borrowers.

Two important observations are noted. First, if, as seen for the case of borrower quality in Section 4.2, the data reveals a decline in all the quantiles of P2P borrower quality and an increased frequency only at the left tail of the P2P borrower quality distribution, one can then conclude with confidence that banks and P2P platforms are substitutes. According to Table 8, these outcomes would not be observed unless FAS 166/166 led banks to exclude low-quality borrowers (and not all borrowers or just high-quality borrowers). Therefore, the conclusion on substitutability in the borrower quality dimension is credible.

Admittedly, this conclusion could be further strengthened with additional information on bank borrowers. Due to data limitation, I do not observe the changes in the bank distribution following the adoption of FAS 166/167. However, such information is available for residential loans. In Section 6.3, I investigate the FinTech-bank relation in the residential lending market using loan data from both types of lenders.

The second important observation from Table 8 is that, if all the quantiles increase and the borrower frequency increases only *beyond* (as opposed to *at*) the right tail of the P2P distribution, then it is reasonable to conclude—no matter which part of the bank borrower distribution is affected by a credit squeeze—that banks and P2P platforms are complements. One implication of this observation is that the conclusion on complementarity does not depend on assuming the considered bank credit supply shock affects only the small-size segment of banks' loans pool.

Recall the results in Section 4.3 that, in the loan size dimension, the positive increase in frequency indeed appears beyond the right end of the distribution (see Figure 6). However, there is also an increase *at* the right tail of the distribution. There could be several explanations for this result. First, borrowers migrating from banks to P2P platforms may not be able to obtain the desired loan amount because P2P loan limits depend on borrower creditworthiness (as explained in Section 2). Because migrating borrowers are of low quality on average as shown in Section 4.2, it comes as no surprise that the actual amounts granted by LendingClub are lower than those requested. Hence, even if the *requested* loan amount is beyond the right tail of the P2P loan size distribution, the *actual* loan amount could still fall within that distribution.

The increased frequency at and beyond the right tail of the distribution may also be observed if, in the case of complementarity, there is a slight overlap between the right tail of the P2P loan size distribution and the left tail of the bank loan size distribution. In this case, the P2P-bank relation could still be characterized predominantly by complementarity. Finally, there is a (remote) possibility that P2P platforms and banks are substitutes with regard to loan size yet the borrowers denied by banks are requesting loans whose sizes are at the highest quantiles of the P2P (and bank) loan-size distribution. This combination of circumstances would generate the observed rightward shift in P2P loan size distribution. Yet, because low-quality bank borrowers are unlikely to be those obtaining the largest loans before the shock, the results reported here are more consistent with P2P complementing banks in the loan size dimension.

To summarize, these considerations lend credibility to the conclusion on the substitutability (complementarity) in the borrower quality (loan size) dimension. The impacts of FAS 166/167 on P2P borrower quality are consistent with those from the shocks leading banks to adjust their loan portfolios away from low-quality borrowers; otherwise, the deterioration in P2P borrower quality would not be observed. Moreover, the findings of complementarity in loan size dimension are plausible given that the low-quality borrowers excluded by banks are more likely to have obtained smaller bank loans before the shock.

6.3 Results from Bank Branch Closings and the HMDA Data

Below I present two sets of additional results. The first is the impact of bank branch closings on P2P lending.[20] Nguyen (2017) reports that branch closings have a negative effect on the credit supply to local small businesses even in markets where the branch network is dense. It is possible that borrowers at all quality levels suffer from branch closings, which therefore can be potentially classified as the first alternative type of shocks.

I begin this analysis by assessing the impact of bank branch closings on P2P lending volume. The results are reported in Online Appendix C. To

[20] I thank the referees for bringing this to my attention and suggesting the empirical analysis.

summarize, I find no evidence that merger-induced bank branch closings lead to increased P2P lending volume. A possible explanation is that consumer credit products (e.g., credit card loans) are relatively easy to transfer across branches within the same bank. When one branch closes, borrower accounts are usually transferred automatically to the nearest branch. Given the insignificant impact on P2P lending volume, I do not continue to analyze how P2P borrower composition is affected by bank branch closings.

The second set of results is FAS 166/167's impact on the residential lending market. The HMDA data reports comprehensive publicly available information on mortgage market activity. Although it does not contain information on FICO score or DTI ratio, the size of each bank and FinTech loan is observable. This allows me to compare the changes in both bank and FinTech loan distributions around the implementation of FAS 166/167. Following the same procedure in Section 4, I implement the lending-volume tests, quantile tests, and frequency tests in the loan size dimension for both banks and FinTech lenders. A detailed description is presented in Online Appendix D.

I find evidence consistent with *substitutability* in the loan size dimension between banks and FinTech lenders. First, the loan size distributions of FinTech lenders and banks are similarly shaped on their common support. Second, following the regulatory shock, banks rejected large loan requests and FinTech lenders stepped in to fill the gap. As a result, the two loan size distributions underwent opposite changes: the one of banks experienced a decline in all the quantiles and a decreased frequency at the right tail, while the one of FinTech lenders experienced an increase in all quantiles and an increased frequency at the right tail. This is exactly the predictions from substitutability for the alternative type II shock. This finding implies that FAS 166/167, when applied to the loan size distribution in the HMDA data, affects the high end of the distribution, i.e., large loans.

That FinTech lenders behave as substitutes for banks in the loan size dimension in the *residential lending* market does not contradict the finding of complementarity in the loan size dimension in the *consumer credit* market. These two credit markets have substantially different characteristics. First, a key feature of residential lending markets is that loan underwriting rules are standardized and apply to both traditional banks and FinTech lenders, which could result in similar loan offers from these two lender types. For instance, a conventional mortgage cannot qualify for purchase and securitization as a government-sponsored enterprises (GSE) unless it conforms to GSE guidelines, among which the most well known is on loan size: it was generally limited to $424,100 for a single-family home in the continental United States. This limit applies to all lenders, and both types have incentives to comply. Another relevant factor is that, in consumer credit markets, online lenders enjoy an advantage in originating small loans because of their lower fixed costs. On the contrary, in residential lending markets, the fixed cost of origination is a much smaller fraction of the loan principal, which dissipates online lender's cost advantage.

7. Concluding Remarks

The rapid emergence of P2P lending, after the 2008 financial crisis, led to debates concerning its impact on the consumer credit market. The answer depends crucially on whether the P2P industry merely displaced incumbents or instead filled gaps in an underserved credit market. This paper addresses that question and provides insights derived 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 given that, when low-quality bank borrowers migrate to P2P platforms, the quality of the P2P borrower pool deteriorates. This result suggests that the credit expansion opportunities brought by P2P lenders only benefit infra-marginal bank borrowers. At the same time, however, P2P platforms complement banks by providing small loans.

Although the empirical analysis carried out here uses data from the largest P2P lending platform in the United States, two caveats are in order. First, the analysis focuses on the unsecured consumer loan market. My results may not generalize to other markets (e.g., the residential lending market) or to countries with a banking market structure unlike the US one. On a precautionary note, I remark that mixed evidence from other countries (e.g., Liao et al. 2017; De Roure, Pelizzon, and Thakor 2018) suggests that the credit market structure in the FinTech era may take distinct forms in equilibrium. Future research could help identify the mechanisms driving these different outcomes. Second, the landscape of P2P lending is changing rapidly. Hence such platforms may not operate as substitutes for banks in the long run, in which case research examining the relevant market structures may still be relevant. Nonetheless, it is noteworthy that—notwithstanding the rapid growth of this sector—LendingClub was the dominant player in the P2P unsecured consumer loan market during the 2009–2012 sample period and remains so in 2018.

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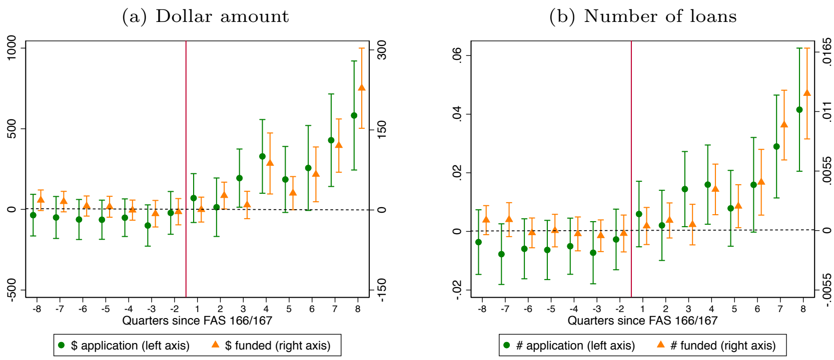

Figure 4
Impact of FAS 166/167 on P2P Application and Loan Volumes
This figure reports the effects of FAS 166/167 on local P2P application volume (dots) and origination volume (triangle) as obtained from estimating Equation (1) using quarterly data. The left (right) vertical axis represents the *magnitude* of the dots (triangles). The P2P lending volume is measured in dollars per thousand inhabitants in Panel (a) and by the number of loans per thousand inhabitants in Panel (b). Quarter $t = -1$ signifies the last quarter of 2010 and is used as the reference point. Error bars mark the 95% confidence intervals. Standard errors are clustered at the county level.

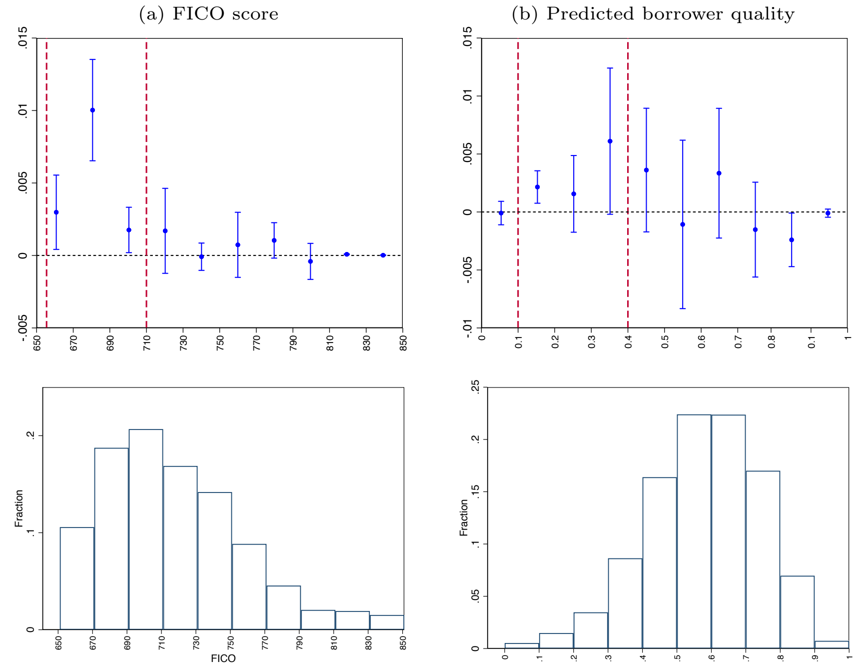

Figure 5
Impact of FAS 166/167 on the Frequency Distribution of P2P Borrower Quality
This figure reports the effects of FAS 166/167 on the number of borrowers (per thousand county inhabitants) in ten equal-width intervals of P2P borrower quality. The plotted coefficients are obtained from the estimation of Equation (1) using annual data. Borrower quality is measured by FICO score in Panel (a) and by predicted borrower quality in Panel (b). The area between the two dashed vertical lines is where the number of borrowers increases significantly. The lower graph in each panel shows the pre-shock distribution of P2P borrower quality at the national level on LendingClub's platform. Error bars mark the 95% confidence intervals. Standard errors are clustered at the county level.

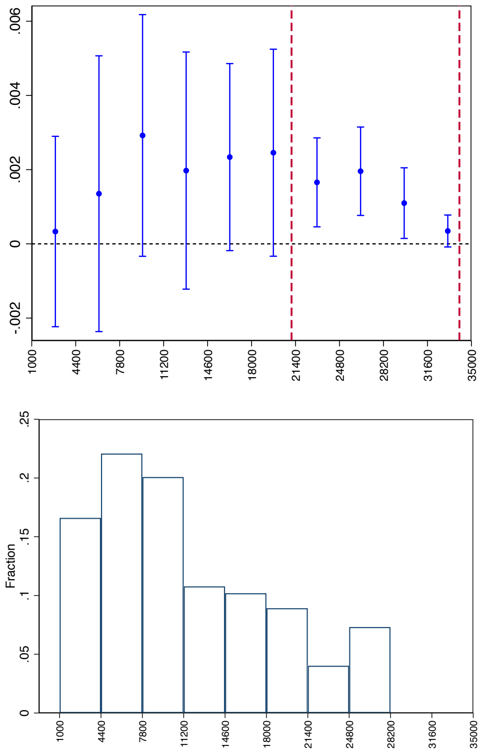

Figure 6
Impact of FAS 166/167 on the Frequency Distribution of P2P Loan Size
This figure reports the effects of FAS 166/167 on the number of borrowers (per thousand county inhabitants) in ten equal-width intervals of P2P loan size. The coefficients plotted in the upper graph are obtained from estimating Equation (1) using annual data. The area between the two dashed vertical lines is where the number of borrowers increase significantly. The lower graph shows the pre-shock distribution of P2P loan size at the national level. Error bars mark the 95% confidence intervals. Standard errors are clustered at the county level.

Table 1
Summary Statistics: LendingClub Loans

	Min.	Mean	Max.	S.D.	*N*
	Panel A. All applications				
Amount	1,000	1,3104	35,000	10,111	880,346
FICO score	457	652	850	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	850	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 last 6 months	0	0.953	5	1.151	93,159
Delinquency last 2 years	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

This table presents summary statistics of LendingClub loan characteristics for all loan applications (Panel A) and funded loans (Panel B). Each variable's definition is given in the Appendix.

Table 2
Summary Statistics: County Characteristics

	Min.	Mean	Max.	S.D.	*N*
			Panel A. Lending volume		
$ applications (000s)	0	972	240,234	4,535	11,726
# applications	0	74	16,278	325	11,726
$ funded loans (000s)	0	99	33,176	573	11,726
# funded loans	0	8	2,526	44	11,726
			Panel B. Normalized Lending Volume		
$ applications	0	7,619	291,908	10010.71	11,726
# applications	0	0.58	18.94	0.68	11,726
$ funded loans	0	599	50,457	1,342	11,726
# funded loans	0	0.05	1.92	0.09	11,726
			Panel C. County Controls		
Treated	0	0.66	1	0.47	11,726
HHI	467	3,107	10,000	2030	11,726
Share(SmallBanks)	0	0.40	1	0.40	11,726
Share(NationalBanks)	0	0.16	1	0.27	11,726
Geo.Diversification	1	3	40	4.60	11,726
Deposits	1,434	17,809	1,795,294	24,381	11,726
Population	670	104,331	10,045,175	325,093	11,726
Personal income	14,360	35,267	176,046	9,641	11,726
Unemployment	1.60	8.92	28.90	3.02	11,726

This table presents the summary statistics of all county-level variables. Panels A and B report, respectively, the overall P2P lending volume and the P2P lending volume per thousand inhabitants; Panel C reports other county-level variables. Here *Treated* is a dummy variable set to 1 if there is at least one bank affected by FAS 166/167 in the county, and *HHI* measures market competition in the local banking industry. *Share*(*SmallBanks*) is the share of banks with total assets of less than $1 billion, and *Share*(*NationalBanks*) is the share of national banks. *Geo.Diversification* is a proxy for the geographical diversification of banks as measured by the median number of the states in which the banks in a given county operate. *Deposits* represents the dollar amount of deposits per thousand country inhabitants, and *Personal income* is the median annual personal income (also in US dollars). *Unemployment* is the county's percentage unemployment rate in a given year.

Table 3
Impact of FAS 166/167 on P2P Application and Loan Volumes

	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)
$1000 \leq$ HHI < 1800	65.618	–0.019	–17.221	–0.000
	(0.130)	(–0.561)	(–0.191)	(–0.019)
HHI ≥ 1800	151.585	–0.014	–36.821	0.000
	(0.242)	(–0.343)	(–0.348)	(0.024)
Share(SmallBanks)	182.530	0.026	162.522	0.013
	(0.163)	(0.366)	(1.452)	(1.614)
Share(NationalBanks)	–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)
Deposits	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	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

This table reports the bank credit supply shock's effects on P2P application and loan volumes as estimated from the following regression, which uses county–year data for the period 2009–2012:

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

The dependent variable is P2P application volume or P2P origination volume. Application volume is measured either by the total amount requested in loan applications per thousand inhabitants (column [1]) or by the total number of loan applications per thousand inhabitants (column [2]) in a given county; the same method is applied to the origination volume (columns [3] and [4]). *Treated* is an indicator for whether there are affected banks in the county. *Post* is a dummy set to 1 for years after 2010, and set to 0 otherwise. Other county-level control variables are defined in the Appendix. Year and county fixed effects (FE) are included in all regressions. Standard errors are clustered at the county level, and t-statistics are given in parentheses.
$^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 4
Impact of FAS 166/167 on P2P Borrower Quality Distribution

	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)
Mean of Dep. Var.	700	702	707	712	715	726	729	737	744	751	722
R^2	0.554	0.515	0.471	0.445	0.431	0.460	0.441	0.417	0.428	0.522	0.447
					Panel B. Predicted borrower quality						
Treated × Post	–0.052***	–0.020	–0.006	–0.013	–0.010	–0.024*	–0.019	–0.026*	–0.024	–0.010	–0.021
	(–3.060)	(–1.241)	(–0.393)	(–0.887)	(–0.630)	(–1.666)	(–1.275)	(–1.776)	(–1.604)	(–0.701)	(–1.479)
Mean of Dep. Var.	0.415	0.436	0.458	0.487	0.500	0.544	0.558	0.587	0.607	0.625	0.523
R^2	0.563	0.475	0.458	0.460	0.463	0.479	0.497	0.514	0.555	0.618	0.489
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
Observations	5,059	5,059	5,059	5,059	5,059	5,059	5,059	5,059	5,059	5,059	5,059

This table reports the bank credit supply shock's effects on the quantiles and the mean of the borrower quality distribution as estimated from the following regression, which uses county–year data for the period 2009–2012:

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

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

Table 5
Impact of FAS 166/167 on P2P Loan Size Distribution

	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)
Mean of Dep. Var.	6,244	6,630	7,161	8,021	8,524	10,270	10,883	12,280	13,501	14,546	9,833
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
Observations	5,059	5,059	5,059	5,059	5,059	5,059	5,059	5,059	5,059	5,059	5,059
R^2	0.511	0.455	0.429	0.417	0.416	0.433	0.459	0.488	0.544	0.660	0.461

This table reports the bank credit supply shock's effects on the quantiles and the mean of the loan size distribution as estimated from the following regression, which uses county–year data for the period 2009–2012:

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

In each of columns [1]–[10], the dependent variable is the kth percentile ($k \in \{5, 15, \ldots, 95\}$) 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 and also include county and year fixed effects. Standard errors are clustered at the county level, and t-statistics are given in parentheses.
$^{**}p < 0.05$, $^{***}p < 0.01$

Table 6
Test of the Elasticity of P2P Credit Supply

	Loan grade		Interest rate	
	[1]	[2]	[3]	[4]
		Panel A. Test results		
Number of counties	1,925	1,925	1,925	1,925
$F(1925,89839)$	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)
Loan Controls	Y	Y	Y	Y
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

This table reports results of testing the elasticity of the P2P credit supply using the following regression equation, which is estimated at loan level for the period 2009–2012:

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

The dependent variable is either the loan grade assigned by LendingClub (columns [1] and [2]) or the interest rate in basis points (columns [3] and [4]). In all columns, loan and borrower characteristics listed in Table 1 Panel B are included. Columns [2] and [4] also include the $Treated \times Post$ interaction term in Panel B. The F-statistics and p-values of the test of the joint significance of county fixed effects are reported in Panel A. Standard errors are clustered at the county level, and t-statistics are given in parentheses.

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)
Loan Controls	N	N	Y	Y
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

This table reports the bank credit supply shock's effects on the probability of listed P2P loans being funded. The estimates are derived from the following probit model, which uses loan-level data for the period 2009–2012:

$$\begin{aligned} &E[Funded_{i,c,t} \mid Treated_{i,c,t}, Post_{i,c,t}, Controls_{i,c,t}] \\ &\quad = \Pr(Funded_{i,c,t} = 1 \mid Treated_{i,c,t}, Post_{i,c,t}, Controls_{i,c,t}) \\ &\quad = \beta\, Treated_c \times Post_t + \gamma_c + \sigma_t + Controls_{i,c,t}, \end{aligned}$$

where the dependent variable is an indicator set to 1 if the loan listing is funded (and set to 0 otherwise). In column [1], the interaction term is included as the explanatory variable. In columns [2] and [4], county-level control variables used in the main specification are included; in columns [3] and [4], borrower characteristics and loan characteristics listed in Table 1 Panel B are included. Year and county fixed effects are always included. Standard errors are clustered at the county level, and t-statistics are given in parentheses.

Table 8
Predictions for different types of shocks

Predictions on P2P loans	P2P–Bank Relation	
	Substitutability	Complementarity
Panel A. Baseline type: Only low-end bank borrowers are excluded		
Quantiles	Decrease.	Increase.
Frequency	Increases at the left tail.	Increases beyond the right tail.
Panel B. Alternative type I: Bank borrowers at all levels are affected		
Quantiles	No change.	Increase.
Frequency	Increases at all levels.	Increases beyond the right tail.
Panel C. Alternative type II: Only high-end bank borrowers are excluded		
Quantiles	Increase.	Increase.
Frequency	Increases at the right tail.	Increases beyond the right tail.

Appendix: Definition of Variables

Variable	**Definition**
Credit supply shock	
Treated	An indicator for whether at least one bank is affected by FAS 166/167 in a given county.
Local market structure	
HHI	Herfindahl–Hirschman index of banking market at the county level (based on deposit shares).
Share(SmallBanks)	Deposit share of small banks with total assets of less than $1 billion.
Share(NationalBanks)	Deposit share of national banks at the county level.
Geo.Diversification	Median number of states in which the local county's banks operate.
Deposits	Total deposits in all county bank branches in the county *divided by* population (in thousands).
County controls	
Population	Total population in the county.
Personal income	Median annual personal income ($).
Unemployment	Unemployment rate (%).
Loan characteristics	
LendingClub interest rate	Interest rate proposed by LendingClub and accepted by borrowers and lenders.
Amount	Dollar amount requested by the borrower.
Maturity	Indicator variable set to 1 if the original maturity is 60 months (or set to 0 otherwise).
DTI	Debt-to-income ratio calculated as the borrower's total monthly debt payments (excluding any mortgage and the requested LendingClub loan) *divided by* the borrower's self-reported monthly income.
LengthEmploy	Employment length reported by the borrower; it can take one of ten values—less than 1 year, 1 year, 2 years, 3 years, . . ., at least 10 years.
LengthCredit	Length (in years) of the borrower's credit history.
Homeowner	Home ownership status provided by the borrower during registration; it is set to 1 only if the borrower owns her home without mortgage.
Mortgage	Home ownership status provided by the borrower during registration; it is set to 1 only if the borrower's home is mortgaged.
Revolving balance	Total outstanding balance that the borrower owes on open credit cards or other revolving credit accounts reported by the credit bureau.
Total credit lines	The total number of credit lines currently in the borrower's credit file.
Open accounts	The number of open credit lines in the borrower's credit file.
Revolver utilization	Amount of credit that the borrower is using relative to all available revolving credit.
Inquiries last 6 months	The number of inquiries within the preceding six months (excluding auto and mortgage inquiries) reported by the credit bureau.
Delinquency last 2 years	Number of borrower delinquencies within the preceding two years.

Online Appendices for "Peer-to-Peer Lenders and Banks: Substitutes or Complements?"

Huan Tang

Appendix A. Effects of FAS 166/167 on Bank Credit Supply

	SBL volume		
	All borrowers	Revenues < \$1 million	Revenues ≥ \$1 million
	[1]	[2]	[3]
Treated × Post	–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)
County×year FE	Y	Y	Y
Bank FE	Y	Y	Y
Observations	277,426	270,404	270,404
R^2	0.208	0.210	0.184

This table reports the effects of FAS 166/167 on small business lending as estimated from the following regression, which uses data at the bank–county–year level for the period 2009–2012:

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

Treated is a time-varying dummy set to 1 only if bank b in county c consolidated assets under FAS 166/167 in year t. The dependent variable is 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 total small business lending; in columns [2] and [3], the dependent variable is the lending volume to small businesses with annual revenues of (respectively) less than or at least \$1 million. Bank-level controls include size (as measured by the logarithm of assets), tier-1 capital ratio, NPL ratio, commercial and industrial loans, deposits, and securitized assets; the last three of these controls are normalized by total assets. I also add county×year and bank fixed effects to control for time-varying local economic conditions (e.g., credit demand) and unobservable bank characteristics. Standard errors are clustered at the bank level, and t-statistics are given in parentheses.
$^*p < 0.10$, $^{**}p < 0.05$

Appendix B. Construction of Predicted Borrower Quality

This appendix describes the procedure for constructing the variable for predicted borrower quality, which combines information about FICO score, debt-to-income ratio, and length of employment. Data on these three components are available for both rejected applications and qualified loans.

I use the following equation to estimate an ordered probit model for application outcomes:

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

here $Q_{i,c,t}$ represents 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 an interaction term, I also control for the amount that borrowers apply for because it may affect the application's outcome. The term $\gamma_{t,s}$ is a state–year fixed effect that controls for time-varying factors at the state level; note that the error term $\varepsilon_{i,c,t}$ has a standard normal distribution.

Although this latent borrower quality is unobservable, it determines the application outcome as follows:

$$
Outcome_{i,c,t} = \begin{cases} 0 & \text{if } Q_{i,c,t} < \underline{c}; \\ 1 & \text{if } \underline{c} \leq Q_{i,c,t} < \overline{c}; \\ 2 & \text{if } Q_{i,c,t} \geq \overline{c}. \end{cases}
$$

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

After estimating Equation (A1), I use the estimated coefficients (i.e., $\beta_1, \ldots, \beta_9$) of the three variables ($FICO_{i,c,t}$, $DTI_{i,c,t}$, and $LengthEmploy_{i,c,t}$), for the squares of these variables, and for the FICO–DTI interaction to calculate the predicted value of $Q_{i,c,t}$. During this process, $Amount_{i,c,t}$ and $\gamma_{t,s}$ are each set to a constant value for all applicants, which amounts to filtering out their effects on the application outcome. In other words, the predicted value of $Q_{i,c,t}$ captures only the contribution of FICO, DTI, and length of employment to $Q_{i,c,t}$. A higher value of the predicted value of $Q_{i,c,t}$ corresponds to higher borrower quality and hence to a greater likelihood of the applicant being qualified and the loan being funded.

The expression for the *predicted* borrower quality is

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

Not surprisingly, predicted borrower quality increases with the FICO score and with the length of employment but decreases with the debt-to-income ratio. All seven coefficients are statistically significant at the 1% level. The pairwise correlations among the predicted borrower quality, FICO score, DTI ratio, and employment length are shown in the following table; all these coefficients, too, are significant at the 1% level.

	Predicted borrower quality	*FICO*	*DTI*
FICO	0.711		
DTI	–0.395	0.050	
LengthEmploy	0.368	0.313	–0.069

I then normalize the predicted borrower quality so obtained via the following affine transformation:

$$\frac{\widehat{Q}_{i,c,t} - \min_{i,c,t}\{\widehat{Q}_{i,c,t}\}}{\max_{i,c,t}\{\widehat{Q}_{i,c,t}\} - \min_{i,c,t}\{\widehat{Q}_{i,c,t}\}}.$$

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

Appendix C. Bank Branch Closing as a Shock to Bank Credit Supply

In this appendix, I use bank branch closing as an alternative shock to bank credit supply and investigate the its effects on P2P lending activities. The purpose of this exercise is to investigate a shock that affects *all* bank borrowers. All borrowers at the closed branches are presumably affected by their closures. Hence I can compare them to the FAS 166/167 regulation, which has already been shown to affect mainly low-quality borrowers. The predictions for this shock are that (i) it will lead to increased P2P lending, (ii) the P2P borrower quality distribution will *not* exhibit a shift, and (iii) the frequency will increase at all levels. See Section 6 and Table 8 for additional details.

The data on bank mergers and branch closings are obtained from the FDIC. Following the procedure in Garmaise and Moskowitz (2006) and Nguyen (2017), I use the mergers between large banks that serve overlapping markets as an instrument for local branch closings. More specifically, a bank merger is included in the sample only if all three of the following criteria are met. First, the merger must be between two banks that each has at least $1 billion in assets in the year of the merger. Second, the merger (a) must be classified as "non-failing" and (b) cannot be between two banks owned by the same bank holding company. Third, each of the two merged banks must have branches in at least one county.

The effects of branch closings on P2P lending volume are estimated with both ordinary least-squares (OLS) and instrumental variables (IV) regressions. The explanatory variable of interest is the total number of closed branches, net of the number of branch openings in a county. I instrument this variable by the previous year's number of mergers between large banks in the focal county.

I first examine the relevance of the instrument—that is, whether more mergers actually lead to a higher number of branch closings. Table C1 reports these first-stage results. The sign of the coefficient of the instrument is as expected: a higher number of mergers is associated with a higher number of net closings (column [3]). This effect is due primarily to an increase in the number of closings (column [1]) rather than a reduction in the number of openings (column [2]).

Table C1
First-Stage Estimates

	$\#Closings$ [1]	$\#Openings$ [2]	$\#NetClosings$ [3]
$\#Mergers$	0.638***	–0.083	0.721***
	(2.583)	(–0.556)	(2.802)
Controls	Y	Y	Y
Year FE	Y	Y	Y
County FE	Y	Y	Y
Observations	10,402	10,402	10,402
R^2	0.631	0.739	0.377

This table reports the effects of mergers on branch changes. The following equation is estimated at the county–year level for the period 2009–2012:

$$y_{c,t} = \beta \# Mergers_{c,t-1} + Controls_{c,t} + \gamma_c + \sigma_t + \varepsilon_{c,t}.$$

The dependent variables are $\#Closings$, $\#Openings$, and $\#NetClosings$ calculated as the difference between the number of closings and openings. The explanatory variable, $\#Mergers$, is the preceding year's number of mergers between two large banks that each have at least one branch in county c. All columns include county and year fixed effects. Standard errors are clustered at the county level, and t-statistics are given in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Next I test the effects of bank branch closings on P2P application amount and lending volume. Table C2 reports both the OLS estimates (Panel A) and the IV estimates (Panel B). The OLS estimates are positive but not significant. Also, the magnitudes of the OLS estimators are small: an increase of one standard deviation in the number of net closings (1.8) leads to an increase of less than \$22 in P2P application volume per thousand inhabitants ($1.8 \times 12.2 = 21.96$). In Panel B I use the number of mergers as an instrument for branch closings; again I find no significant effect of branch closings on either the application amount or the lending volume of P2P platforms. In contrast, P2P lending volume was strongly affected by FAS 166/167: as reported in Panel C of the table, this regulatory shock led to an increase of \$1,107 in P2P application amount per thousand inhabitants. Comparing Panels A and C of Table C2 shows how different are the magnitudes of these two shocks.

A possible explanation for this difference is that, following a merger, borrowers from the closed branch are referred to other branches of the same bank. These borrowers might, alternatively, decide to take their business to a different bank in the same county. There was insufficient statistical power to identify the effect of bank mergers on P2P lending volume at the county level, so I was not able to test for any post-shock changes in the composition of P2P borrowers.

Table C2
OLS and IV Estimates of the Effects of Branch Closings on Local P2P Lending

	Applications		Funded loans	
	Amount ($)	Number (#)	Amount ($)	Number (#)
	[1]	[2]	[3]	[4]
	Panel A. OLS estimates			
$\#NetClosings$	12.221	0.000	2.390	0.000
	(0.454)	(0.035)	(0.682)	(0.996)
	Panel B. IV estimates			
$\#NetClosings$	–210.795	–0.019	59.193	0.005
	(–0.298)	(–0.437)	(0.498)	(0.645)
	Panel C. FAS 166/167 as a comparison			
$Treated \times Post$	1107.690***	0.070***	300.542***	0.016***
	(2.888)	(2.918)	(6.310)	(4.741)
Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
County FE	Y	Y	Y	Y
Observations	10,246	10,246	10,246	10,246

This table reports the OLS and IV regression results obtained from estimating the following equation, at the county–year level, for the period 2009–2012:

$$P2P\_Volume_{c,t} = \beta \#NetClosings_{c,t} + Controls_{c,t} + \gamma_c + \sigma_t + \varepsilon_{c,t}.$$

The dependent variables are the P2P loan application volume and origination volume. The term $\#NetClosings$ is the number of branch closings minus the number of branch openings during year t in county c. Panels A and B report (respectively) OLS and IV estimates of the coefficients of $\#NetClosings$; Panel C reports, for comparative purposes, the effect of FAS 166/167 on P2P lending. The instrument $\#Mergers$ is the preceding year's number of mergers between two large banks that each have at least one branch in county c. All columns include the full set of baseline controls as well as county and year fixed effects. Standard errors are clustered at the county level, and t-statistics are reported in parentheses.
* $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Appendix D. Quantile and Frequency Tests on Loan Size Using HMDA Data

In this appendix, I supplement the main results with evidence from the residential lending market. The advantage of using HMDA data is that it provides information on mortgages originated by banks and FinTech lenders both. I first offer reassuring evidence that borrowers switched from banks to FinTech lenders after banks were hit by the negative shock of FAS 166/167. In addition, I provide evidence for *substitutability* in the loan size dimension by applying quantile and frequency tests to both bank and FinTech lenders. In particular, I show that FAS 166/167 led banks to reduce their origination of *large* mortgages and that FinTech lenders stepped in to fill the resulting gap. These findings are consistent with banks and FinTech lenders being substitutes in the loan size dimension. This finding implies that FAS 166/167, when applied to the loan size distribution in the HMDA data, affects the high end of the distribution, i.e., large loans. When interpreting these results, one must bear in mind the different natures of the consumer credit market and the residential lending market (as discussed in Section 6.2 of the main text).

I use a variety of sources to identify major FinTech lenders in the HMDA data, sources that include the emerging literature on FinTech lenders in the mortgage market (e.g., Buchak et al. 2018; Fuster et al. 2018). I thereby identify six major FinTech lenders (and their respective market shares), which have been in operation since the start of this study's sample period: Quicken Loans (4.7%), PennyMac Financial Services (2.9%), Movement Mortgage (2.5%), Guaranteed Rate Inc. (2.3%), LoanDepot.com (1.7%), and Stearns Lending Inc. (1.5%). Banks are identified as the depository institutions in the HMDA data. For this analysis, the lending volume of banks and of FinTech lenders are aggregated at the county–year level during the sample period 2009–2012.

I first estimate the effect of FAS 166/167 on mortgage lending by banks and FinTech lenders via the same regression specification; results are reported in (respectively) Panels A and B of Table D1. All four columns of the table show that, following the implementation of FAS 166/167, FinTech lenders experienced a 6.3% (5.5%) increase in the dollar amounts requested by applications (number of applications) and a 12.5% (10.6%) increase in loan dollar volume (number of loans). These results are consistent with the main findings reported in Table 3, which show that P2P lending volume increased once FAS 166/167 went into effect. Furthermore, a closer look at Panel B reveals the driving force behind this expansion of P2P lending: banks reduced their origination volume by 2.3% after the shock.

Combining the results on FinTech lenders and banks, I conclude that the negative shock to bank credit supply led traditional banks to reduce their lending but led FinTech lenders to increase their lending. This outcome is further confirmation of evidence, presented in the main text, that FinTech lending's post-shock growth in the consumer credit market was driven by the concomitant reduction in bank lending.

Although HMDA data do not include FICO scores, we can implement the quantile and frequency tests on loan size following the procedures detailed in Section 5. For both types of lenders, more than 90% of mortgages are for no larger than $400,000 and the rest are sparsely distributed within a wide interval between $400,000 and $850,000; so in order to obtain a realistic presentation of the distribution, I exclude all loans in the latter interval.

Results from quantile tests are reported in Table D2, according to which all the quantiles of post-shock distribution of FinTech mortgage size (Panel A) exhibited a rightward shift while all quantiles of the distribution of bank mortgage size (Panel B) exhibited a leftward shift. Because these changes are in opposite directions, we conclude that bank

Table D1
Effects of FAS 166/167 on Mortgage Demand and Supply

	Applications		Funded loans	
	log(amount)	log(number)	log(amount)	log(number)
	[1]	[2]	[3]	[4]
		Panel A. FinTech lenders		
Treated × Post	0.063***	0.055***	0.125***	0.106***
	(3.124)	(3.073)	(5.565)	(5.360)
Observations	12,172	12,172	12,172	12,172
R^2	0.799	0.765	0.778	0.747
		Panel B. Banks		
Treated × Post	0.015*	0.013**	–0.023**	–0.009
	(1.874)	(2.051)	(–2.286)	(–1.181)
Observations	12,237	12,237	12,230	12,230
R^2	0.995	0.996	0.992	0.994
Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
County FE	Y	Y	Y	Y

This table reports the bank credit supply shock's effect on HMDA application and origination volumes as estimated from the following regression, which uses county–year data for the period 2009–2012:

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

The dependent variable is either HMDA application volume or HMDA origination volume. Panel A reports the results for FinTech lenders and Panel B for banks. *Treated* is an indicator for whether there are affected banks in the county; *Post* is a dummy set to 1 for years after 2010 and set to 0 otherwise. Other county-level control variables are defined in the Appendix. Year and county fixed effects are included in all regressions. Standard errors are clustered at the county level, and t-statistics are given in parentheses.
* $p<0.10$, ** $p<0.05$, *** $p<0.01$.

(FinTech) lenders originated mortgages that were smaller (larger) after the regulatory shock. This result is consistent with banks and FinTech lenders being substitutes—as seen for the second alternative type of shocks in Section 6.1.2, were banks are assumed first to exclude loans at the right tail of the distribution.

Table D2
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. FinTech lenders											
Treated × Post	3.874***	4.087***	3.573***	3.421***	2.231*	3.682**	2.113	1.681	0.258	−1.978	2.562**
	(2.990)	(3.201)	(2.866)	(2.617)	(1.690)	(2.390)	(1.326)	(0.946)	(0.123)	(−0.822)	(2.075)
Observations	11,260	11,260	11,260	11,260	11,260	11,260	11,260	11,260	11,260	11,260	11,260
R^2	0.543	0.635	0.708	0.738	0.773	0.752	0.780	0.781	0.784	0.820	0.824
Panel B. Banks											
Treated × Post	−2.138***	−3.788***	−4.509***	−4.650***	−4.841***	−4.982***	−4.890***	−5.285***	−5.454***	−9.036*	−3.463***
	(−6.084)	(−9.663)	(−11.119)	(−10.379)	(−10.160)	(−7.369)	(−6.044)	(−5.112)	(−3.512)	(−1.681)	(−3.613)
Observations	12,229	12,229	12,229	12,229	12,229	12,229	12,229	12,229	12,229	12,229	12,229
R^2	0.900	0.947	0.963	0.964	0.968	0.958	0.953	0.928	0.904	0.734	0.929
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

This table reports the bank credit supply shock's effect on the quantiles and the mean of the borrower quality distribution as estimated from the following regression, which uses county–year data for the period 2009–2012:

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

In each of columns [1]–[10], the dependent variable is the kth percentile ($k \in \{5,15,\ldots,95\}$) of the distribution of FICO scores (Panel A) or of 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. Standard errors are clustered at the county level, and t-statistics are given in parentheses.
* $p<0.10$, ** $p<0.05$, *** $p<0.01$.

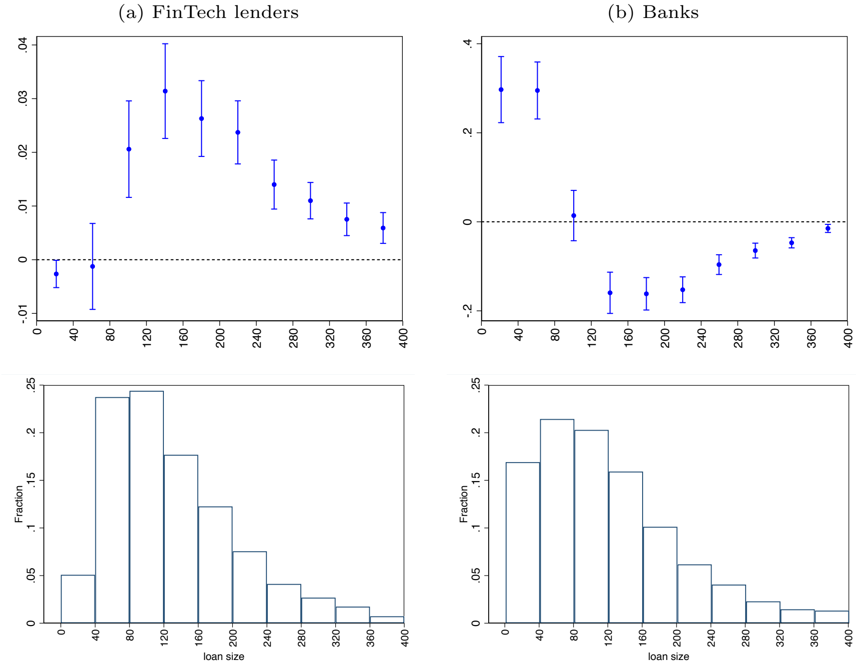

Figure D1
Frequency Change: HMDA Loan Size
This figure reports the effects of FAS 166/167 on the number of mortgage loans originated by FinTech lenders (Panel (a)) and banks (Panel (b)), per thousand inhabitants, in the ten equal-width intervals of loan size. The coefficients plotted in the upper two graphs are obtained from Equation (1); the lower two graphs illustrate the pre-shock distribution of loan size (measured in thousands of dollars). Error bars mark the 95% confidence intervals. Standard errors are clustered at the county level.

Evidence from frequency tests confirms this result. First, as shown in the lower two graphs of Figure Appendix D, the loan size distributions of FinTech lenders and banks are similarly shaped on their common support (from \$0 to \$400,000. Second, Panel (b) of the figure clearly shows that, after the regulatory shock, banks reduce their originations of loans for more than \$120,000 and focus on smaller mortgages. Figure Appendix D(a) reveals that, although FinTech lenders increase their lending in each loan size interval, the increase among large loans is the most prominent—that is, in comparison with the pre-shock loan size distribution (lower graph in the panel). This result constitutes direct evidence that, with respect to the loan size dimension, FinTech lenders and banks are substitutes in residential lending markets.

That FinTech lenders and banks are *substitutes* in the loan size dimension in residential lending markets is not at odds with them being *complements* in that dimension in consumer credit markets. The reason is that there are several important differences between these two markets, as detailed in Section 6.2 of the main text.