Crowding Out Banks: Credit Substitution by Peer-to-Peer Lending[†]

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Abstract

Through superior technology, financial technology (FinTech) firms may expand credit markets. Alternatively, consumers may substitute one credit provider for another, generating adverse selection problems for incumbent lenders. We analyze the unsecured consumer loan market and identify the influence of FinTech lending on commercial banks using a novel approach that takes advantage of regulatory restrictions for FinTech borrowers and investors. We show that high-risk FinTech loans substitute for bank loans while low-risk loans may be credit expansionary. However, the influence on banks is heterogeneous. Our results highlight the changing landscape of financial intermediation and the regulatory challenges faced by FinTech firms.

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Technological advancements in the banking industry have sparked multiple waves of industry change. From automated teller machines to credit scoring models,"technology is slowly breaking the tyranny of distance" (Petersen and Rajan (2002)). Recent advances in the financial technology, or FinTech, sector have allowed peer-to-peer lending platforms to rapidly enter the traditional financial intermediation market without any geographic footprint. In 2015, the two largest peer-to-peer lending platforms originated around $12 billion in unsecured consumer loans, compared to the $241 billion in unsecured consumer loans outstanding reported by the Federal Reserve.

Our goal is to empirically identify how encroaching FinTech competitors have affected the lending behavior of commercial banks. Our study is the first to directly examine how these emerging nonbank intermediaries impact the traditional financial intermediation system of commercial banks. Banking entry models founded on information production such as that of Hauswald and Marquez (2003, 2006) predict that better informed,"informationally close" nonbank lenders may be able to poach the profitable borrowers from incumbents and create adverse selection problems for traditional intermediaries. As suggested by Petersen and Rajan (2002), FinTech lenders may indeed use technology instead of close geographic distance to generate private information on borrowers. It is possible that these technological advancements in credit modeling allow borrowers with *observably* poor but actually good credit to gain new access to credit. If this is the case, rather than stealing borrowers away from traditional banks, these new financial intermediaries may be expanding access to credit without creating a "poisoned well" for subsequent lenders, leaving commercial banks undisturbed.

We focus on these potential outcomes and provide empirical evidence that clarifies the impact of emerging FinTech firms on traditional financial intermediaries. While we examine one particular segment of the debt markets – unsecured consumer loans – our results are likely representative of a larger trend in the financial intermediation markets. The rapid growth of disintermediated financing driven by technological change and inflamed by the regulatory environment gives our results additional significance. We employ a novel identification strategy that uses FinTech platform restrictions on the borrower side as well as on the investor side to show causality. Our identification strategy highlights the complexity of financial intermediation regulation and the difficulty faced by FinTech firms attempting to enter these markets.

Initially, we use the cross-sectional heterogeneity in state-level peer-to-peer lending to identify how loan origination on these platforms affects commercial bank lending. Because peer-to-peer lending platforms solicit borrowers through the internet, technology should allow them to compete for borrowers without any geographic restrictions. However, state banking regulators can create various types of barriers to entry for peer-to-peer platforms such as origination rebates, licensing, reviews, and enforcement actions, among others. We provide evidence that the barriers can be binding in multiple ways and can effectively prevent peer-to-peer platforms from entering these markets, sheltering some banks from the influence of peer-to-peer lending. These borrower restrictions vary from state to state and over time and offer plausibly exogenous variation in peer-to-peer lending competition. Using this approach, we observe a 1.2% decrease in the volume of personal loans across commercial banks that see a one-standard-deviation increase in peer-to-peer lending activity in their market. Our results likely represent a conservative lower bound. The personal loan subsegment reported to the Federal Deposit Insurance Corporation (FDIC) by commercial banks is a combination of multiple types of loans, including automotive, student, and unsecured consumer loans. Peer-to-peer lending is very likely to compete with the unsecured consumer loan portion of this segment for a variety of reasons, and according to the Federal Reserve, aggregate unsecured consumer loan debt is only 9.2% of these combined segments.[1] We next divide the flow of peer-to-peer loans into high- and low-risk loans to see if there is a symmetric impact from these different types of loans. We find that loan levels at the commercial banks are negatively affected by the high-risk portion of the peer-to-peer loan flow and indifferent to lower risk peer-to-peer loan volume, suggesting that the aggregate displacement is driven by the poor credit quality borrowers' net substation away from commercial banks. Interestingly, the lack of peer-to-peer influence indicates that high-credit-quality borrowers' access to credit expands with peer-to-peer expansion.

Our second contribution is to provide evidence that commercial banks do not uniformly feel the

[1] In 2015, the Federal Reserve estimated $2,597 billion in nonrevolving consumer credit facilities outstanding at financial intermediaries, of which $1,318 billion was for student loans and $1,038 billion was for motor vehicle loans, leaving $241 billion in unsecured consumer loans. The majority of borrowers on the peer-to-peer platforms claim to use the funds for debt consolidation, credit card repayment, or home improvement purposes (US Treasury, 2016). Peer-to-peer loans require no collateral but are still dischargeable in bankruptcy, making them most comparable to the Federal Reserve unsecured consumer loan segment. If commercial banks hold a similar fraction of their personal loan portfolio in unsecured consumer loans relative to the aggregate Federal Reserve statistics, our results likely represent a lower bound on the impact of peer-to-peer lending.

pressure from peer-to-peer platforms. First, we show that the loss in personal loan volume is concentrated among small commercial banks with assets under $300 million, whereas large commercial banks do not appear to suffer any loan losses as a result of increased competition from peer-to-peer lending. We estimate that small commercial banks lose 1.8% of their personal loan volume for each standard deviation increase in peer-to-peer lending. One potential benefit of the expansion of peer-to-peer lending is increased access to banking services in rural areas or areas with less banking competition. However, if community banks in less competitive markets are disproportionately affected by peer-to-peer expansion, a tension emerges between supporting the growth of new banking technology and maintaining access to existing brick-and-mortar financial services. We show that banks in less competitive markets such as rural counties experience a 2.0% decline in personal loan volume for each standard deviation increase in peer-to-peer lending, while banks with branches in more competitive areas appear unaffected.

An additional concern with increased competition is that lenders may lower credit standards to maintain loan volume. Our third contribution is to examine loan delinquency and charge-off activity among commercial banks, and we find evidence that personal loan quality also deteriorates among small banks with increasing peer-to-peer pressure. A one-standard-deviation increase in peer-to-peer lending appears to drive a 3.9% increase in quarterly charge-off rates. We find additional evidence of increases in 30- to 89-day delinquencies. As a whole, these results provide strong evidence that in addition to losing volume in the personal loan segment, commercial banks begin to hold loans with higher default probabilities as a result of the peer-to-peer competition. We note that the deterioration of borrower quality helps alleviate reverse causality concerns in our loan volume results, i.e., that banks are choosing to decrease personal loan issuances because of increased capital requirements, which creates a vacuum that encourages peer-to-peer entry.

Finally, we provide some modest evidence comparing loan pricing among commercial banks and peer-to-peer platforms. In their theoretical models, Hauswald and Marquez (2003, 2006) assume that the encroaching lender (in our case, the peer-to-peer platform) has a pricing advantage. We provide evidence that peer-to-peer lending platforms indeed offer such a pricing advantage to borrowers (an interest rate discount). For borrowers with the highest credit ratings, we show that peer-to-peer platforms offer loans that are an average of 164 basis points (BPs) lower than the average commercial banking loan. However, commercial banks do not appear to adjust loan pricing in response to peer-to-peer encroachment, indicating that loan markets are already sufficiently competitive to force banks to offer competitive interest rates. Because almost the entirety of peer-to-peer platform revenue is generated by origination fees, when we examine the spread between commercial banking loans and the peer-to-peer lending interest rates that are not adjusted for origination fees, this should provide an estimate of the cost of intermediation. Using this approach, we estimate the cost of intermediation at 281 BPs which is in line with the 2-3% cost of intermediation suggested by Philippon (2015) and Hanson, Shleifer, Stein, and Vishny (2015).

Taken together, our results show that a substantial portion of peer-to-peer lending platform volume is a credit substitute for consumers and that small commercial banks appear to shoulder the loan volume and quality losses. This substitution appears to be driven by lower credit quality loans, but our results also indirectly point to greater credit opportunities for higher credit quality borrowers. Given the initial narrow focus of peer-to-peer lending platforms in unsecured consumer loans and the emergence of other lending platforms focused on additional segments such as real estate, student loans, and automotive loans, our work helps to shed light on the evolving financial intermediation markets. Using a subsample of small banks, we show that these substitutions represent a large portion of the peer-to-peer loan volume. We estimate that 26.7% of the peer-to-peer loan volume appears to substitute for personal loan volume at small commercial banks.

Our initial empirical approach uses the time series and cross-sectional variation in the peer-to-peer platform's ability to issue loans to borrowers in a particular state to identify changes in commercial bank lending behavior. Still, we cannot rule out the possibility that additional omitted time-varying local market conditions may be correlated with both the origination volume of peer-to-peer lending and bank lending behavior, which could confound our results. We therefore augment our initial findings with evidence from an instrumental variables (IV) approach in which we instrument the volume of peer-to-peer lending in each bank market with the fraction of the US population available to *invest* in peer-to-peer lending markets. Investment on the peer-to-peer lending platforms is governed by state security regulators, which are separate from state banking regulators and concerned with investor welfare as opposed to borrower welfare. We interview state security regulators to determine the time-varying fraction of the US population able to supply funds on the peer-to-peer lending platforms. Using this second set of regulatory hurdles on the investment side, we show results from IV regressions that are consistent with the initial ordinary least squares (OLS) analysis results and in most cases increase the magnitude and statistical significance of our findings. This IV approach should further alleviate endogeneity concerns about omitted variables and reverse causality in the main tables.

Our paper contributes to both the emerging FinTech literature and the established body of work on financial intermediation. The majority of the peer-to-peer lending literature focuses on individual investor behavior and borrower characteristics. For example, multiple papers show rational and irrational herding behavior among individual investors (Duarte, Siegel, and Young (2012); Zhang and Liu (2012); Lin, Sias, and Wei (2015); Kim and Viswanathan (2016)) and that investors are able to glean private information on borrowers from geography or textual analysis of the loan application (Ramcharan and Crowe (2013); Agrawal, Catalini, and Goldfarb (2015); Iyer, Khwaja, Luttmer, and Shue (2016); Senney (2016)). Butler, Cornaggia, and Gurun (2016) show that the concentration of local commercial banking activities influences the interest rate caps set by borrowers. They determine that borrowers in more competitive banking markets demand lower reservation interest rates on the peer-to-peer platform Prosper during the period when an auction process set the interest rates on the loans. In contrast to these previous studies, we abstract from borrower and investor characteristics and focus on the aggregate effect of peer-to-peer lending on traditional financial intermediaries.

Our paper is also related to two strands of the traditional financial intermediation literature. The first strand, from which we draw our main hypothesis, includes banking competition models founded on informational differences among lenders due to geographic breadth or technology. Models based on informational advantages such as those produced by Hauswald and Marquez (2003, 2006), Chiesa (1998), and Almazan (2002) suggest that peer-to-peer lenders might steal volume and create adverse selection problems for incumbent commercial lenders. Empirically, there are other examples of the role that information production plays in financial intermediation (Petersen and Rajan (2002); Loutskina and Strahan (2011); Einav, Jenkins, and Levin (2013); Filomeni, Udell, and Zazzaro

(2016)). Our paper is the first to examine this issue in the context of unsecured consumer loans and provides a unique opportunity to directly test some of the implications from theory.

A second branch of the financial intermediation literature examines the influence of changing regulatory burdens within financial intermediated services. Begenau and Landvoigt (2017) describe an economy in which commercial banks with increasing capital requirements compete with nonbank intermediaries with less liquid liabilities. Buchak, Matvos, Piskorski, and Seru (2017) find mixed empirical evidence of this regulatory shift in the residential real estate market following the 2009 financial crisis. They show less nonbank participation in counties with tightening capital constraints but more nonbank growth in counties with more exposure to fair lending lawsuits and enforcement actions in the wake of the Great Recession. We take care to control for such shifting regulatory burdens in the main regressions and show that our results are independent of other regulatory adjustments in the robustness tests presented in Section 5. While it is likely that regulatory policy plays a part in the changing landscape, our results reveal how technological progress affects the evolving role of commercial banking activities.

Three recent papers focused on FinTech lending imply that these platforms compete with commercial banks at some level. In a contemporaneous paper, De Roure, Pelizzon, and Tasca (2016) examine German peer-to-peer lending on Auxmoney and conclude that such platforms serve a market neglected by German commercial banks. Second, Havrylchyk, Mariotto, Rahim, and Verdier (2017) investigate the drivers of peer-to-peer lending expansion and find evidence of both the internet's role in the expansion and weak banking competition. Our paper is most similar to that of Buchak et al. (2017), who study the growth of shadow banks, particularly FinTech shadow banks, in the residential mortgage market. They conclude that both regulatory burdens and improved technology may explain the growth in shadow banking in that market.

Our paper differs from these studies in three key dimensions. First, while Havrylchyk et al. (2017) and Buchak et al. (2017) show evidence of higher participation rates by shadow banks/FinTech firms in counties with low banking competition, we examine the issue of peer-to-peer lending from the perspective of the commercial bank. Further, we directly estimate the change in lending activity of the bank as a result of peer-to-peer lending. Our paper uniquely estimates this substitution away from commercial banks toward the peer-to-peer lending platforms. We can ascribe a portion of FinTech growth to competition with traditional intermediaries instead of simply to credit expansion. We also provide direct evidence of the particularly influential role of riskier loans in this substitution, whereas lower risk loan contracts appear to have little influence on commercial bank loan activity. This lack of influence is the first empirical evidence to suggest that credit expansion occurs among the borrowers with high credit quality. Thus, our substitution result is consistent with the lower interest rates in Butler et al. (2016) due to increased competition within the lower credit quality borrower segment, but our results also point to increased access to capital among the higher credit quality borrowers.

Second, through our empirical design, we can establish a causal relationship between the peer-to-peer lending encroachment and commercial bank lending by using the differences in regulatory barriers to peer-to-peer lending on the borrower side and on the investor side. We, therefore, are able to rule out reverse causality arguments such as a regulatory vacuum drawing in peer-to-peer lending. Finally, we highlight the cross-sectional differences in bank size and market competitiveness that influence peer-to-peer lending substitution at commercial banks.

1 Peer-to-Peer Market Background

Peer-to-peer lending began in the mid-2000s as technology prompted change among financial intermediaries. Many forms of capital accumulation emerged during that time: crowdfunding reward-based platforms like Kickstarter and Indiegogo, debt-based platforms like SoFi and LendingClub, nonprofit sourcing of funds like Kiva, and more recently equity-based platforms like SeedInvest and StartEngine with the passage of Regulation Crowdfunding (Freedman and Nutting (2015)). Out of this field, we focus on one segment of the debt-based crowdfunding market, unsecured consumer loans, to identify its influence on the traditional financial intermediary system of commercial banks. Two debt-based platforms have dominated in the US and originate the majority of peer-to-peer loans in the unsecured consumer loan segment during our sample period. Both founded in 2006, LendingClub and Prosper provide a mechanism to match borrowers' demand for credit with investors looking to supply credit.

As shown in Figure 1, Panel A, borrowers apply for a loan online through the platform, which performs some screening based on hard information like credit scores and outstanding debt. Opportunities to fund loans are then listed on the peer-to-peer platform for investors to evaluate. Investors can fractionally fund the loan in $25 increments over a 3- to 14-day window.[2] Platforms suggest that the entire process (application to funding receipt) takes an average of seven days. However, the average funding time for a loan on the platform appears to happen within minutes (Balyuk and Davydenko (2017)). Borrowers then receive their funds, and an issuing bank, not the lending platform, originates an unsecured consumer loan. The issuing bank sells the loan to the lending platform within a few days, and the lending platform holds the loan on its balance sheet. Investors that fund the loan receive a separate, new security issued by the lending platform that we refer to as a borrower dependent note (BDN).[3] The payments on the BDN are tied to the principal and interest payments of the borrower for the original loan.

In Figure 1, Panel A, we show that regulators monitor the operations of the platforms on *both* the borrower side in the loan origination process and the investor side during the issuing of the new security (BDN). Our initial identification approach takes advantage of the regulatory barriers existing on the origination side, while our identification in the robustness checks in Section 5 with instrumental variables uses the hurdles created by new security creation (registration) on the investment side. We briefly describe the regulatory hurdles that create origination restrictions and supply shocks below. A more detailed explanation of both restrictions is outlined in the Appendix.

Our sample begins in the third quarter of 2009, after both platforms had restructured their business model due to issues with federal regulations. Before that time, the platforms used the structure in Figure 1, Panel B and originated loans in almost every state. After the restructuring period, however, both platforms temporarily ceased origination activities in multiple states. It appears that the

[2]After September 2012 (LendingClub)/ April 2013 (Prosper), the platforms created a second market for institutional investors, allowing for the whole loan to be purchased. With the establishment of this second funding marketplace, loans are randomly assigned to either the retail (fractional) or institutional (whole) loan marketplaces to be funded.

[3]A borrower dependent note corresponds with a particular loan. Thus, for each loan funded on the platforms, a new note is issued with N shares, where N is determined by the number of investors and their bid size in a loan. For example, Borrower Dependent Note Series 416275 (https://www.prosper.com/published/sec/sales/2009/sales_20090720-1211.htm) was a $3,500 loan. The loan had 92 investors with notes ranging from $25 to $350 in principal.

majority of these cessations were regulatory in nature. For example, to allow individuals to borrow on the platform, intermediaries must meet state-level banking and consumer financing standards, which can require the platform to obtain a variety of licenses, including lending, loan brokering/supervising, money transferring, and collection licenses. During the restructuring or in the period that followed, regulators had the opportunity to review these requirements and in some cases impose temporary restrictions on the platforms. While we note multiple examples of such restrictions in the Appendix, the list is not exhaustive because of the myriad ways in which peer-to-peer lenders can be excluded. Given the observed withdrawal in origination and the previous lending activity, we assume that a lack of loan origination in a state after the restructuring is due to regulatory issues that arose during the restructuring period.[4] Our first identification strategy uses the cross-sectional and time-series differences among states to identify banks less exposed to peer-to-peer competition due to the borrower-side (origination) restrictions.

Our second identification strategy uses the regulatory hurdles on the investment side of peer-to-peer lending. Prior to our sample period, investment on the platforms was open and allowed investors to provide capital without restrictions on investor participation. However, following the restructuring period in 2008-2009, the platforms were forced to seek state-level security registration to be able to issue BDN to investors within a particular state. Without an effective registration in a state, the platforms were forced to exclude that state's investors from the lending process. During the restructuring period and in the ensuing years, platforms continually sought state security registrations to allow more investors to participate on the platform. As detailed in the Appendix, this staggered state-level registration process created capital supply shocks on the platforms that we use in our robustness tests in Section 5.

2 Hypothesis Development

We draw our formal hypothesis largely from the banking competition literature that emphasizes information production differences among intermediaries. Hauswald and Marquez (2006) model banking competition when intermediaries can invest in costly information production technology.

[4]We provide multiple examples of such regulatory issues in the Appendix

They introduce the idea of informational distance whereby intermediaries can create information production technology that becomes less precise with "distance." The authors suggest geography, technology, or expertise as potential interpretations of distance. In the model, informationally close lenders can poach customers from rivals. This setup is similar to other information production models such as those of Chiesa (1998), Almazan (2002) and Hauswald and Marquez (2003) and implies that peer-to-peer lending volume substitutes for credit at traditional intermediaries like commercial banks. It is also possible that the technological innovation allows borrowers on the margin that are observably poor but actually high credit quality (i.e., the current technology signal incorrectly types the borrower as low quality) to gain incremental access to credit (Hauswald and Marquez (2006)). Technological advancement of this sort would lead to credit expansion outside of the traditional commercial banking origination process and leave the commercial banks unaffected by peer-to-peer lending origination. Thus, we reach our first testable hypothesis:

Hypothesis 1. *If peer-to-peer lending platforms provide incremental access to credit, incumbent lenders should be unaffected ($H1_0$). Alternatively, personal loan volume will decrease among incumbent lenders as peer-to-peer origination increases ($H1_A$).*

Technological advancements at peer-to-peer lending platforms may uniformly improve lending decisions and pricing. That is, assuming that peer-to-peer lending volume substitutes for commercial loan volume, we would expect to see similar decreases in loan volume across all credit grades. However, there are some reasons to think that substitution may not be uniform. For example, if a portion of the riskier credit grade peer-to-peer loan origination volume is the result of credit expansion as suggested above, origination from this portion of the peer-to-peer loan flow may influence bank lending less. Additionally, empirical evidence from Freedman and Jin (2011) implies that peer-to-peer lenders learn over time and shift investment from risky loans to safer loans. Both of these findings point to peer-to-peer-originated low-risk loans having a greater substitutionary impact than high-risk loans. Alternatively, commercial banks may be able to charge higher interest rates for captured borrowers with higher risk profiles that traditionally require soft information during the loan application process or private information from demandable deposit transactions (Berger and Udell (2002)). If technology allows peer-to-peer lenders to substitute broader hard information for such soft/private information (Einav et al. (2013)), these captured borrowers may benefit the most from loan pricing competition. Thus, the higher risk portion of the peer-to-peer loan origination may drive substitution at the commercial bank. These predictions lead us to our second testable hypothesis:

Hypothesis 2. *Personal loan volume at commercial banks will decrease uniformly across credit grades ($H2_0$). Substitution from peer-to-peer loan volume will not be uniform and may occur more strongly among certain credit grades ($H2_A$).*

Another consequence of this informational advantage is the increase in adverse selection faced by rivals after peer-to-peer lenders have poached the best borrowers. Competitors that are less informed must select from the pool of borrowers after the informed intermediary rejects low-quality borrowers, and thus they face higher adverse selection costs. These possibilities motivate our third testable hypothesis:

Hypothesis 3. *Delinquency and charge-off activity increase among commercial banks as peer-to-peer loan origination increases in a market-period ($H3_A$) relative to market-periods when peer-to-peer loan origination is low or not present ($H3_0$).*

Finally, if lender characteristics such as size drive down the cost of technology, Hauswald and Marquez (2003) suggest that small commercial banks may be less likely to use new technological innovations and thus be more likely to face competition from new entrants with informational advantages. Thus, we reach our final two hypotheses:

Hypothesis 4. *Small commercial banks lose more loan volume ($H4_A$) than large commercial banks ($H4_0$) as peer-to-peer loan origination increases in a market-period.*

Hypothesis 5. *Small commercial banks experience higher charge-off and delinquency rates ($H5_A$) relative to large commercial banks ($H5_0$) as peer-to-peer loan origination increases in a market-period.*

3 Sample and Variable Construction

Our sample includes all deposit-taking FDIC-insured commercial banks. The sample contains 7,758 unique lenders over the 25 quarters from 2009Q3 to 2015Q3. We build the sample of financial intermediaries from the Summary of Deposits (SOD) database, which is publicly available from the FDIC. SOD data are available annually as of June 30 and provide branch-level detail on location and deposits of commercial banks. We use the SOD data to generate a dynamic geographic footprint for each commercial bank. Later we use the deposit information to weight the impact of local economic factors and peer-to-peer lending volume.

We merge the SOD data with financial and lending information for each bank taken from the Statements of Condition and Income (Call Reports), which are also available on the FDIC website. The Call Reports provide quarterly balance sheet and income data for each financial institution. We collect information on the bank's total assets, equity capital, net income, and interest expense, then scale the equity capital and net income by the lender's total assets, and scale interest expense by the lender's total deposits. We also obtain loan volume information for personal loans and the delinquency measures (loans 30-89 days delinquent and still accruing interest, charge-offs).[5] In some of the robustness tests in Section 5, we also use mortgage loan volume and mortgage-backed securities (MBS) holdings.

The Appendix contains variable definitions and the associated Call Report IDs. We gather peer-to-peer lending information from two of the largest peer-to-peer lending platforms, Prosper Marketplace Inc. and the LendingClub Corporation. These two platforms comprise the majority of the peer-to-peer lending market for unsecured consumer loans, although other smaller platforms exist for unsecured consumer debt and similarly sized platforms for student loan refinancing. Average interest rates on the platforms for three-year loans in our sample were 14.8% on Prosper and 12.2% on LendingClub. Loan sizes range from $1,000 to $35,000, with an average of $11,225 on Prosper and $12,475 on LendingClub. Both platforms provide details on successfully funded loans to the Securities and Exchange Commission (SEC) that includes a wealth of information on the borrowers, such as state of residence, loan amount, interest rates, credit scores, and so forth. We use this information to calculate a single aggregate loan issuance volume in each state-quarter. To better measure the amount

[5]We conduct a parallel analysis for commercial bank credit card facilities. Results are available upon request. In general, the results are similar in sign but statistically insignificant. This is likely due to the concentrated nature of revolving credit among commercial banks, with approximately 60% of the aggregate level of credit card debt being issued by the 20 largest commercial banks. However, Demyanyk, Loutskina, and Kolliner (2017) also suggest that borrowers fail to consolidate debt after receiving an online loan. Their sample consists of a much broader set of online lenders, but their result may also explain why credit card volume may be unaffected.

of competition faced by commercial bank lenders, we then weight this state-quarter loan issuance volume by the fraction of a lender's deposits recorded in that state-quarter and for each lender sum across all states. For a bank with branches in only one state, our measure would be equivalent to the quarterly origination volume on the peer-to-peer lending platforms in that state. The measure for a multistate bank is the average origination volume across the states where the bank has branches.[6] Our branch deposit weighting scheme implicitly assumes that demand for unsecured consumer loan volume is local and that banks draw most of their loan assets from the geographic footprint of their branches. A contemporaneous paper by Carbo-Valverde and Perez-Saiz (2016) shows that the probability of holding a credit card or line of credit from a bank increases by more than 60% when a bank has a branch within 10 kilometers of the household. This approach is also consistent with other forms of credit for small entities/individuals as shown by Agarwal and Hauswald (2010) for small businesses and implied by Loutskina and Strahan (2009) for individual mortgages.

The above approach, which is similar to Chakraborty, Goldstein, and MacKinlay (2017)'s analysis of real estate originations by commercial banks, seems reasonable given the type of loan product we examine (personal loans). Our setup takes advantage of the heterogeneous level of competition faced by commercial banks when peer-to-peer lending is absent (intense). For example, the state of Iowa makes originate-to-distribute (OTD) models difficult for lenders to execute;[7] as a result, no borrowers in Iowa have received loans from Prosper and only three borrowers have gotten loans through LendingClub over the 25 quarters we examine. Our weighting scheme, thus, helps to identify the lack of competition faced by commercial banks in states like Iowa compared to states that are open to peer-to-peer borrowing like New York. Iowa is not the only state that holds some barrier to entry. We observe at least eight additional states that experience droughts in the peer-to-peer lending data over the course of the sample.

[6] For example, Evans Bank (*rssdid* 292908) has branches and deposits in only the state of New York in the first quarter of 2015. Thus, for that quarter, we assume Evans Bank will face the New York peer-to-peer loan volume as competition. However, PNC Bank (*rssdid* 817824) holds deposits in 20 states in first quarter of 2015 and will likely face pressure from a different set of peer-to-peer loans. For our main specification in that quarter, we would calculate the deposit-weighted peer-to-peer lending volume for PNC Bank over the 20 states. Note that PNC Bank's deposits are not equally distributed among these states. In fact, the fraction of deposits is dynamic; over 50% of the deposits reside in Pennsylvania in 2006, but that fraction falls to almost 30% by 2015. This approach captures the dynamic nature of PNC's changing deposit base.

[7] See Appendix B.1 for more detail.

We also obtain unsecured consumer loan interest rate data for commercial banks from RateWatch for the period of 2009Q3 to 2015Q3. RateWatch surveys commercial banks monthly to gather loan pricing data for most of the loan products they offer.[8] The survey asks the lender to report the interest rate offered to the most creditworthy borrowers for a particular loan type and term. The lender also reports the applicable loan size buckets for that loan product. RateWatch reports the data at the bank-month level and includes Federal Reserve identifiers, which allows us to match the interest rate data to the Call Reports and SOD data. We filter the RateWatch sample of banks to single-state banks. While this restriction excludes some of the largest commercial banks, it is necessary when comparing interest rates because of assignment issues related to state-level usury laws.[9]

Finally, we obtain local economic factors similar to those used in Butler et al. (2016) to help control for cross-sectional differences in the demand for loans. State-level annual data on income per capita, unemployment, auto debt, credit card debt, mortgage debt, automotive debt delinquencies, credit card delinquencies, mortgage delinquencies, and population come from the Bureau of Economic Analysis (BEA). The local economic factors are also weighted based on the commercial bank's deposit base, similar to the peer-to-peer loan volume measure. We also obtain a state coincident index from the Federal Reserve Bank of Philadelphia, which is a time-varying, state-level measure of economic indicators originally developed by Stock and Watson (1989). All independent variables from the call reports and local economic conditions are winsorized at the 1% and 99% levels to eliminate the influence of sample outliers.

Table 1, Panel A presents summary statistics for each of these variables for the full sample. Table 1, Panel B shows statistics for subsamples based on bank size. The average commercial bank in the sample has \$494 million in total assets ($TotalAsset$) and \$342 million in total loans. Commercial banks hold an average of \$42.6 million in consumer credit facilities. This loan category

[8] While the survey process is driven by customer requests, RateWatch surveys a large fraction of the US commercial banking market. Survey data are collected multiple ways, via email, web scraping, and phone interview.

[9] Because RateWatch surveys for the lowest interest rate offered by the bank, a multistate bank presents an assignment issue. The lowest rate reported would likely not be applicable to all borrowers in all states. While omitting such banks from the sample may limit the applicability of our findings across all banks, it allows us to more confidently state the results. However, we do note that the average size and lending activity are similar in both the RateWatch sample and our broader sample of commercial banks.

is composed of revolving accounts (credit cards) and personal loans. The average commercial bank holds \$21.2 million in personal loans, which includes loans for automotive purchases, student loans, and unsecured consumer loans. To compare commercial banks of various sizes, we scale the total consumer credit facilities and personal loans by the lender's total assets. Consumer credit facilities, $AllConsumer_{it}$, account for an average of 3.32% of the commercial bank's total assets, while personal loans, $PLoans_{it}$, account for an average of 3.17% of the commercial bank's total assets. For the personal loan segment, the average bank volume of loans delinquent 30-89 days is \$249,000 or 5.9 BPs of total assets ($PL30Past$). The average volume of charge-off activity each quarter is \$49,800 or 0.8 BPs of total assets ($PLChgOff$).

Table 1, Panel C presents summary statistics for the sample of banks used in the interest rate tests as well as interest rate information for loan offers for both the banks and peer-to-peer platforms. The average interest rate on unsecured consumer loans offered by the commercial banks ($BankRate$) is 10.8%. Looking at the highest rated (AA) loans issued on the Prosper peer-to-peer lending platform, the interest rate is 8.74% with adjustments for origination fees ($ProsperAPR$) or 7.56% without adjustments for origination fees ($ProsperRate$). Figure 2 (left) shows the time-series average for all three interest rate measures. We also look at the difference between commercial banks and Prosper over the time series. To do so, we average the peer-to-peer interest rates for loans sized between \$12,000 and \$18,000 in each state-month (36-month term) and do the same for commercial banks at the state-month level. We then calculate the difference between the bank interest rates and the peer-to-peer interest rates for each state-month and then average over the 50 states and the District of Columbia for each month. We report the time series of the average difference in interest rates in Figure 2 (right). The graph on the right in Figure 2 suggests that peer-to-peer platforms provide loans to borrowers at substantially reduced interest rates, similar to the aggregate averages reported in Table 1, Panel C.

To collect registration information used in the robustness tests in Section 5, we interview state security regulators in 49 states and the District of Columbia to determine effective registration dates for both platforms. Security registration at the state level often involves a renewal process, and both platforms have multiple lapses in registrations during our study period. Using the security registration dates and population data from the BEA, we calculate the population able to invest on the platform and then compare it to the US population in 2008. Figure 3 displays the fraction of the population $PopPR$ ($PopLC$) able to invest on Prosper (LendingClub) compared to the daily dollar investment on the platform. We discuss the investor population fraction further in Section 5.

4 Empirical Results

Our principal goal is to empirically identify changes in the lending behavior of commercial banks due to the encroachment of peer-to-peer lending platforms. We first examine quarterly loan volume among commercial banks. If the increased peer-to-peer lending activity does not affect commercial bank loan volumes ($H1_0$), then it may be that peer-to-peer lending provides individuals with expanded access to credit or competes with other financial intermediaries such as payday lenders. However, if we find a negative relation between peer-to-peer lending and commercial bank loan levels ($H1_A$), this evidence would suggest that borrowers are at least partially substituting away from traditional commercial bank products. The dependent variable is presented as the natural log of one plus the loan volume as a fraction of total assets to ease interpretation. We use the following specification:

$$\begin{aligned} ln(1 + LoanVolume_{it}) = \beta_0 + \beta_1 \cdot P2PVolume_{it} + \pi_1 \cdot Bank_{it} + \pi_2 \cdot Macro_{it} + \pi_3 \cdot Bank_i \\ + \pi_4 \cdot Year\text{-}Quarter_t + Error_{it} \end{aligned} \tag{1}$$

As personal loans tend to be riskier loan products, we control for cross-sectional differences in bank risk preferences using bank equity as a fraction of total capital, total assets, and net income. Note that these differences may be cross-sectionally based on lender preference but may also include more exogenous drivers of risk selection such as increasing capital constraints from regulators. The inclusion of the equity fraction of total assets should address such concerns. The difference in cost position may also influence a bank's preference for credit products (Stein (2002); Berger, Miller, Petersen, Rajan, and Stein (2005)), so we add scaled deposit interest expense to proxy for the bank's cost of deposits. Because the local economic environment will influence both the household demand for credit and the bank's willingness to supply credit, we follow Butler et al. (2016) and include market-level controls for personal income, unemployment, debt levels (auto, credit card, mortgage), and delinquencies (auto, credit card, mortgage).

Persistent unobservable bank characteristics that influence loan portfolio selection and correlate with peer-to-peer volume may still be present. These unobservable omitted characteristics would bias the coefficient estimates. To address such concerns, we include bank fixed effects to eliminate any time-invariant omitted variables connected with bank structure, risk tolerance, etc.[10] Additionally, there may be time-varying macroeconomic factors that influence lending activity across all banks not captured by our market-level debt and delinquency controls. Thus, we also include year-quarter fixed effects to control for omitted macro trends like increases in the credit spread over the risk-free rate.

Columns (1) and (2) of Table 2 report the results of Equation (1). To correct for the correlation among commercial bank observations, we cluster standard errors at the bank level. If peer-to-peer lending substitutes for commercial bank credit products, the sign on β_1 should be negative. We first regress bank i's total consumer credit facilities on deposit-weighted peer-to-peer loan volume. In column (1), the coefficient on peer-to-peer lending is -0.0105. The coefficient magnitude suggests a decline in total consumer credit facilities of 1.0% ($0.0105 \times 0.0314/ln(1 + 0.0332) = 0.010$) of total assets for a one-standard-deviation increase in peer-to-peer volume, although the result is not statistically significant. We repeat the exercise in column (2) for the subsegment of personal loans. The coefficient on $P2PVolume$ is statistically significant at the 5% level with a magnitude of -0.0126. This coefficient indicates that a one-standard-deviation increase in peer-to-peer lending activity reduces the relative fraction of the bank's personal loan segment by 1.2%. As noted before, commercial banks report three types of loans in the personal loan category: student loans, automobile loans, and unsecured consumer loans. Both student loans and automobile loans carry significantly lower interest rates because of contractual features to lower their risk. For example, student loans are nondischargeable, and automotive loans are typically collateralized. Thus, it is extremely likely that

[10]We limit the analysis to a bank-level fixed effect because it is impossible to implement a market-level and bank-level fixed effect concurrently due to the presence of multistate banks. Multistate banks often are the sole bank in a market because of the way we define a market, i.e., the aggregate of the states containing bank i's branches. This makes the bank-level and market-level fixed effects collinear.

our results understate the degree of substitution felt by commercial banks in the unsecured consumer loan subsegment. The results in columns (1) and (2) reject the null hypothesis for $H1$, suggesting that commercial banks experience loan losses as a result of peer-to-peer lending encroachment.

The coefficient estimates indicate that more profitable banks tend to have a higher level of personal loan facilities. The coefficient on net income is positive and statistically significant in columns (1) and (2). A one-standard-deviation increase in profitability is associated with a 2.3% ($0.0972 \times 0.00783/ln(1{+}0.0332) = 0.0233$) increase in the volume of personal credit. Bank size is also positively associated with personal credit volume. As local levels of automotive and mortgage debt increase, lenders appear to curtail personal loan lending. Surprisingly, we find no evidence that average local credit card debt levels influence personal credit facility lending volume among banks. However, credit card delinquencies appear to increase personal loan lending, suggesting that borrowers may use personal loans as a vehicle for debt consolidation activities. Higher unemployment levels are associated with a lower fraction of personal credit facilities.

The results imply that technological improvements in credit modeling allow peer-to-peer lenders to encroach on commercial bank lending. It is possible that advancements in credit modeling are uniformly applicable for all borrower types, allowing peer-to-peer lenders to undercut commercial banks for all borrowers. However, if borrowers on the margin that do not receive approval are incorrectly typed and the bulk of peer-to-peer lending origination is credit expansionary for these types of borrowers, it could be that low-quality borrower volume drives less of the credit substitution. The results in Butler et al. (2016) are most sensitive for borrowers with low credit scores, which suggests that these borrowers gain more from the increase in competition from peer-to-peer lenders. Additionally, Freedman and Jin (2011) find that peer-to-peer investors shift toward safer loans over time. Their results indicate that peer-to-peer lenders may target higher credit grade borrowers as they learn through investing, which would imply again that the lower risk segment of peer-to-peer loan originations might be driving our substitution results.

To better understand if a particular part of the commercial bank's portfolio is being influenced, we divide the flow of peer-to-peer lending by high ($P2PHighRating$) and low credit grade

($P2PLowRating$) and report the results in columns (3) and (4).[11] The coefficient on $P2PLowRating$ is negative and statistically significant at the 1% level in both the total consumer credit and personal loan specifications, while the coefficient on $P2PHighRating$ is positive and only statistically significant at the 10% level in the total consumer loan regression in column (3). The economic impact of the $P2PLowRating$ is significantly larger than the aggregate flow of peer-to-peer loans. A one-standard-deviation increase in the volume of low-credit-rating peer-to-peer loans decreases the personal loan volume by 3.3%. The coefficient on $P2PHighRating$ in column (4) is not statistically significant, implying that as higher quality peer-to-peer loans are originated in a bank's market, lending is unaffected. Thus, borrowers with better credit may gain more access to credit with increased peer-to-peer lending activity. We conclude that the substitution from a commercial bank to peer-to-peer lenders is strongest in the poorer credit segment, which is most consistent with an informational capture story as in Berger and Udell (2002). Thus, we reject the null hypothesis $H2_0$.

Interestingly, the coefficient on $P2PHighRating$ in column (3) implies that as higher quality peer-to-peer loans are originated in a bank's market, total consumer credit facilities increase by 2.9% for each standard deviation increase in $P2PHighRating$. The $PLoan$ results in column (4) suggest that this may be driven by the revolving (credit card) portion of this aggregate consumer credit segment. In unreported results, we verify that the increase is driven by this subsegment.[12]

The results in Table 2 show that commercial banks lose personal loan volume in response to aggregate increases in peer-to-peer lending competition in their market. While we observe a significant decrease in personal loan activity, commercial banks may address this increased competition in other ways that would not necessarily alter the segment size of their lending portfolio. For example, lenders may compete on the price of the loan by lowering the interest rate (Butler et al. (2016)), or commercial banks could adjust contractual features of the loan such as collateral or the loan term.

[11] We use the platform credit designation as a sufficient statistic for the riskiness of the loan. This designation is determined by observable information such as borrower credit score, loan size, and other common credit metrics according to the platforms. We attempt to identify a similar split between high and low for the two platforms using average interest rate information per credit grade.

[12] We also examine the cross-sectional results for the loan quality trend similar to what follows in Section 4.1. It appears the positive coefficient on $P2PHighRating$ in Table 2 column (3) is driven by the time series of credit card volume in the sample, with the positive coefficient stemming from loan originations late in the sample. It is possible that through credit consolidation, more creditworthy consumers are able to access greater revolving credit levels. However, further analysis is outside the scope of the current study.

Additionally, banks could alter the quality of borrowers accepted to maintain loan volume if positive net present value loans were previously unfunded due to capital constraints. Changes in the quality of borrowers in the pool may be competitor-driven if peer-to-peer lending investors leave poor quality borrowers for the less competitive commercial banks, as in Hauswald and Marquez (2006). We attempt to identify such changing behavior, first in borrower quality by examining the volume of delinquent loans, and then through interest rate changes among the commercial banks. For the borrower quality tests, we use the following specification:

$$\begin{aligned} ln(1 + Loan\,Payment\,Status_{i,t+k}) = \beta_0 + \beta_1 \cdot P2P\,Volume_{it} + \pi_1 \cdot Bank_{it} + \pi_2 \cdot Macro_{it} \\ + \pi_3 \cdot Bank_i + \pi_4 \cdot Year\text{-}Quarter_t + Error_{it} \end{aligned} \tag{2}$$

We analyze two delinquency measures: late by less than 90 days and accruing interest, and loans charged off. Because loan competition in period t may influence delinquencies in the future, we look at contemporaneous delinquencies as well as delinquencies in the next two quarters. We report the results for the personal loan delinquencies in Table 3. Similar to Table 2, we scale each of these by the total assets of the lender and take the natural log of one plus the delinquency measure. In the personal loan delinquency measures in Table 3, the coefficients on peer-to-peer loan volume are all positive and statistically significant. The late payment measure in column (1) is statistically significant at the 10% level and implies an increase of 1.7% in 30- to 89-day delinquencies in the contemporaneous quarter. The coefficients on peer-to-peer lending for the charge-off measures are all statistically significant at the 1% level, which translates to an increase in charge-off activity of 3.9% to 4.4%. Because of the increase in delinquency measures, we reject the null hypothesis 3 ($H3_0$) in favor of the alternative, that peer-to-peer lending volume increases delinquency and charge-off activity at the commercial banks.

Our results indicate that increased encroachment of peer-to-peer lending forces commercial banks to take on loans from lower quality borrowers. The results could be driven by reverse causality if peer-to-peer platforms target areas where banks are worse at anticipating loan losses (delinquency and charge-off activity). We find this unlikely for two reasons. First, while peer-to-peer platforms may control the advertising and borrower screening process, it is platform investors that would have to make this strategic decision to disproportionately fund loans from a certain area. Still, it is possible that through advertising and promotional efforts, the platform could sway demand to emphasize certain geographic areas. Second, our results strengthen when we repeat the OLS analysis from Table 3 in the Section 5 robustness tests, but instead instrument for peer-to-peer loan volume. Assuming our instrument is valid and meets the exclusion criteria, the IV approach should help alleviate additional concerns of reverse causality.

The other local economy controls reveal some interesting additional trends. Elevated levels of automotive and real estate debt/delinquencies appear to decrease the volume of personal loan delinquencies. The decrease may be due to credit rationing on the part of commercial banks as consumers are more likely to default on a personal loan than on other debt contracts during financial distress. Conway and Plosser (2017) report a similar default priority for consumer credit. However, the credit card debt/delinquencies control variables appear to be positively related to delinquency measures, suggesting that consumer default behavior for personal loans may be most similar to other unsecured forms of credit. Banks with higher costs of capital appear to be more likely to have higher delinquency volumes. Looking at the interest expense from deposits, banks with a high cost of deposits seem to carry higher levels of past-due personal loans and experience higher charge-off levels, implying that the higher cost of capital may be passed on to consumers who then may be more likely to default.

Another possible response from incumbent banks would be to adjust interest rates for their unsecured consumer loan products. Figure 2 suggests that encroaching peer-to-peer lenders undercut their traditional commercial bank competitors. We formally test this conclusion using the sample of banks from RateWatch. We combine the RateWatch sample of bank-month level loan offers with the peer-to-peer loan data from Prosper. We limit this analysis to Prosper because it provides the annual percentage rate (APR) for each loan that adjusts the interest rate for the origination fee, but LendingClub does not provide origination fee information. Note that the peer-to-peer loan data are originated loans, but the RateWatch dataset contains only loan offers; however, as long as we observe a peer-to-peer loan from each state in each loan category used by the commercial bank, the peer-to-peer originated loan data could be viewed as the analogous loan offer from the peer-to-peer platforms with no sample selection bias. In this test, we omit banks and peer-to-peer lending data from Maine, North Dakota, and Iowa because of such concerns. RateWatch publishes the interest rate the bank would offer to the most creditworthy individuals, so we filter the peer-to-peer loan data to include only the highest loan credit rating (AA) on Prosper. We retain other loan characteristics like loan amount and term. To control for the price of risk in the economy, we include time-varying macroeconomic controls for the state of the borrower, year-month fixed effects, and a time-invariant state fixed effect. To compare interest rates among lenders, we include a time-invariant bank fixed effect using Prosper as the base (omitted) bank. We then test whether peer-to-peer lenders undercut traditional commercial banks using the following specification:

$$\begin{aligned} Interest\,Rate\,Offer_{it} = \beta_0 + \beta_1 \cdot Bank_i + \pi_1 \cdot LoanCharacteristics_{it} + \pi_2 \cdot StateMacro_{it} \\ + \pi_3 \cdot Year\text{-}Month_t + \pi_4 \cdot State_i + Error_{it} \end{aligned} \tag{3}$$

The variables of interest are the time-invariant bank fixed effects, which will suggest on average the interest rate difference between the commercial banks and the peer-to-peer platform. We omit an indicator for the Prosper loans. Thus, all the other bank fixed effects are relative to it. The results reported in Table 4, column (1) use the *ProsperAPR* as the interest rates from the peer-to-peer lender. The constant suggests that Prosper charges an average APR of 7.1% for the base loans (<\$8K, 12-month, Alaska, July 2009) once we control for macroeconomic conditions and variations in geography. We graph the distribution of bank fixed effects for the regression on the left side of Figure 4. Banks with a positive fixed effect appear to lend at rates above the Prosper's APR, while negative fixed effects indicate that banks offer loan rates below Prosper's APR. The average bank fixed effect for the APR comparison is 1.64, suggesting that most banks offer loans at a substantial premium (164 BPs) compared to Prosper's loans even after adjusting for origination fees. Note that not all banks appear to be undercut by Prosper, as approximately 31.4% of banks have a negative fixed effect. We repeat this test in a slightly different form, using a dummy to indicate loans from the peer-to-peer platform instead of including bank fixed effects. This test essentially creates one average bank fixed effect. We report the results in column (2). The Prosper indicator is consistent with the previous specification and suggests that the interest rate on peer-to-peer loans is an average of 1.98% lower than that of commercial banks. Note the constant of 11.6, which means that after controlling for variations in loan features and macroeconomic conditions, the average bank charges an interest rate of 11.6% for small 12-month loans.

The vast majority of commercial banks issue unsecured consumer loans with no origination fee. In the RateWatch sample, only 0.01% of bank loan observations list any origination fee. Commercial banks may be indifferent to income from interest rates relative to income from origination fees because they typically hold the loans on their balance sheet. Peer-to-peer platforms, on the other hand, do not retain any exposure to the originated loans and thus the bulk of the cost of intermediation must be borne by the origination fees.[13] Therefore, by comparing the histogram on the left in Figure 4 to a histogram of bank fixed effects from the regression using raw interest rates charged by the peer-to-peer platform, we can infer the cost of intermediation and how much the technological change from peer-to-peer lending has reduced intermediation costs for borrowers. In Table 4, column (3), we repeat the exercise from Equation (3) with raw interest rates ($ProsperRate$) from the peer-to-peer platform and graph the distribution of bank fixed effects on the right side of Figure 4. From the figure, the average bank fixed effect increases to 2.81%, meaning that the average bank cost of intermediation is 281 BPs and that the technological improvement captured by disintermediation is split between consumers, 117 BPs, and peer-to-peer lenders who retain 164 BPs over the average bank. We verify the results from column (3) using an alternative approach with the peer-to-peer lending dummy (Prosper) and raw peer-to-peer interest rates. The results in column (4) indicate that the interest rate difference between the peer-to-peer lender and the average bank increases to 3.15% when origination fees are not considered.

We note a few limitations to our approach. First, as shown in Table 1, Panel C, the sample of banks in RateWatch includes neither the smallest commercial banks because of the cost to survey, nor the largest commercial banks because of their multistate presence. We expect larger commercial banks to be more competitive based on their ability to model credit default, and smaller, nonsurveyed banks to be the opposite. The sampling bias would likely fatten the left and right tails of the distribution in Figure 4. Given that far more small banks are omitted from RateWatch than large banks, the mean estimate in Figure 4 would likely increase. Second, it is possible that banks hedge their interest rates

[13] From 10-K filings, LendingClub received between 88% and 92% of its revenue from origination fees in the most recent years (2014-2016); Prosper's percentage was slightly lower over the same time period, ranging from 72% to 88%.

reported to RateWatch to reserve lower interest rates for their best customers. However, for this to influence our estimation, it would have to be a global practice among banks. We are not aware of any such practice, but if this were the case, we would observe interest rates that appear to be higher than are issued to bank customers, and our estimates would be upward biased. Third, banks can offer interest rate discounts of between 25 and 50 BPs for customers that hold other accounts with the bank. RateWatch would report these loans separately from loans that receive no relationship discount. We use the unassociated loan data as they are the most similar to the peer-to-peer loan, but we recognize that borrowers may open a checking account or elect to borrow from a relationship bank to receive the additional discount. Note that if all bank loans carried such a discount and all borrowers elected loans with such a discount, peer-to-peer lenders would still undercut the average bank but the mean would simply be shifted by the degree of discount provided for associated services. Fourth, if the technology implemented by peer-to-peer lenders allows them to evaluate the marginal borrower better, as suggested by the Table 2 results, there is no guarantee that the interest rate difference between a commercial bank and the peer-to-peer platforms is linear, and the gap may widen (narrow) considerably. Because the RateWatch data only cover the most creditworthy borrowers, we hesitate to extrapolate our results across all credit grades. Still, our estimate of intermediation costs is in line with those of previous studies (Hanson et al. (2015); Philippon (2015)) and implies a substantial improvement in intermediation through the improved technology and business model employed by peer-to-peer lending.

After establishing that peer-to-peer platforms are low-cost competitors to the majority of commercial banks, we investigate whether incumbent commercial banks alter their pricing behavior with pressure from peer-to-peer lending platforms. If banking markets are already competitive, we would expect to see no reaction by incumbent lenders as they are already lending at the equilibrium interest rate. However, if frictions exist that prevent borrowers from receiving the fully competitive interest rate (Petersen and Rajan (1995); Dell'Ariccia and Marquez (2004)), the incumbent lenders may adjust their interest rates in response to peer-to-peer encroachment. For this test, we use the following specification:

$$
\begin{aligned}
Interest\,Rate\,Offer_{it} = \beta_0 + \beta_1 \cdot P2PVolume_{it} + \pi_1 \cdot Bank_{it} + \pi_2 \cdot Macro_{it} + \pi_3 \cdot Bank_i \\
+ \pi_4 \cdot Year\text{-}Month_t + \pi_5 \cdot LoanCharacteristics_{it} + Error_{it}
\end{aligned}
\tag{4}
$$

The variable of interest is $P2PVolume$, and the results are presented in Table 5. In column (1), the coefficient on $P2PVolume$ is 0.151 but statistically insignificant. The coefficient suggests that the entrance of peer-to-peer lending does not influence incumbent lending rates, which appear to be fully competitive. It is possible that differences in credit scoring technology could elicit different lender responses. As we discuss further in the next section, if these screening differences are based on lender size, then reactions to peer-to-peer lending could differ by commercial bank size. We split the sample into large and small commercial banks but find no significant differences among banks in columns (2) and (3). When we narrow the data to examine only the 36-month loan contracts, the most popular type of loan contract on peer-to-peer platforms, the results in columns (4)-(6) are qualitatively similar. We conclude that while it is likely that peer-to-peer lending platforms can undercut traditional banks in loan pricing, commercial banks do not seem to alter their pricing behavior.

The results in this section show that personal loan volume falls with increased pressure from peer-to-peer loan activity (Table 2). In Table 3, we find clear evidence of elevated delinquency and charge-off activity for personal credit facilities, while Table 5 suggests that incumbent commercial banks do not alter their loan pricing. While incumbent loan rates may not respond, it is clear from Table 4 and Figure 4 that the improved technology used by peer-to-peer platforms benefits borrowers, who receive an interest rate discount over the average bank offering. As mentioned briefly above, it is possible that banks differ along observable dimensions in their ability to respond to peer-to-peer lending pressure. Similar to the Hauswald and Marquez (2003, 2006) competition models, if bank information production capabilities vary with size, then we may observe different responses to peer-to-peer lending among commercial banks. In Section 4.1, we analyze how heterogeneity in bank size leads to different responses within the cross-section of commercial banks.

4.1 Cross-Sectional Heterogeneity

If larger, more sophisticated commercial banks are better able to compete on price than smaller banks, possibly because of better "processing" technology as in Hauswald and Marquez (2003), it is plausible that larger banks may be affected differently by peer-to-peer lending competition. We divide the sample of banks by size based on the bank's total assets and then repeat the analysis on loan volume (Table 6) and loan quality (Table 7) to formally test Hypotheses 4 and 5.

Table 6 shows the different subsamples of commercial bank size with total assets under \$300 million in column (1) and larger commercial banks in column (2). We report only the main variable of interest, but the full table can be found in the Internet Appendix. The coefficient on peer-to-peer lending remains negative in column (1) for the personal loan segment and is stronger in statistical and economic significance than the aggregate bank sample in Table 2. Based on the coefficient, a one-standard-deviation increase in peer-to-peer lending decreases personal loans at small commercial banks by 1.8%. Also similar to the aggregate sample, we verify in unreported results that the loan volume among borrowers with low credit ratings appears to drive this result. Turning to the large commercial banks in column (2), the coefficient on peer-to-peer lending is negative but not statistically significant. The coefficient suggests that the aggregate results in Table 2 may be driven by small commercial banks, whereas large commercial banks are relatively unaffected by peer-to-peer encroachment. Thus, we reject the null hypothesis $H4_0$, which asserts that bank loan levels are uniformly impacted by peer-to-peer lending volume encroachment. When we repeat the tests in Table 6 with alternative size thresholds (\$161 million (median), \$1 billion), the results are stronger for the \$161 million threshold but diluted as more large banks are added in the \$1 billion split. We also perform a Chow test and verify that the coefficient values are indeed different for the two samples.[14]

To better understand the degree to which peer-to-peer loan volume is substituting for small commercial bank loan volume, we further limit the small bank sample to those bank-quarters when a bank has a geographic footprint in only one state. Using this filter removes 3,002 observations from the small bank sample in column (1) but allows us to calculate the average number of banks

[14] We also repeat the analysis using a pooled sample and include an interaction term for bank size. The results are similar.

per state-quarter.[15] We repeat the regression from column (1), this time with the unscaled personal loan volume, and report the results in column (3). We find that a one-standard-deviation increase in peer-to-peer lending, \$28.9 million in the restricted sample, causes an average decrease of \$86,783 ($-0.0032 \times \$28.9 = -\$0.086$ million) in personal loans per bank. Because we have limited the banks to 50 states plus the District of Columbia over 25 quarters, there is an average of 89.1 banks per state ($113,630/(51 \times 25) = 89.1$). Therefore, a one-standard-deviation increase in peer-to-peer lending causes an aggregate decrease in personal loan volume of \$7.7 million ($\$86,783 \times 89.1 = \$7.7$ million) per state among the small banks. Thus, roughly 26.7% ($7.7/28.9 = 0.267$) of the peer-to-peer loan volume in a state-quarter appears to be a direct substitution away from small commercial bank lending. Because the sample is limited to single-state banks, we can test for additional time-invariant state-level effects that may bias our coefficient estimates. We repeat the analysis in column (3) with an additional state fixed effect and in unreported results find that the coefficient on peer-to-peer lending volume remains economically similar and statistically significant.

One potential benefit of peer-to-peer lending expansion is that areas with less access to financial institutions might benefit from the ability to obtain services through the internet. However, given the cross-sectional results above, a concern emerges that if small banks exist mostly in rural areas with low levels of banking competition, then the online provision of services may begin to drive out the brick-and-mortar banks currently available. Indeed, if the informational distance in Hauswald and Marquez (2006) is driven by geographic distance, as is common in the relationship banking literature, banks with branches in counties with sparse branch density might be more distant from consumers and thus more likely to have customers poached by peer-to-peer lenders. In a contemporaneous paper, Havrylchyk et al. (2017) provide aggregate evidence that counties with poor branch networks have more peer-to-peer loans per capita. While the Havrylchyk et al. (2017) results are suggestive of

[15] Throughout the analysis, the unit of observation is at the bank-quarter because this is the level at which commercial banks report loan volume to the FDIC. Implied in this unit of observation is that each bank issues loans across a market j, which could be as small as a single state or, in the case of a multistate bank, an agglomeration of states where the bank holds physical branches. To calculate the portion of peer-to-peer loan volume that is attributable to loan volume losses from commercial banks, we need non-overlapping markets to avoid double counting peer-to-peer volume. Thus, we limit the sample to the banks whose market is equivalent to a single state. This restriction allows for a clean interpretation of the number of markets and the average number of banks per market. More importantly, it provides non-overlapping peer-to-peer volume of origination per market so that the impact at the bank level can be aggregated to the state (market) level.

greater substitution in poor branch network areas, it could be that the branch network proxies for other financial intermediation services like payday lending.

To examine this issue directly, we create a measure of bank-level competitiveness ($Competitiveness$). First, we calculate the county-level deposit concentration using a Herfindahl index based on deposit data from the FDIC. We then match this local measure of competition to each branch of a bank and average these branch-level measures of competition for each bank-quarter. We report the above-median index bank (low competitiveness) results in column (4) of Table 6 and the results for below-median index banks (high competitiveness) in column (5). The coefficient on peer-to-peer lending shows a decrease in personal loan lending activity for banks in less competitive markets. A one-standard-deviation increase in peer-to-peer lending leads to a decrease of 2.0% from the mean level of personal loans. Banks with branches in more competitive markets appear to be unaffected by peer-to-peer lending. The asymmetric influence of peer-to-peer lending on commercial banks seems to lend credence to concerns that policymakers should be mindful of the substitution that occurs in rural areas when encouraging nonbank growth.

The results in Table 6 are consistent with the foreign bank competition model of Dell'Ariccia and Marquez (2004) in which foreign entrants like peer-to-peer lenders compete most heavily in the transparent segments where they are best able to use hard information to make screening and lending decisions. While unsecured consumer loans may not typically be considered transparent, we note that they pass an initial screen on the peer-to-peer platforms solely on the hard information provided by the borrower. Since 2010, both platforms have set the interest rates on the loans based on hard information (Wei and Lin (2016)). Thus, investors only have the opportunity to incorporate private/soft information such as borrower geography, employment industry, and the like in the decision to fund a loan. The results in Table 6 are also consistent with the substitution of soft information for credit score models similar to what Einav et al. (2013) find in the automotive loan market. In the Hauswald and Marquez (2006) model, informationally "close" lenders can both poach the profitable loans from competitors and create larger adverse selection problems in the remaining pool of borrowers for follow-on lenders. The adverse selection might result in poorer loan quality for traditional lenders that are informationally more distant. Again, if lender size drives the ability to generate private information, we should observe deterioration in loan quality across bank size. We repeat the loan quality analysis in Table 7, dividing the lenders in each panel based on bank size. We report only the variable of interest, but the full table can be found in the Internet Appendix.

In Table 7, Panel A, the small bank sample again shows signs of borrower quality deterioration with increased peer-to-peer loan competition. In column (5), the next-period scaled charge-off activity increases with peer-to-peer lending volume. The coefficient of 0.496 suggests a 4.5% increase in charge-off activity per standard deviation increase in peer-to-peer lending in the period following the peer-to-peer volume increase. The increase is similar in magnitude to the aggregate results in Table 3. In Panel B, the large commercial banks exhibit much weaker results. All of the peer-to-peer lending coefficients are positive, but none are statistically significant. Based on the results in Table 7, we again reject the null hypothesis 5 ($H5_0$), which posits a homogeneous deterioration in credit quality among commercial banks.

The subsample results reveal a heterogeneous impact of peer-to-peer lending on the commercial banking sector. As peer-to-peer platforms enter into markets, small commercial banks appear to lose loan volume in the personal loan segment. While these OLS results only provide weak evidence of an increase in the risk character of small bank personal loans, the robustness tests in Section 5 show that these results significantly strengthen when we attempt to instrument for peer-to-peer loan volume. In the OLS estimates, large commercial banks appear relatively unaffected by this encroachment, losing little to no loan volume. We find little evidence of increased riskiness in the facilities issued by large commercial banks, but later in Section 5, we show some evidence that even large commercial bank loan quality measures fall.

5 Robustness Tests

The results in Table 2 and Table 3 suggest that peer-to-peer loans compete with commercial banks' ability to issue personal credit facilities. The impact on commercial banks is multifold, ranging from loan volume loss to loan quality deterioration. Thus far, our identification strategy relies on a geographically weighted peer-to-peer lending measure to exploit the cross-sectional and time-series variation in peer-to-peer lending in a particular banking market. We use multiple local economic indicators and quarterly fixed effects to control for cross-sectional heterogeneity and changes in the demand for credit. We also employ lender fixed effects to control for any persistent bank characteristics that might also influence lending activity. While these measures should alleviate most forms of endogeneity associated with omitted variable bias, we cannot rule out additional time-varying market-level effects that might also correlate with the volume of peer-to-peer lending. For example, Kroszner and Strahan (1999) find that the structure of the banking industry influenced the timing of state-level deregulation in the 1980s. While banking lobbyists may be able to sway legislative officials, regulatory officials are less likely to be influenced by lobbying activity. However, if indeed banking regulatory agents are swayed by banking lobbyists, it is possible that their decisions regarding peer-to-peer entry may also be driven by such time-varying state-specific effects. There is also some concern that the results could be driven by reverse causality, which would cast doubt on our initial conclusions. To further alleviate these concerns, we use a second set of regulatory restrictions on the *investor* side of peer-to-peer lending to create three instruments for peer-to-peer lending volume. The results strengthen our initial findings.

For the first two instruments, we use the quarterly average fraction of the US population able to invest on each peer-to-peer platform ($PopLC$ and $PopPR$). These variables use the state security registration information and Figure 3 to capture the level of the US population able to invest on the platforms. Our intuition is that the larger the fraction of the population able to invest on the platform is in aggregate, the larger the supply of capital from investors and the more peer-to-peer loans will be funded. The benefit of these two instruments is that they likely meet the exclusion criteria for a good instrument. That is, because the instruments are at the aggregate level, any confounding effect would have to be derived from an omitted variable that correlates with the national fraction of the investment population. The downside is that the variables are driven solely by the time series of the peer-to-peer investment fluctuations and omit any cross-sectional differences highlighted in the previous tests.

We therefore add a third instrument to capture some of the cross-sectional differences in competitive pressure experienced by banks from peer-to-peer lending. Lin and Viswanathan (2016) provide evidence that investors on peer-to-peer lending platforms have a home bias to fund local, same-state borrowers. Using repeat borrowers that relocate to different states, they are able to show a consistent local bias among investors. Senney (2016) similarly finds that local investors bid earlier and larger amounts on peer-to-peer platforms. Hornuf and Schmitt (2016) show a similar local bias among equity crowdfunding investors. If investors have such a bias, when a state approves an effective security registration of a platform, we would expect to see additional pressure on banks in that state above the pressure felt by an aggregate increase in investors. For our third instrument, we take the fraction of the US population granted access to invest on Prosper and LendingClub for lending bank i's geographic market segment during quarter t, Pop_{it}. For a single-state bank, this indicator would equal zero for the quarters when neither platform has an effective investor registration within bank i's state. The measure would equal two, one for each platform, if both platforms hold an effective registration for the entire quarter in bank i's state. If a platform transitions within a quarter, we scale the indicator by the number of days the platform holds an effective registration within that state. Our instruments imply that the probability of funding should change when states register a security offering. Venkatesan, Wolfe, and Yoo (2017) show that because of platform incentives, either the interest rate or the probability of funding might change around these dates. We test this implication on the Prosper platform and find not only that the instruments positively increase the probability of funding, but that registration changes on the competing platform may negatively impact funding probability.[16] In the first stage below, we predict $P2PVolume$ using three instrumental variables, $PopLC$, $PopPR$, and Pop_{it}:

$$\begin{aligned} P2PVolume_{it} = \beta_0 + \beta_1 \cdot PopLC_t + \beta_2 \cdot PopPR_t + \beta_3 \cdot Pop_{it} + \pi_1 \cdot Bank_{it} \\ + \pi_2 \cdot Macro_{it} + \pi_3 \cdot Bank_i + \pi_4 \cdot Year_t + Error_{it} \end{aligned} \tag{5}$$

In the second stage, we then substitute the instrumented $P2PVolume$ into the Equation (1) and estimate the following regression:

$$\begin{aligned} ln(1 + LoanVolume_{it}) = \beta_0 + \beta_1 \cdot P2\widehat{PVolume}_{it} + \pi_1 \cdot Bank_{it} + \pi_2 \cdot Macro_{it} + \pi_3 \cdot Bank_i \\ + \pi_4 \cdot Year_t + Error_{it} \end{aligned} \tag{6}$$

[16] See the Internet Appendix for the full table.

Table 8 reports the results of the IV loan volume regressions, and Table 9 reports the loan quality results. Table 8, column (1) shows that all three instruments pass the relevancy test, as they are positive and statistically significant in the first stage.

The instrument variables must also meet the exclusion restriction to be valid instruments, suggesting that they only influence bank loan origination volume through peer-to-peer lending volume. They cannot be correlated with any of the other independent or omitted variables. We think these conditions are plausible for two reasons. First, by construction, our instruments are the fraction of the US population able to invest, either in aggregate ($PopLC_t$) or in the bank's market (Pop_{it}). Thus, an omitted variable breaking the exclusion restriction would have to correlate with the timing and cross-sectional changes in the population measures. Such concerns about regulatory capture of banking regulatory bodies or security regulators on the part of banks would have to vary with both the aggregate and local population fraction changes. We view this as unlikely. Second, we have saturated the current model with local demand characteristics, including unemployment, per capita income, and debt/delinquency measures for multiple debt contract types to avoid concerns that these market-level characteristics might correlate with demand and population instruments.

After instrumenting for the peer-to-peer lending volume, the aggregate sample results appear unaffected by peer-to-peer loans. The coefficient on peer-to-peer loan volume becomes statistically insignificant, as shown in Table 8, column (2). However, when we split the sample by commercial bank size as in Table 6, the results for small commercial banks in Panel B again show a loss in personal loans. A one-standard-deviation increase in peer-to-peer lending produces a decrease of 29 BPs or 8.5% of the average small bank personal loan segment. For the large banks, after instrumenting for peer-to-peer loan volume, the implied effect of peer-to-peer lending on personal loan volume continues to be statistically insignificant.

While the increase in delinquency and charge-off rates from Section 4 may be evidence of an adverse selection problem, it is possible that the reverse causality story may also explain this association. For example, if banks in an area with a particularly poor ability to anticipate loan delinquency are targeted by peer-to-peer lending platforms, the higher delinquency rates among those banks may cause the increase in peer-to-peer lending encroachment. We repeat the analysis using an instrumental variable approach and report the abridged results for personal loans in Table 9. Again, the full table can be seen in the Internet Appendix. For the personal loan quality regressions, the aggregate sample in Panel A suggests a significant increase in loan delinquency and charge-off activity of personal loans. The coefficient on peer-to-peer lending is positive for all six columns and statistically significant in four out of the six specifications. When we split the sample by lender size in Panels B and C, the increase in delinquencies and charge-off activity is present for both large and small commercial banks. As is common for IV estimation, the coefficient size on peer-to-peer volume is substantially larger, indicating economic magnitudes of increased delinquencies and charge-off activity. For example, the next-period charge-off activity implied by the coefficient in Panel B, column (5) is an increase of 15.1%. Large banks also show some evidence of increased delinquency and charge-off activity. The coefficient for contemporaneous delinquency in Panel C, column (1) implies an increase in late paying loans by 7.95%. The larger, statistically significant coefficients suggest that both large and small banks are forced to adjust their composition of borrowers to include riskier borrowers, either intentionally to prop up loan volumes or unintentionally as peer-to-peer platforms poison the well.

The IV results are broadly consistent with the OLS results in Table 6 and Table 7. Small commercial banks appear to suffer volume losses in the personal loan segment as peer-to-peer lending increases. They also substitute stolen borrowers with lower quality borrowers. Large commercial banks appear largely unaffected from a credit volume perspective. The OLS results indicate little change in borrower quality at large commercial banks, while the IV results show a substantial increase in delinquency and charge-off activity.

In a contemporaneous paper, Chakraborty et al. (2017) show that commercial banks substitute away from commercial and industrial loans for more mortgage origination activity to take advantage of the Federal Reserve's quantitative easing (QE) program. This substitution could also be motivated by heterogeneous asset specificity among the different loan products, as in Bleck and Liu (2017). In either case, it is possible that the loan volume results may be driven by a similar phenomenon if the QE program is correlated with the peer-to-peer lending volume increases, which would cause our results to be spurious. We repeat the OLS analysis from Table 2 and include the Federal Reserve mortgage-backed security ($MBSActivity$) and Treasury bond purchasing activity ($TBActivity$) measures and lender sensitivity measure ($MBSHolding$) from Chakraborty et al. (2017). Table 10 reports the results of this exercise. Similar to the results in Chakraborty et al. (2017), banks seem to be substituting away from consumer loans toward residential real estate, as the QE program incentivizes banks to originate more residential mortgages. The coefficient on $MBSActivity_t$ is negative and statistically significant in all three columns. However, the results for loan volume in Table 2 and Table 6 appear robust to such concerns. The coefficient on peer-to-peer loan volume remains similar in magnitude and is statistically significant at the 5% level.

6 Conclusion

Peer-to-peer lending and other forms of disintermediated financing are an emerging area of non-bank activity that competes with traditional deposit-taking lenders. The rapid growth of these platforms largely has been painted as an opportunity to expand credit access to individuals and small businesses. However, we show that peer-to-peer lending represents an emerging competitor to traditional depository lenders such as commercial banks. We find that small commercial banks lose 1.8% of their personal loan volume for each one-standard-deviation increase in aggregate peer-to-peer lending, and these banks also see increases in loan delinquency and charge-off measures. The personal loan segment, as reported to the FDIC, includes automotive, student, and unsecured consumer loans. Because automotive and student loans are each three to four times the size of the unsecured consumer loan segment, and peer-to-peer loans most closely resemble unsecured consumer loans, our empirical results represent the lower bound on the volume of substitution at small commercial banks. Surprisingly, this volume loss appears to be driven by loan origination in the lower-credit-grade peer-to-peer loans. We also show evidence that large commercial banks with more than $300 million in total assets maintain loan volume. Despite their ability to maintain volume, however, the largest commercial banks also experience deteriorating loan quality as competition from peer-to-peer lending increases.

We also investigate whether commercial banks respond to peer-to-peer encroachment by changing loan interest rates, but we find no significant change in loan pricing. Using a sample of low-risk loan offers from commercial banks, we show that peer-to-peer lenders are able to undercut most commercial banks on interest rates. We estimate that the average bank issues loans at rates approximately 164 BPs higher than the peer-to-peer platform Prosper after accounting for origination fees. Comparing the raw interest rate of the platform to the average commercial bank gives us some sense of the cost of intermediation for commercial lenders, which we estimate to be 281 BPs. The results suggest that the benefits of quasi-disintermediated finance are split between the platform and the borrowers.

We anticipate that the current regulatory shift toward higher capital ratios will encourage the encroachment of nonbank intermediaries like peer-to-peer platforms. The peer-to-peer advance might include additional platforms focused on unsecured consumer loan products as well as other debt contracts such as student loans, automotive loans, commercial and industrial loans, and even real estate. Indeed, even large traditional financial intermediaries have begun to enter the space previously occupied by only LendingClub and Prosper. Our results highlight the heterogeneous impact of increased competition. Policymakers should keep in mind the detrimental effect of increasing peer-to-peer expansion on loan volume and loan quality for small commercial banks that we document as more commercial bank segments become targets for nonbank expansion. Our identification strategy reveals how the current regulatory environment drastically influences the expansion of FinTech firms like the peer-to-peer platforms examined in our study.

Appendix A Variable Definitions

Variable	Definition
$P2PVolume_{it}$ (in \$B)	Bank i's competing peer-to-peer loan volume in quarter t. $P2PVolume_{it} = \sum_k w_{ikt} \times P2PVolume_{kt}$, where w_{ikt} is $\frac{Bank\ i's\ deposits\ in\ state\ k\ in\ quarter\ t}{Bank\ i's\ total\ deposit\ in\ quarter\ t}$ and $P2PVolume_{kt}$ is aggregate peer-to-peer loan volume issued in state k by both Prosper Marketplace Inc. and LendingClub Corp. in quarter t.
$P2PHigh(Low)Rating_{it}$ (in \$B)	Bank i's competing peer-to-peer loan volume to borrowers who receive high (low) credit rating from peer-to-peer lenders in quarter t. (Similar to $P2PVolume_{it}$ above. $P2PHighRating_{it}$ includes Prosper loans with Prosper rating above or equal to C and LendingClub loans with LendingClub rating above or equal to D only. $P2PLowRating_{it}$ includes Prosper loans with Prosper rating below C and LendingClub loans with LendingClub rating below D only.)
$ProsperAPR$	Annual percentage rate on AA-grade Prosper peer-to-peer loans, which includes an adjustment for the cost of origination fees incurred by borrowers.
$ProsperRate$	Raw borrower interest rate on AA-grade Prosper peer-to-peer loans. This variable does not include any adjustment for the cost of origination fees incurred by borrowers.

Bank Characteristics

$AllConsumer_{it}$	Bank i's consumer credit facilities, including revolving accounts (credit cards) and personal loans in quarter t (RCONB538 +RCONB539), scaled by total assets in quarter t (RCON2170).
$PLoans_{it}$	Bank i's personal loans to individuals in quarter t scaled by total assets in quarter t (RCON2170). Personal loans are (RCONB539) from 2009Q2 until 2010Q4. From 2011Q1 onward, personal loans are (RCONB539 + RCONK137 + RCONK207).
$PL30Past_{it}$	Bank i's personal loans that have become past due with the minimum payment not made for 30 days or more (but not over 89 days), scaled by total assets in quarter t (RCON2170). Past-due loans are (RCONB578) until 2010Q4 and then (RCONK213 + RCONK216) for 2011Q1 onwards.

$PLChgOff_{it}$	Bank i's personal loans charged off against the allowance for personal loans in quarter t scaled by total assets in quarter t (RCON2170). Note that banks report the cumulative amount for each calendar year. We use the quarterly change from $t-1$ to t. This is (RIADB516) until 2010Q4 and then (RCONK215 + RCONK218) for 2011Q1 onwards.
$BankRate_{it}$	Interest rate offer for bank i in month t for unsecured consumer loans (00020) with no associated service accounts contingent on loan size and term.
$TotalAsset_{it}$ (in \$B)	Bank i's total asset in quarter t. (RCON2170)
$TotalLoans_{it}$ (in \$B)	Bank i's total loans and leases, net of unearned income in quarter t. (RCON2122)
$TotalEquity_{it}$	Bank i's total equity capital (RCON3210) scaled by its total asset in quarter t (RCON2170).
$NetIncome_{it}$	Bank i's net income (RIAD4340) scaled by its total asset in quarter t (RCON2170).
$InterestExp_{it}$	Bank i's interest on deposits (RIAD4073) scaled by its total deposits (RCON2200) in quarter t.
$Competitiveness_{it}$	Equal-weighted average Herfindahl index across bank i's branches in period t. The Herfindahl index is calculated for each county based on branch deposits and assigned to each bank branch within the county.
$MBSHolding_{it}$[17]	Bank i's balance in MBS (Mortgage-backed security) holdings scaled by its total asset in quarter t (RCON2170). MBS holdings are the sum of 1) MBS held for trading, 2) MBS held not for trading, and 3) MBS for sale.

[17] Before 2009Q2, MBS held for trading = RCON3534 + RCON3535 + RCON3536, MBS held not for trading = RCON1698 + RCON1703 + RCON1709 + RCON1714 + RCON1718 + RCON1733, and MBS for sale = RCON1698 + RCON 1703 + RCON 1709 + RCON 1714 + RCON 1718 + RCON 1733. From 2009Q2 to 2010Q4, MBS held for trading = RCONG379 + RCONG380 + RCONG381, MBS held not for trading = RCONG300 + RCONG304 + RCONG308 + RCONG312 + RCONG316 + RCONG320 + RCONG324 + RCONG328, and MBS for sale = RCONG302 + RCONG306 + RCONG310 + RCONG314 + RCONG318 + RCONG322 + RCONG326 + RCONG330. From 2011Q1 and on, MBS held for trading = RCONG379 + RCONG380 + RCONG381 + RCONK197 + RCONK198, MBS held not for trading = RCONG300 + RCONG304 + RCONG308 + RCONG312 + RCONG316 + RCONG320 + RCONK142 + RCONK146 + RCONK150 + RCONK154, and MBS for sale = RCONG302 + RCONG306 + RCONG310 + RCONG314 + RCONG318 + RCONG322 + RCONK144 + RCONK148 + RCONK152 + RCONK156.

Economy Controls[18]

$PerCapitaInc_{it}$ (in \$)	Bank i specific weighted average income per capita across states in quarter t.
$Unemp_{it}$ (in %)	Bank i specific weighted average unemployment rate across states in quarter t.
$AutoDebt_{it}$ (in \$)	Bank i specific weighted average auto debt balance per capita across states in quarter t.
$CCDebt_{it}$ (in \$)	Bank i specific weighted average credit card debt balance per capita across states in quarter t.
$MortDebt_{it}$ (in \$)	Bank i specific weighted average mortgage debt balance per capita across states in quarter t.
$AutoDebtDelinq_{it}$ (in %)	Bank i specific weighted average percentage of auto debt balance that is 90 days or more delinquent across states in quarter t.
$CCDebtDelinq_{it}$ (in %)	Bank i specific weighted average percentage of credit card debt balance that is 90 days or more delinquent across states in quarter t.
$MortDebtDelinq_{it}$ (in %)	Bank i specific weighted average percentage of mortgage debt balance that is 90 days or more delinquent across states in quarter t.
$CoincidentIndex$	Index of current economic conditions at the state-month level developed by Stock and Watson (1989) that combines nonfarm payroll employment, unemployment rate, average hours worked in manufacturing by production workers, and wage and salary disbursements deflated by the Consumer Price Index.

[18]Constructing specific bank i's weighted average economy control is similar to calculating bank i's competing peer-to-peer loan volume in quarter t above. Bank i's weighted average economy control across states in quarter t, $EconControl_{it} = \sum_k w_{ikt} \times EconControl_{kt}$, where w_{ikt} is $\frac{Bank\ i's\ deposits\ in\ state\ k\ in\ quarter\ t}{Bank\ i's\ total\ deposit\ in\ quarter\ t}$ and $EconControl_{kt}$ is state k's economic variable at quarter t.

Instruments

$PopPR(LC)_t$	Population granted access to Prosper (LendingClub) for lending in quarter t. $PopPR(LC)_t = \frac{1}{\#\, of\, days\, in\, quarter\, t} \sum_{d \in t} PopPR(LC)_d$, where $PopPR(LC)_d = \sum_k \left[\mathbb{1}_{\{if\ registered\}} \times population_{kd}\right] / US\ population\ in\ 2008$. $\mathbb{1}_{\{if\ registered\}}$ is 1 if Prosper (LendingClub) has a current security registration active in state k on day d, and 0 otherwise. $Population_{kd}$ is the population in state k at calendar day d, and it is updated quarterly.
Pop_{it}	The fraction of the US population located in bank i's market able to invest on either platform. In the case of multistate banks, we use deposit weights for each state within bank i's market. $Pop_{it} = \sum_k w_{ikt} \times \left[\frac{1}{\#\, of\, days\, in\, quarter\, t} \sum_{d \in t} PopLC_d + \frac{1}{\#\, of\, days\, in\, quarter\, t} \sum_{d \in t} PopPR_d\right]$, where $PopPR(LC)_d = \sum_k \left[\mathbb{1}_{\{if\ registered\}} \times population_{kd}\right] / US\ population\ in\ 2008$, and w_{ikt} is $\frac{Bank\ i's\ deposits\ in\ state\ k\ in\ quarter\ t}{Bank\ i's\ total\ deposit\ in\ quarter\ t}$. $\mathbb{1}_{\{if\ registered\}}$ is 1 if Prosper (LendingClub) has a current security registration active in state k on day d, and 0 otherwise. $Population_{kd}$ is the population in state k at calendar day d, and it is updated quarterly.

QE Variables

$MBSActivity_t$ (in \$B)	Sum of daily MBS amount purchased by the Federal Reserve in quarter t.
$TBActivity_t$ (in \$B)	Sum of daily total par amount of Treasury bonds purchased by the Federal Reserve in quarter t.

Appendix B Peer-to-Peer Regulatory Background

B.1 Borrower (Origination) Restrictions

To allow individuals to borrow on the platform, intermediaries must meet state-level banking and consumer financing standards. Banking regulators require a variety of licenses from the platform, including lending, loan brokering/supervising, money transferring, and collection licenses. Indiana, for example, requires the platforms to seek a collection agency license. Mississippi requires platforms to hold a loan brokering license. Other states have no license requirements at all for the platforms and only regulate the issuing bank. The regulatory restrictions and degree of monitoring vary widely from state to state. In some cases, the licensing process simply requires disclosure on the part of the platform, while in other cases a more thorough review of the firm is conducted. As might be expected of an innovative industry, in some instances the platforms' lending process does not fit within the regulatory structure of a state and can draw additional scrutiny from the banking regulator or attorney general's office. We find at least two instances when the platforms have been subject to specific enforcement actions that have prevented lending activities, both of which we can connect to gaps in the aggregate lending data.[19] In other cases, like the state of Pennsylvania, we can verify that a platform is restricted from originating loans, but regulators will not confirm the details around origination restrictions for a particular platform.

While licensing is the most common regulatory barrier to entry, states can erect additional hurdles by making the financial intermediation model of peer-to-peer lending less profitable. For example, the state of Iowa makes originate-to-distribute (OTD) models of financial intermediation difficult for lenders to execute due to a statute that rebates origination fees in the event of loan prepayment.[20] Thus, peer-to-peer lenders are technically able to operate in Iowa, but the state has created barriers to entry through this set of fee rebates. As a result, essentially no borrowers in the state of Iowa

[19] The state of Mississippi issued a cease-and-desist order to LendingClub in 2009 after its loan broker license expired. This prevented any additional lending activity until the Mississippi Division of Banking and Consumer Finance was satisfied that LendingClub had sufficiently met the requirements of the order. LendingClub resumed lending activity within the state in 2014. The state of Kansas came to a consent judgement/settlement agreement with LendingClub in 2010. During the negotiation period, in the first three quarters of 2010, LendingClub ceased origination activities in Kansas.

[20] The state of Iowa entitles consumers to a finance charge rebate under statute 537.2510 if the consumer loan is prepaid.

have received loans from either platform over the 25 quarters we examine.

Our sample begins in the third quarter of 2009, after both platforms had switched their business model to the one depicted in Figure 1, Panel A. Before that time, the platforms had originated loans under a previous structure, discussed below, so there is evidence that the platforms are able to issue loans in almost every state.[21] Thus, both platforms appear to have desired to and were able to lend to borrowers nationwide. Following the restructuring period, however, both platforms temporarily ceased origination activities in multiple states.[22] While it is possible that the peer-to-peer platforms failed to originate loans in these state-quarters due to local demand, multiple large marketplaces such as Indiana and North Carolina are among the initially omitted states. We also note that the cessation of loan issuance on only one of the platforms in states like Pennsylvania runs counter to local demand arguments, suggesting the origination droughts are likely the result of regulatory issues. Given this retreat, we assume that a lack of loan origination in a state is due to regulatory issues that arose during the restructuring period. However, because of the myriad ways barriers to entry can be created on the borrower side of the process, we can only pinpoint some of the mechanisms that create the barrier.

B.2 Investment Restrictions

Our second identification strategy uses the regulatory hurdles on the investment side of peer-to-peer lending. In this section, we briefly review how this regulation developed to demonstrate how the security registration process used by the lending platforms has been binding for investment. Below, we argue that these regulatory changes should provide some exogenous variation in the supply of loanable funds.

Before the restructuring in 2008, peer-to-peer platform investors directly funded a loan as opposed to indirectly through the BDN process depicted in Figure 1, Panel A. The full amount requested by borrowers was fractioned to allow each investor to fund a "mini-loan" for the borrower. Figure 1,

[21] Prosper had originated loans in all states except South Dakota before its restructuring. LendingClub had issued loans to borrowers in every state except North Dakota and West Virginia prior to its restructuring.

[22] LendingClub fails to issue loans in Iowa, Idaho, Maine, North Dakota, and Nebraska for almost the entire sample period. The LendingClub platform initiates lending part way through the sample period in Indiana, Mississippi, North Carolina, and Tennessee. Prosper does not issue loans in Maine, North Dakota, and Iowa over the entire sample period. Prosper ceases to issue loans in the state of Pennsylvania part way through the sample.

Panel B depicts this early peer-to-peer lending process. The drawback of this format was that the lending platforms were subject to the local usury interest rate caps established in the borrower's state of residence. As Rigbi (2013) discusses, the usury caps restricted loan origination volume and drove the platforms to adopt the process depicted in Figure 1, Panel A. When an issuing bank was brought into the lending process, a nationally chartered bank could export the interest rate cap of its home state when originating out-of-state loans (Honigsberg, Jackson, and Squire (2016)).[23] Borrowers entering into a loan contract with an issuing bank thus could be issued loans with an interest rate up to the cap of the issuing bank's state rather than the borrower's state.[24]

While the format shift resolved the interest rate cap for the lending platforms, the new strategy required the platforms to hold loans on their balance sheet and create new securities for each funded loan. This new process attracted the attention of federal regulators, who forced one of the platforms to begin to register its BDNs federally.[25] The other platform preemptively selected a similar approach. At the time of the change in 2008, the majority of platform investors were non-accredited investors. By allowing non-accredited investors to participate in the security creation process depicted in Figure 1, Panel A, the platforms could not qualify for a federal registration exemption.[26] Thus, all BDNs needed to be registered at the federal level. Similar to firms undergoing the process to create equity securities, the lending platforms went through a "quiet period" and ceased origination operations in 2008.[27] Because the platforms did not qualify for federal registration exemptions, they issued a continuous security offering,[28] which allows the platforms to file a single federal security registration that acts as an umbrella under which BDNs can be created or "taken off the shelf." As BDNs

[23]The interest rate exportation ability comes from Section 85 of National Banking Act of 1864 and Section 521 of the Depository Institution Deregulation and Monetary Control Act of 1980, in addition to multiple federal case laws.

[24]Over the course of most of their operations, both platforms have used a Utah bank as their issuing bank. According to Title 70C of the Utah Code, banks are not limited on the interest rate charged or the fees levied for the loan types issued on the platform.

[25]Securities and Exchange Commission Administrative Proceeding 33-8984 on November 24, 2008.

[26]Common exemptions include Regulation D Rule 506(b) or Rule 506(c) exemptions but are only available to securities offered to accredited investors. Later exemptions available to non-accredited investors as part of the JOBS Act were not available at the time.

[27]During an IPO, a firm must undergo a quiet period as directed by the SEC when the firm issues only clarifying statements concerning its prospectus and other federally filed information (Bradley, Jordan, and Ritter (2003)). The intent is to confine all material information to the prospectus for potential investors to reference. Although the security being issued post quiet period for the lending platforms were BDNs and supposedly not tied to the platform's performance, the SEC directed the platforms to undergo a "quiet period" during the federal registration process of the BDN.

[28]Continuous security offerings are covered under Rule 415 of the Securities Act of 1933.

are offered (listed) to investors, the federal security registration prospectus is updated through a Form 424(b)(3) filing. When the BDNs are funded, a second, separate 424(b)(3) is filed for the final creation (sale) of the BDN. The lending platforms file multiple 424(b)(3) forms a day containing this information. This makes the peer-to-peer lending firms among the most active filers with the SEC. As of the end of 2017, LendingClub was the 10th largest filer of all time and Prosper Marketplace was the 25th largest filer.

Not all FinTech platforms are subject to such scrutiny. Following the JOBS Act, the SEC revised Regulation D rules in September 2013 to allow "general solicitation" for securities exempted under Regulation D. This allowed other competing platforms to use the internet to "generally solicit" accredited investors (Manbeck, Franson, and Henry (2017)). While we focus on two platforms, LendingClub and Prosper, other lending platforms such as Upstart fund borrower loans solely through accredited investors. Upstart's subsidiary Upstart Networks files a federal exemption so that the BDNs created on Upstart's platform do not have to be federally registered.[29]

Normally, when securities are federally registered, they are considered "covered," i.e., exempt from additional state-level registration of the security. Thus, federal registration implies that the peer-to-peer platforms should be exempt from any additional state-level registration requirements. However, to be considered a federally covered security, peer-to-peer lending platforms must meet the requirements of section 18(b) of the Securities Act of 1933. According to that section, the security, or more junior security, must be listed by and trade on a national market system (a registered exchange). Because the BDNs are never listed on or traded on a national market system, the platforms are forced to register the BDNs again at the state level.

During the quiet periods and in the ensuing years, platforms have sought state security registration to allow investors to participate on the platform. We interviewed state security regulators to collect effective registration dates for both platforms and discovered that both platforms have applied to almost every state for security registration, but not all states have been willing to grant registration. There is a spectrum of rigor around financial suitability and disclosure required by state security regulators. At one end, disclosure states require the least amount of information, whereas merit

[29]Upstart Networks files a Regulation D Rule 506 exemption for its BDNs. Upstart Networks also files registration exemptions within the states where Upstart investors live to satisfy state-level registration laws.

states require a firm-level review before security registration approval (Warren (1987); Colombo (2013)). Once a platform is approved to issue securities within a state, it has an effective security registration. In some states, effective registrations are perpetual and require no additional filings until the amount of security registered is issued in full. In other states, unissued security needs to be renewed annually. Thus, it is possible for an effective registration to lapse until the platform renews its original registration or files for an additional security registration. As a result of these state-level security registration changes, the evolution of investor participation on the platforms varies over time and by platform. In Section 5 we use this cross-sectional and time-varying supply of investors to instrument for peer-to-peer lending volumes faced by banks as competition.

It is possible that lending platforms ignore state security regulators after federally registering their securities due to the cost of state-level compliance. However, we note two details that suggest state-level security registrations are at least partially binding for the platforms. First, both lending platforms acknowledge the lender restrictions in their Prospectus filings. Thus, they clearly are aware of the need for state-level registration and the risks of noncompliance. Second, in 2008, Prosper entered into a settlement with the North American Security Administrators Association, the industry organization for state security regulators, several of whom had brought forward investigations against the platform. Under that settlement, "Prosper agreed not to offer or sell any securities in any jurisdiction until it is in compliance with that jurisdiction's securities registration laws."

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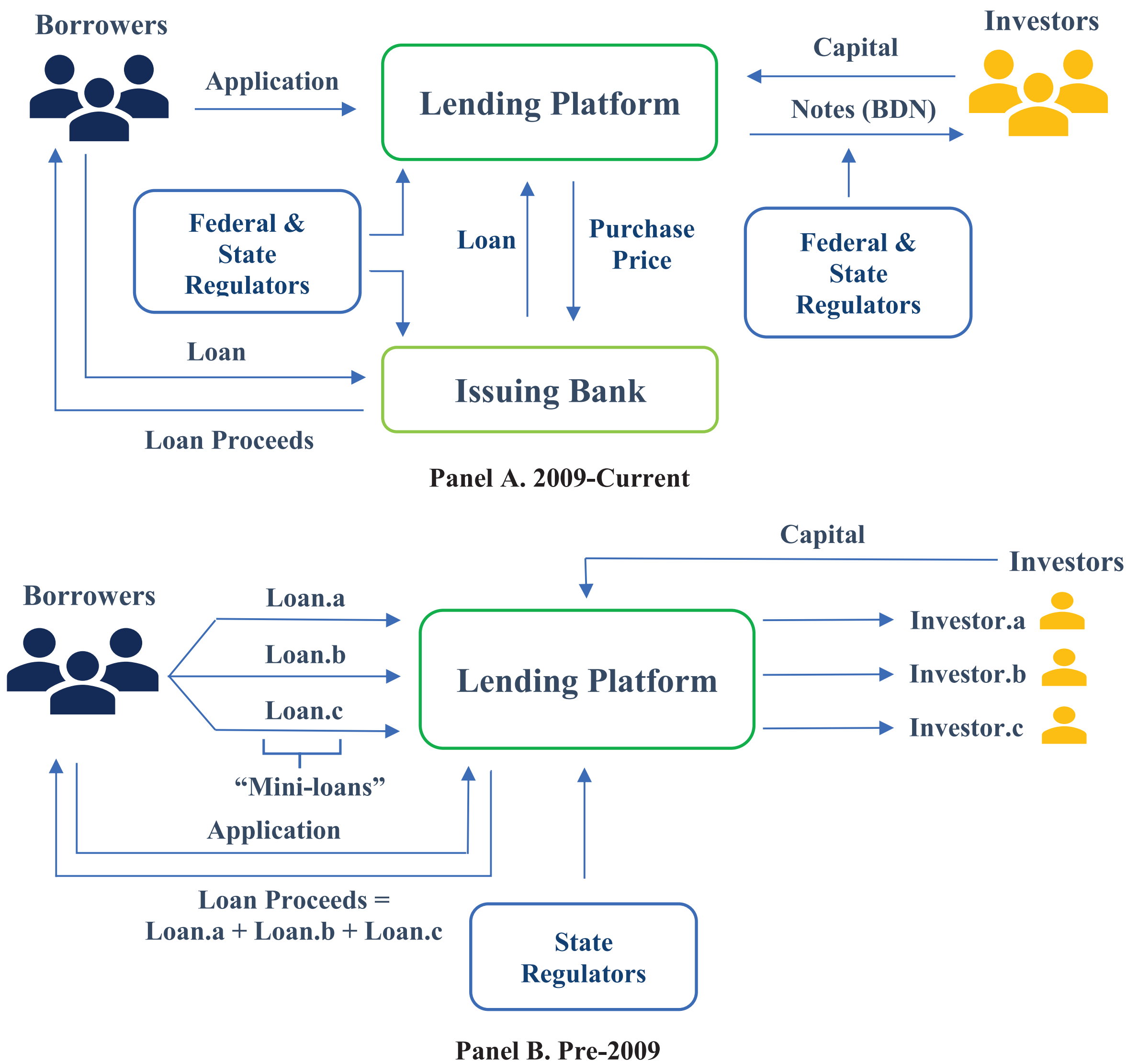
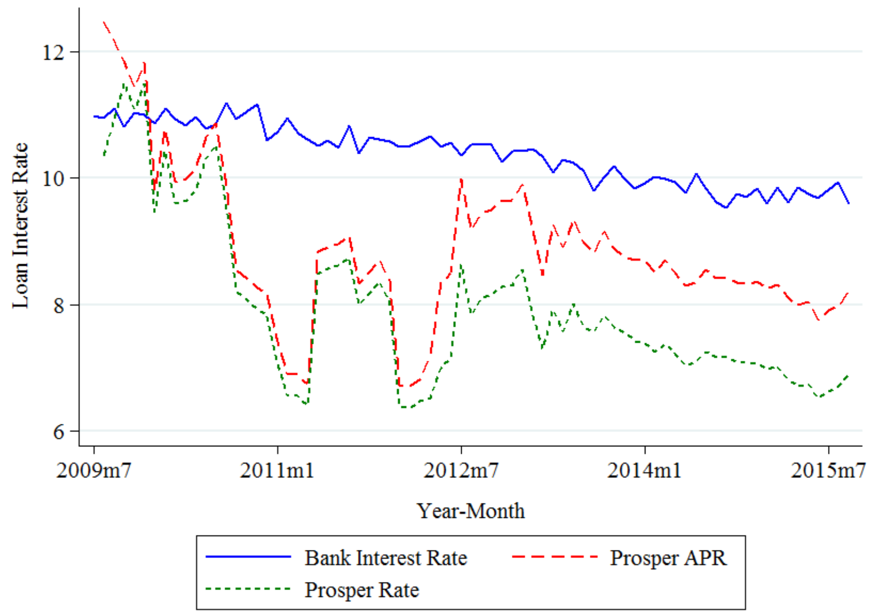


Figure 1. Peer-to-Peer Lending Process

Panel A depicts the lending process for peer-to-peer lending during our sample period in 2009-2015. The borrower submits a loan application to the platform, and upon funding commitment from investors, the issuing bank originates a loan to the borrower. The loan is sold to the lending platform within a few days, and then the lending platform creates a new security called a borrower dependent note (BDN) that is sold to the investors that commit to funding the loan. Panel B depicts the lending process for peer-to-peer lending before our sample period in 2006-2009. The borrower submits a loan application to the platform, and upon funding commitment from investors, the platform originates a set of mini-loans with the borrower. The total principal of the mini-loans is equivalent to the aggregate loan amount funded by investors. The mini-loans are sold to the investors that fund the loan. Each mini-loan has a principal amount equivalent to the capital pledged by the individual investor.



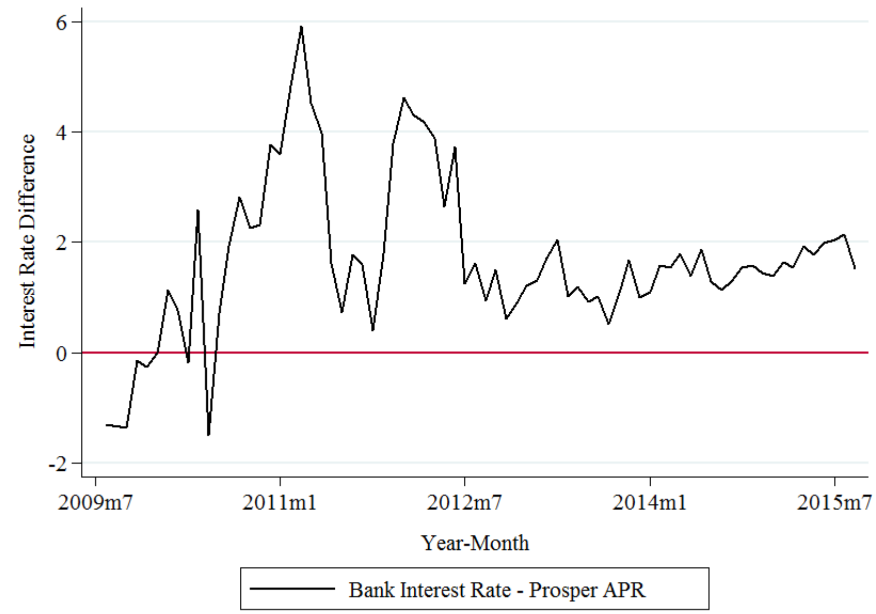
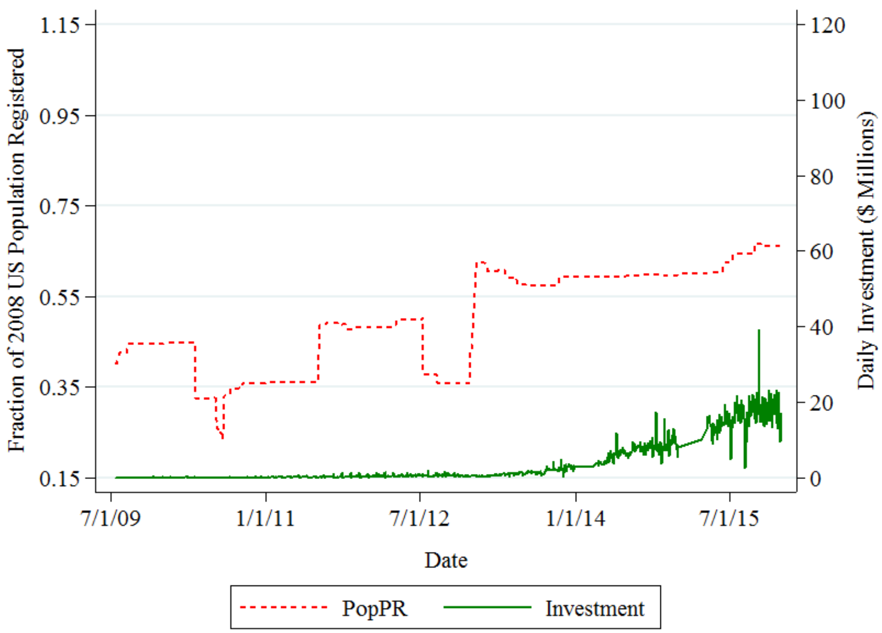


Figure 2. Average Interest Rate for Commercial Bank and Peer-to-Peer Unsecured Consumer Loans (36 month, $12K-$18K, highest credit rating) over Time

The figure shows the average interest rate for both the commercial banks and peer-to-peer platforms (left) and the average difference between commercial bank loan interest rates and the peer-to-peer loan annual percentage rate (right). The commercial banks report interest rates for a given term and loan size for borrowers with the best credit rating to RateWatch. The Prosper interest rates are the highest loan credit grade (AA), reported as both the raw interest rate charged by the platform ($ProsperRate$) and the annual percentage rate ($ProsperAPR$), which adjusts the average rate charged to borrowers with origination fees. Commercial banks do not typically levy origination fees for unsecured consumer loans. To calculate the difference, we first average the interest rate across all banks in a state-month and all peer-to-peer loans in a state-month. We compute the state-month level differences between bank interest rates and peer-to-peer interest rates and then average across all states for each month.



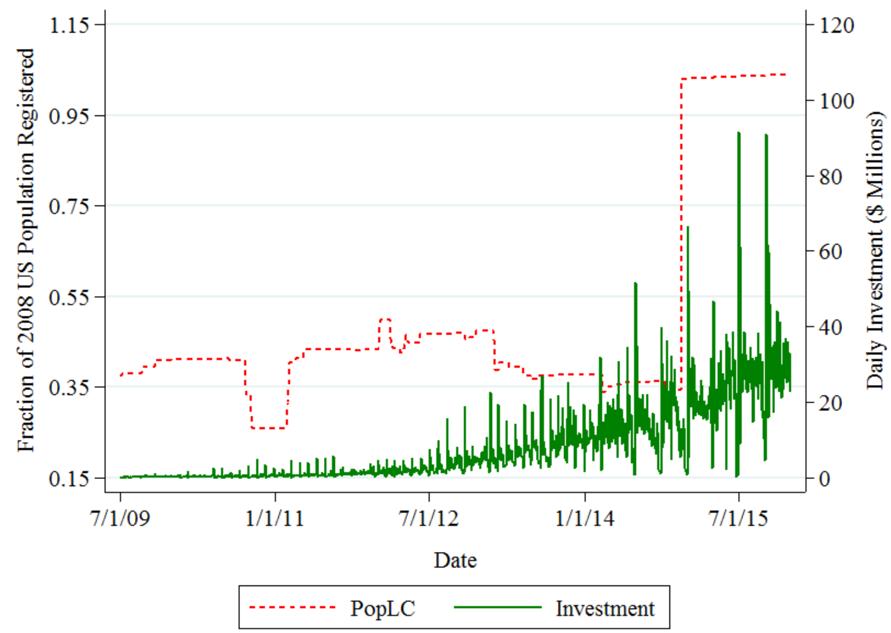


Figure 3. Daily Investment and Fraction of US Population Residing in States Registered to Purchase Securities on the Peer-to-Peer Platforms

The figure above graphs the fraction of the 2008 US population able to invest on Prosper (left) and LendingClub (right) according to state security regulator interviews. The population measure incorporates registration lapses. Daily investment volume is graphed on the right axis. We assume all U.S. residents can invest on LendingClub after the public listing of common stock on the NYSE on December 11, 2014.

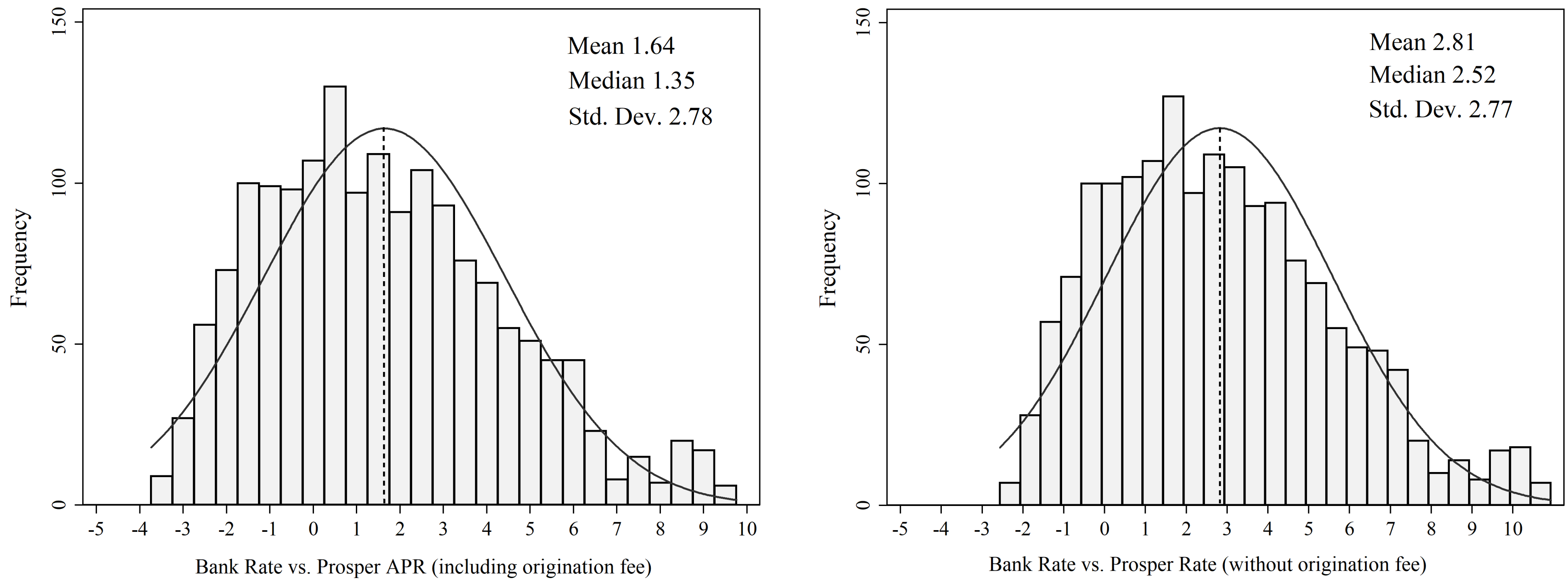


Figure 4. Interest Rate Differences between Commercial Banks and Peer-to-Peer Lending

The figures above graph the bank fixed effects from Equation (3) where we regress lender interest rates on loan characteristics, state fixed effects, monthly fixed effects, state coincident index, and bank fixed effects. The base, omitted bank fixed effect is the peer-to-peer platform (Prosper) and the figure above displays the distribution of bank fixed effects for the banks in the sample. The peer-to-peer interest rate used in the left figure is the *ProsperAPR* which adjusts interest rates charged by the peer-to-peer platform by the additional cost of origination fees. The figure on the right uses raw, unadjusted peer-to-peer interest rates, *ProsperRate*. Bank interest rates are the same in both figures. Thus the figures above should capture the difference in interest rates between the peer-to-peer lending platform Prosper and each bank. The figure on the left suggests Prosper undercuts the average bank by 164 BPs even after considering origination fees. Since Prosper's origination fees account for 80-90% of revenue, the figure on the right suggests that the cost of intermediation is approximately 281 BPs for the average bank.

Table 1. Summary Statistics

The table reports the number of observations, the mean, and distribution of the main variables used in the analysis. Panel A presents summary statistics for the full sample, and Panels B.1 and B.2 present summary statistics for the small and large commercial bank subsamples. Panel C presents summary statistics for the sample used in the interest rate tests.

Panel A. Full Sample

Variable Name	N	Mean	Std. Dev.	P25	P50	P75
P2PVolume ($B)	164,711	0.0170	0.0314	0.000732	0.00365	0.0182
P2PLowRating ($B)	164,711	0.00243	0.00493	0.000117	0.000642	0.00249
P2PHighRating ($B)	164,711	0.0155	0.0323	0.000574	0.00297	0.0152
PopLC	164,711	0.475	0.205	0.377	0.412	0.460
PopPR	164,711	0.492	0.103	0.385	0.482	0.594
Pop	164,711	0.00948	0.0139	0	0.00464	0.0128
Total Loans ($B)	164,711	0.342	1.71	0.0451	0.0994	0.227
Total Assets ($B)	164,711	0.494	1.67	0.0799	0.161	0.350
Consumer Credit ($B)	164,711	0.0426	1.08	0.00127	0.00311	0.00750
AllConsumer	164,711	0.0332	0.0392	0.00885	0.0218	0.0428
Personal Loans ($B)	164,711	0.0212	0.319	0.00122	0.00300	0.00721
PLoans	164,711	0.0317	0.0356	0.00830	0.0210	0.0418
PL 30 days Past ($M)	164,711	0.249	3.51	0	0.0240	0.102
PL30Past	164,711	0.000585	0.00115	0	0.000136	0.000607
PL Charged Off ($M)	164,711	0.0498	0.722	0	0.00100	0.0140
PLChgOff	164,711	0.0000753	0.000178	0	0.00000718	0.0000648
TotalEquity	164,711	0.111	0.0423	0.0900	0.103	0.122
NetIncome	164,711	0.00394	0.00783	0.00160	0.00393	0.00745
InterestExp	164,711	0.00632	0.00577	0.00232	0.00445	0.00841
MBSHolding	164,711	0.0798	0.0988	0.00210	0.0470	0.120
Competition	164,711	0.0815	0.0732	0.0391	0.0607	0.0908
PerCapitaInc ($)	164,711	42500	5620	38400	42200	45900
Unemp (%)	164,711	7.07	2.06	5.50	6.90	8.47
AutoDebt ($)	164,711	3350	682	2860	3190	3670
CCDebt ($)	164,711	2720	425	2410	2680	2990
MortDebt ($)	164,711	28800	9400	23000	25100	34000
AutoDebtDelinq (%)	164,711	3.69	1.45	2.62	3.47	4.47
CCDebtDelinq (%)	164,711	9.15	2.67	7.11	8.76	10.6
MortDebtDelinq (%)	164,711	3.93	2.90	2.18	3.20	4.51
MBSActivity ($B)	164,711	0.116	0.102	0.00665	0.0909	0.201
TBActivity ($B)	164,711	0.102	0.0836	0.036	0.132	0.135

Panel B.1. Small Banks (Total Assets<\$300M)

Variable Name	N	Mean	Std. Dev.	P25	P50	P75
Total Loans (\$B)	116,632	0.0764	0.0532	0.0331	0.0646	0.110
Total Assets (\$B)	116,632	0.123	0.0744	0.0616	0.108	0.175
Consumer Credit (\$B)	116,632	0.00400	0.00685	0.00104	0.00234	0.00484
AllConsumer	116,632	0.0355	0.0365	0.0116	0.0257	0.0469
Personal Loans (\$B)	116,632	0.00386	0.00609	0.00101	0.00229	0.00473
PLoans	116,632	0.0345	0.0346	0.0112	0.0251	0.0463
PL 30 days Past (\$M)	116,632	0.0750	0.218	0	0.0180	0.0740
PL30Past	116,632	0.000685	0.00124	0	0.000186	0.000768
PL Charged Off (\$M)	116,632	0.0106	0.0519	0	0	0.00700
PLChgOff	116,632	0.0000794	0.000189	0	0	0.0000658
TotalEquity	116,632	0.113	0.0455	0.0902	0.104	0.125
NetIncome	116,632	0.00377	0.00789	0.00144	0.00381	0.00740
InterestExp	116,632	0.00628	0.00557	0.00235	0.00448	0.00842
MBSHolding	116,632	0.0730	0.0986	0.0000685	0.0352	0.109

Panel B.2. Large Banks (Total Assets≥\$300M)

Variable Name	N	Mean	Std. Dev.	P25	P50	P75
Total Loans (\$B)	48,079	0.985	3.07	0.261	0.389	0.702
Total Assets (\$B)	48,079	1.39	2.90	0.401	0.588	1.07
Consumer Credit (\$B)	48,079	0.136	2.00	0.00307	0.00884	0.0216
AllConsumer	48,079	0.0276	0.0445	0.00483	0.0135	0.0293
Personal Loans (\$B)	48,079	0.0632	0.588	0.00278	0.00825	0.0201
PLoans	48,079	0.0246	0.0371	0.00439	0.0124	0.0277
PL 30 days Past (\$M)	48,079	0.670	6.47	0.003	0.052	0.234
PL30Past	48,079	0.000343	0.000843	0.00000445	0.0000722	0.000308
PL Charged Off (\$M)	48,079	0.145	1.33	0	0.0100	0.0480
PLChgOff	48,079	0.0000652	0.000149	0	0.0000138	0.0000633
TotalEquity	48,079	0.107	0.0332	0.0897	0.102	0.118
NetIncome	48,079	0.00436	0.00766	0.00194	0.00423	0.00754
InterestExp	48,079	0.00641	0.00624	0.00225	0.00437	0.00836
MBSHolding	48,079	0.0964	0.0974	0.0212	0.0724	0.141

Panel C. Interest Rate Sample

Variable Name	N	Mean	Std. Dev.	P25	P50	P75
BankRate	137,547	10.8	2.85	8.61	10.5	12.8
ProsperAPR	6,523	8.74	1.36	8.03	8.50	9.26
ProsperRate	6,523	7.56	1.24	6.81	7.26	8.00
LoanTerm	137,547	39.5	15.0	36	36	60
CoincidentIndex	137,547	152	24.4	135	147	167
TotalLoans (\$B)	136,090	0.406	0.913	0.0975	0.185	0.384
TotalAssets (\$B)	136,090	0.647	1.57	0.169	0.287	0.580
TotalEquity	135,149	0.104	0.0248	0.0897	0.100	0.115
NetIncome	136,090	0.00415	0.00671	0	0.00404	0.00719
InterestExp	136,090	0.00613	0.00541	0.00229	0.00436	0.00828

Table 2. Effect of Peer-to-Peer Lending on Personal Loan Volume of Commercial Banks

The table presents ordinary least squares regression results from Equation (1) in which total consumer credit volume and personal loan volume are regressed on peer-to-peer loan volume, bank characteristics, and local economy controls. As specified in Equation (1), the dependent variable is the natural log of one plus the variable reported in each column. $P2PVolume$ is the volume of peer-to-peer loans originated in lender i's market, which is defined by its deposit-weighted geographic footprint in quarter t. $P2PLowRating$ is the volume of low-credit-rating peer-to-peer loans originated in lender i's market. $P2PHighRating$ is the volume of high-credit-rating peer-to-peer loans originated in lender i's market. Bank characteristic variables are winsorized at 1% and 99%. Local economy controls are state-level statistics weighted by bank i's deposit-weighted geographic footprint. See the variable appendix for further details on variable definitions and construction. The regression includes bank and year-quarter fixed effects. Standard errors are clustered at the bank level. Numbers in parentheses are t-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)
	$AllConsumer_{it}$	$PLoans_{it}$	$AllConsumer_{it}$	$PLoans_{it}$
$P2PVolume_{it}$	−0.0105	−0.0126**		
	(−1.632)	(−2.139)		
$P2PLowRating_{it}$			−0.226***	−0.200***
			(−2.717)	(−2.632)
$P2PHighRating_{it}$			0.0278*	0.0217
			(1.830)	(1.579)
Bank Characteristics				
$TotalAsset_{it}$	0.00127*	0.00104***	0.00127*	0.00104***
	(1.940)	(3.040)	(1.939)	(3.040)
$TotalEquity_{it}$	0.00987	0.00246	0.00986	0.00244
	(1.088)	(0.382)	(1.087)	(0.378)
$NetIncome_{it}$	0.0972***	0.0915***	0.0975***	0.0917***
	(7.864)	(7.983)	(7.875)	(7.996)
$InterestExp_{it}$	−0.068*	−0.106***	−0.071*	−0.109***
	(−1.745)	(−3.352)	(−1.840)	(−3.460)
Local Economy				
$PerCapitaInc_{it}$	0.115	0.161	0.096	0.146
	(0.847)	(1.317)	(0.705)	(1.192)
$Unemp_{it}$	−0.0167	−0.0107	−0.0137	−0.0077
	(−0.993)	(−0.694)	(−0.827)	(−0.504)
$AutoDebt_{it}$	−5.45***	−5.23***	−5.51***	−5.29***
	(−5.632)	(−5.900)	(−5.674)	(−5.961)
$CCDebt_{it}$	2.53	1.81	2.36	1.62
	(1.423)	(1.087)	(1.331)	(0.977)
$MortDebt_{it}$	−0.437***	−0.479***	−0.427***	−0.470***
	(−3.186)	(−4.018)	(−3.116)	(−3.949)
$AutoDebtDelinq_{it}$	0.00955	0.00521	0.00980	0.00460
	(0.290)	(0.173)	(0.295)	(0.151)
$CCDebtDelinq_{it}$	0.0705***	0.0562***	0.0780***	0.0629***
	(3.428)	(2.977)	(3.897)	(3.456)
$MortDebtDelinq_{it}$	−0.0415**	−0.0358**	−0.0415**	−0.0352**
	(−2.449)	(−2.440)	(−2.472)	(−2.417)
$Constant$	0.0519***	0.0539***	0.0519***	0.0540***
	(7.007)	(8.332)	(7.013)	(8.353)
Year-Quarter FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
SE clustered	Bank	Bank	Bank	Bank
R^2	0.931	0.933	0.931	0.933
$Adj.R^2$	0.927	0.930	0.927	0.930
Obs.	164,711	164,711	164,711	164,711
Number of Banks	7,758	7,758	7,758	7,758

Table 3. Late Payment Status for Personal Loans

The table shows ordinary least squares regression results from Equation (2) in which contemporaneous and future late payment status variables are regressed on peer-to-peer loan volume, bank characteristics, and local economy controls. In columns (1)-(3), the dependent variable is the volume of personal loans that are 30-89 days delinquent. In columns (4)-(6), the dependent variable is the volume of personal loans charged off. As specified in Equation (2), the dependent variable is the natural log of one plus the variable reported in each column. $P2PVolume$ is the volume of peer-to-peer loans originated in lender i's market, which is defined by its deposit-weighted geographic footprint in quarter t. Bank characteristic variables are winsorized at 1% and 99%. Local economy controls are state-level statistics weighted by bank i's deposit-weighted geographic footprint. See the variable appendix for further details on variable definitions and construction. The regression includes bank and year-quarter fixed effects. Standard errors are clustered at the bank level. Numbers in parentheses are t-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	PL30Past$_{it}$	PL30Past$_{it+1}$	PL30Past$_{it+2}$	PLChgOff$_{it}$	PLChgOff$_{it+1}$	PLChgOff$_{it+2}$
$P2PVolume_{it}$	0.369*	0.447**	0.557**	0.360***	0.430***	0.483***
	(1.677)	(1.967)	(2.332)	(3.322)	(3.823)	(4.061)
Bank Characteristics						
$TotalAsset_{it}$	0.0223**	0.0208**	0.0203**	0.0005	0.0039	0.0024
	(2.451)	(2.350)	(2.434)	(0.100)	(0.703)	(0.471)
$TotalEquity_{it}$	−0.472**	−0.563***	−0.569***	−0.566***	−0.462***	−0.515***
	(−2.560)	(−3.102)	(−2.905)	(−5.614)	(−4.514)	(−5.028)
$NetIncome_{it}$	0.80*	0.57	0.86*	−1.55***	−0.56**	−1.33***
	(1.705)	(1.210)	(1.859)	(−5.320)	(−2.068)	(−5.032)
$InterestExp_{it}$	3.14***	3.47***	3.04***	1.95***	2.04***	1.72***
	(2.689)	(3.084)	(2.805)	(2.721)	(3.269)	(2.875)
Local Economy						
$PerCapitaInc_{it}$	−2.78	−3.10	−4.42	3.65	3.65	1.96
	(−0.632)	(−0.701)	(−1.000)	(1.545)	(1.520)	(0.837)
$Unemp_{it}$	2.90***	2.24***	1.92***	2.20***	1.76***	1.46***
	(4.493)	(3.440)	(2.930)	(6.143)	(4.870)	(4.079)
$AutoDebt_{it}$	−154***	−144***	−124***	−34*	−20	−10
	(−4.425)	(−4.116)	(−3.464)	(−1.800)	(−1.096)	(−0.516)
$CCDebt_{it}$	155**	173***	197***	48	73**	90***
	(2.518)	(2.872)	(3.305)	(1.494)	(2.312)	(2.933)
$MortDebt_{it}$	−17.3***	−15.2***	−11.2***	−7.2***	−6.3***	−4.1*
	(−3.959)	(−3.563)	(−2.688)	(−3.013)	(−2.739)	(−1.814)
$AutoDebtDelinq_{it}$	−0.423	−0.172	0.649	0.250	0.691	0.568
	(−0.367)	(−0.150)	(0.562)	(0.393)	(1.100)	(0.917)
$CCDebtDelinq_{it}$	1.37*	1.38*	0.91	2.29***	2.06***	1.78***
	(1.871)	(1.915)	(1.250)	(5.772)	(5.252)	(4.545)
$MortDebtDelinq_{it}$	−1.05**	−0.84*	−0.78	−0.93***	−0.70**	−0.57**
	(−2.092)	(−1.699)	(−1.584)	(−3.314)	(−2.523)	(−2.026)
$Constant$	1.75***	1.68***	1.40***	0.17	0.10	−0.07
	(6.828)	(6.648)	(5.531)	(1.210)	(0.719)	(−0.538)
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
SE clustered	Bank	Bank	Bank	Bank	Bank	Bank
R^2	0.786	0.789	0.791	0.560	0.563	0.565
$Adj.R^2$	0.775	0.778	0.780	0.538	0.540	0.542
Obs.	164,711	157,384	149,638	164,711	157,394	149,657
Number of Banks	7,758	7,758	7,683	7,758	7,758	7,683

Table 4. Interest Rate Regression

The table shows ordinary least squares regression results from Equation (3) in which the lender interest rate is regressed on loan characteristics, borrower state fixed effects, year-month fixed effects, the state coincident index, and lender fixed effects. In columns (1) and (2), the dependent variable is the interest rate of loan offers made by commercial banks (*BankRate*) or the origination-fee-adjusted interest rate of loan offers made by the peer-to-peer lending platform Prosper (*ProsperAPR*). In columns (3) and (4), the dependent variable is the interest rate of loan offers made by commercial banks (*BankRate*) or the raw interest rate of loan offers made by the peer-to-peer lending platform Prosper (*ProsperRate*). *Prosper* is an indicator for all Prosper loans in the data. The regression includes indicators for loan term ($Term\,36\,mo.$ and $Term\,60\,mo.$) and loan size indicators. See the variable appendix for further details on variable definitions and construction. Standard errors are clustered at the bank level. Numbers in parentheses are t-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	BankRate and ProsperAPR		BankRate and ProsperRate	
	(1)	(2)	(3)	(4)
$Prosper$		-1.98^{***}		-3.15^{***}
		(-14.936)		(-23.223)
$Term\,36\,mo.$	0.099	-0.280	0.103	-0.280
	(0.312)	(-1.113)	(0.326)	(-1.115)
$Term\,60\,mo.$	0.620	-0.825^{**}	0.560	-0.836^{***}
	(1.135)	(-2.569)	(1.095)	(-2.639)
$LoanSize\{8K-12K\}$	-0.677^{***}	-0.730^{***}	-0.681^{***}	-0.733^{***}
	(-9.830)	(-10.377)	(-10.244)	(-10.800)
$LoanSize\{12K-18K\}$	-0.740^{***}	-0.862^{***}	-0.747^{***}	-0.868^{***}
	(-9.328)	(-9.940)	(-9.992)	(-10.573)
$LoanSize\{18K-35K\}$	-0.754^{***}	-0.880^{***}	-0.763^{***}	-0.888^{***}
	(-9.025)	(-9.782)	(-9.829)	(-10.581)
$CoincidentIndex$	0.0169^{*}	-0.0030	0.0149	-0.0041
	(1.882)	(-0.273)	(1.627)	(-0.367)
$Constant$	7.1^{***}	11.6^{***}	6.1^{***}	11.7^{***}
	(6.210)	(8.856)	(5.323)	(8.861)
Bank FE	Yes	No	Yes	No
Month FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
SE clustered	Bank	Bank	Bank	Bank
R^2	0.811	0.189	0.820	0.218
$Adj.R^2$	0.809	0.189	0.818	0.217
Obs.	144,070	144,070	144,070	144,070
Number of Banks	1,631	1,631	1,631	1,631

Table 5. Bank Interest Rate Response to Peer-to-Peer Lending Volume

The table presents the ordinary least squares results from regressing bank loan interest rate offers, *BankRate*, from bank i in month t on peer-to-peer loan volume, time-varying bank characteristics, loan contract terms, time-invariant bank fixed effects, and year-month fixed effects, as shown in Equation (4). The unit of observation is at the bank-loan level. $P2PVolume$ is the volume of peer-to-peer loans originated in lender i's state in month t. Bank characteristic variables are winsorized at 1% and 99%. In columns (1)-(3), we use the full sample of RateWatch loan terms and sizes, whereas in columns (4)-(6) the bank loan sample is restricted to 36-month term loans, which are the most prevalent in the peer-to-peer loan data. In columns (2) and (5), we use the subsample of small commercial banks with total assets of less than \$300 million, and columns (3) and (6) contain the subsample of large commercial banks with total assets of more than \$300 million. See the variable appendix for further details on variable definitions and construction. Standard errors are clustered at the bank level. Numbers in parentheses are t-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	BankRate$_{it}$ - All terms			BankRate$_{it}$ - 36 month term only		
	(1)	(2)	(3)	(4)	(5)	(6)
	Full	Small	Large	Full	Small	Large
$P2PVolume_{it}$	0.151	−0.027	0.282	0.181	0.042	0.280
	(0.887)	(−0.125)	(1.223)	(1.040)	(0.188)	(1.201)
$TotalAsset_{it}$	0.084	0.343	0.083	0.096	0.615	0.091
	(0.998)	(0.128)	(0.895)	(1.092)	(0.219)	(0.940)
$TotalEquity_{it}$	−1.50	5.09	−7.59*	−2.24	4.54	−9.25*
	(−0.463)	(1.123)	(−1.685)	(−0.634)	(0.959)	(−1.851)
$NetIncome_{it}$	−2.93	−7.72	4.01	−3.65	−8.27	3.30
	(−0.554)	(−1.445)	(0.441)	(−0.658)	(−1.438)	(0.352)
$InterestExp_{it}$	5.95	6.41	6.87	2.58	2.55	5.52
	(0.437)	(0.356)	(0.355)	(0.182)	(0.134)	(0.277)
$Term$ 36 $mo.$	−0.030	0.133	−0.432			
	(−0.067)	(0.237)	(−0.804)			
$Term$ 60 $mo.$	0.240	0.640	−0.373			
	(0.445)	(0.921)	(−0.561)			
$LoanSize\{8K-12K\}$	−0.794***	−0.830***	−0.762***	−0.806***	−0.841***	−0.777***
	(−11.281)	(−9.325)	(−7.194)	(−11.142)	(−9.289)	(−7.109)
$LoanSize\{12K-18K\}$	−0.909***	−0.879***	−0.935***	−0.923***	−0.908***	−0.941***
	(−11.908)	(−9.045)	(−8.107)	(−11.636)	(−8.980)	(−7.835)
$LoanSize\{18K-35K\}$	−0.931***	−0.909***	−0.957***	−0.944***	−0.936***	−0.956***
	(−11.482)	(−8.556)	(−7.928)	(−11.123)	(−8.401)	(−7.591)
$Constant$	12.0***	11.2***	12.9***	12.1***	11.4***	12.6***
	(18.418)	(11.027)	(15.521)	(24.528)	(13.439)	(18.315)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
SE clustered	Bank	Bank	Bank	Bank	Bank	Bank
R^2	0.851	0.870	0.840	0.855	0.875	0.843
$Adj.R^2$	0.847	0.865	0.835	0.852	0.871	0.840
Obs.	49,812	23,765	26,047	46,321	21,952	24,369
Number of Banks	1,297	750	625	1,006	589	480

Table 6. Cross-Sectional Variation in Loan Volume Based on Lender Size and Market Competitiveness

The table shows ordinary least squares regression results from Equation (1) in which personal loan volume is regressed on peer-to-peer loan volume, bank characteristics, and local economy controls. As specified in Equation (1), the dependent variable is the natural log of one plus the variable reported in each column except for column (3). In column (1), we use the subsample of small commercial banks with total assets of less than $300 million, and column (2) contains the subsample of large commercial banks with total assets of more than $300 million. In column (3), we use the subsample of small banks with branches in only one state, and the dependent variable is the unscaled volume of personal loans in ($ billions). In column (4), we use the subsample of banks with branches in above-median $Competitiveness$ areas (low competition), and column (5) contains the subsample of banks with branches in below-median $Competitiveness$ areas (high competition). $P2PVolume$ is the volume of peer-to-peer loans originated in lender i's market, which is defined by its deposit-weighted geographic footprint in quarter t. Bank characteristic variables are winsorized at 1% and 99%. Bank characteristics include $TotalAsset$, $TotalEquity$, $NetIncome$, and $InterestExp$. Local economy controls are state-level statistics weighted by bank i's deposit-weighted geographic footprint and include $PerCapitaInc$, $Unemp$, $AutoDebt$, $CCDebt$, $MortDebt$, $AutoDebtDelinq$, $CCDebtDelinq$, and $MortDebtDelinq$. See the variable appendix for further details on variable definitions and construction. The full table is reported in the internet appendix. The regression includes bank and year-quarter fixed effects. Standard errors are clustered at the bank level. Numbers in parentheses are t-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Small	Large	Small Single	Low Competitiveness	High Competitiveness
	(1)	(2)	(3)	(4)	(5)
	$PLoans_{it}$	$PLoans_{it}$	$PLoans_{it}$ (unscaled)	$PLoans_{it}$	$PLoans_{it}$
$P2PVolume_{it}$	-0.0212^{***}	-0.0059	-0.0032^{**}	-0.0157^{**}	-0.0112
	(-2.701)	(-0.694)	(-2.397)	(-2.095)	(-1.153)
Bank Characteristics	Yes	Yes	Yes	Yes	Yes
Local Economy	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes
SE clustered	Bank	Bank	Bank	Bank	Bank
R^2	0.934	0.945	0.934	0.932	0.947
$Adj.R^2$	0.931	0.942	0.931	0.928	0.944
Obs.	116,632	48,078	113,630	82,313	82,398
Number of Banks	5,819	2,760	5,691	4,545	4,839

Table 7. Cross-Sectional Variation in Personal Loan Quality Based on Lender Size

The table shows ordinary least squares regression results from Equation (2) in which contemporaneous and future late payment status variables are regressed on peer-to-peer loan volume, bank characteristics, and local economy controls. As specified in Equation (2), the dependent variable is the natural log of one plus the variable reported in each column. Panel A presents the results for the subsample of small commercial banks with total assets of less than \$300 million, and Panel B contains the subsample of large commercial banks with total assets of more than \$300 million. In columns (1)-(3), the dependent variable is the volume of personal loans 30-89 days delinquent. In columns (4)-(6), the dependent variable is the volume of personal loans charged off. $P2PVolume$ is the volume of peer-to-peer loans originated in lender i's market, which is defined by its deposit-weighted geographic footprint in quarter t. Bank characteristic variables are winsorized at 1% and 99%. Bank characteristics include $TotalAsset$, $TotalEquity$, $NetIncome$, and $InterestExp$. Local economy controls are state-level statistics weighted by bank i's deposit-weighted geographic footprint and include $PerCapitaInc$, $Unemp$, $AutoDebt$, $CCDebt$, $MortDebt$, $AutoDebtDelinq$, $CCDebtDelinq$, and $MortDebtDelinq$. See the variable appendix for further details on variable definitions and construction. The full table is reported in the internet appendix. The regression includes bank and year-quarter fixed effects. Standard errors are clustered at the bank level. Numbers in parentheses are t-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A. Small Banks (<\$300 Million Total Assets)

	(1)	(2)	(3)	(4)	(5)	(6)
	PL30Past_{it}	PL30Past_{it+1}	PL30Past_{it+2}	PLChgOff_{it}	PLChgOff_{it+1}	PLChgOff_{it+2}
$P2PVolume_{it}$	0.337	0.312	0.312	0.447***	0.496***	0.536***
	(1.097)	(0.973)	(0.925)	(3.003)	(3.194)	(3.260)
Bank Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Local Economy	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
SE clustered	Bank	Bank	Bank	Bank	Bank	Bank
R^2	0.769	0.771	0.773	0.517	0.520	0.522
$Adj.R^2$	0.757	0.758	0.760	0.492	0.494	0.494
Obs.	116,632	111,731	106,540	116,632	111,731	106,540
Number of Banks	5,819	5,808	5,752	5,819	5,808	5,752

Panel B. Large Banks (≥\$300 Million Total Assets)

	(1)	(2)	(3)	(4)	(5)	(6)
	PL30Past_{it}	PL30Past_{it+1}	PL30Past_{it+2}	PLChgOff_{it}	PLChgOff_{it+1}	PLChgOff_{it+2}
$P2PVolume_{it}$	0.089	0.253	0.453	0.093	0.151	0.163
	(0.286)	(0.805)	(1.402)	(0.566)	(0.909)	(0.927)
Bank Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Local Economy	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
SE clustered	Bank	Bank	Bank	Bank	Bank	Bank
R^2	0.846	0.848	0.852	0.724	0.729	0.735
$Adj.R^2$	0.837	0.838	0.842	0.707	0.711	0.717
Obs.	48,079	45,653	43,098	48,079	45,663	43,117
Number of Banks	2,760	2,735	2,687	2,760	2,735	2,687

Table 8. Robustness Tests Using Instrumental Variables - Loan Volume

This table contains two-stage least squares instrumental variable (2SLS IV) regression results from instrumenting $P2PVolume$. We instrument $P2PVolume$ with $PopLC$, $PopPR$, and Pop_{it}, which are, respectively, the fraction of the US population assumed to be able to invest on the LendingClub platform in quarter t, the fraction of US population assumed to be able to invest on the Prosper platform in quarter t, and the population fraction of bank i's market that can invest in quarter t as per Equation (5). The table shows the first stage in column (1) and the second stage in columns (2)-(4). In column (2), the full sample of banks is used and the personal loan volume is regressed on instrumented peer-to-peer loan volume, bank characteristics, and local economy controls. In columns (3) and (4), we use the subsample of small (total assets <\$300 million) and large (total assets ≥\$300 million) banks, respectively. As specified in Equation (6), the dependent variable is the natural log of one plus the variable reported in columns (2)-(4). $P2PVolume$ is the volume of peer-to-peer loans originated in lender i's market, which is defined by its deposit-weighted geographic footprint in quarter t. Bank characteristic variables are winsorized at 1% and 99%. Local economy controls are state-level statistics weighted by bank i's deposit-weighted geographic footprint. See the variable appendix for further details on variable definitions and construction. The regression includes bank and year fixed effects. Standard errors are clustered at the bank level. Numbers in parentheses are t-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	$P2PVolume_{it}$	$PLoans_{it}$		
	(1)	(2)	(3)	(4)
	First Stage	Full	Small	Large
$PopLC_t$	0.0158***			
	(31.991)			
$PopPR_t$	0.00525***			
	(10.418)			
Pop_{it}	0.114***			
	(4.724)			
$P2PVolume_{it}$		−0.0255	−0.0948***	0.0401
		(−0.884)	(−2.667)	(0.847)
Bank Characteristics				
$TotalAsset_{it}$	0.00104	0.00108***	0.00531	0.00057*
	(1.571)	(3.099)	(0.685)	(1.691)
$TotalEquity_{it}$	−0.0198***	0.0022	0.0026	−0.0111
	(−2.868)	(0.361)	(0.396)	(−0.653)
$NetIncome_{it}$	−0.0558***	0.0911***	0.0872***	0.0595***
	(−4.650)	(8.341)	(7.224)	(3.589)
$InterestExp_{it}$	−0.131***	−0.161***	−0.158***	−0.168***
	(−5.773)	(−8.144)	(−6.407)	(−6.346)
Local Economy				
$PerCapitaInc_{it}$	5.48***	0.18	0.47**	−0.23
	(33.081)	(0.979)	(2.196)	(−0.737)
$Unemp_{it}$	−0.629***	−0.018	−0.054*	−0.026
	(−41.548)	(−0.751)	(−1.838)	(−0.708)
$AutoDebt_{it}$	−14.0***	−5.3***	−4.1***	−3.9**
	(−8.038)	(−5.481)	(−3.610)	(−2.404)
$CCDebt_{it}$	26.6***	2.0	−1.5	4.1
	(10.137)	(1.079)	(−0.686)	(1.389)
$MortDebt_{it}$	−0.757***	−0.472***	−0.300**	−0.561***
	(−3.847)	(−4.105)	(−2.068)	(−3.467)
$AutoDebtDelinq_{it}$	−0.538***	0.001	−0.030	−0.005
	(−11.566)	(0.029)	(−0.663)	(−0.113)
$CCDebtDelinq_{it}$	−1.26***	0.04	−0.04	0.10
	(−39.651)	(0.896)	(−0.851)	(1.595)
$MortDebtDelinq_{it}$	−0.0800***	−0.0374**	−0.0600***	−0.0030
	(−3.810)	(−2.559)	(−3.346)	(−0.135)
Year FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
SE clustered	Bank	Bank	Bank	Bank
R^2	0.753	0.140	0.168	0.065
$Adj.R^2$	0.753	0.0971	0.125	0.008
Obs.	164,711	164,711	116,581	48,022
Number of Banks	7,758	7,758	5,768	2,703

Table 9. Robustness Tests Using Instrumental Variables - Personal Loan Quality

This table presents two-stage least squares instrumental variable (2SLS IV) regression results from instrumenting $P2PVolume$. We instrument $P2PVolume$ with $PopLC$, $PopPR$, and Pop_{it} which are the fraction of US population assumed to be able to invest on the LendingClub platform in quarter t, the fraction of US population assumed to be able to invest on the Prosper platform in quarter t, and the population fraction of bank i's market that can invest respectively in quarter t. The table reports Equation (2) where late payment status variables are regressed on instrumented peer-to-peer loan volume, bank characteristics, and local economy controls. As specified in Equation (2), the dependent variable is the natural log of one plus the variable reported in each column. Panel A presents the results for the full sample. Panel B presents the subsample of small commercial banks with $TotalAsset$ less than $300 million, while Panel C contains the subsample of large commercial banks with $TotalAsset$ greater than $300 million. In columns (1)-(3) the dependent variable is the volume of personal loans 30-89 days delinquent. In columns (4)-(6) the dependent variable is the volume of personal loans charged off. $P2PVolume$ is the volume of peer-to-peer loans originated in lender i's market where a lender's market is defined by its deposit-weighted geographic footprint in quarter t. Bank characteristics are winsorized at 1% and 99%. Local economy controls are state-level statistics weighted by bank i's deposit-weighted geographic footprint. The variable appendix contains further details on variable definitions and construction. The full table is reported in the internet appendix. The regression includes bank and year fixed effects. Standard errors are clustered at the bank level. Numbers in parentheses are t-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A. Full Sample

	(1)	(2)	(3)	(4)	(5)	(6)
	PL30Past$_{it}$	PL30Past$_{it+1}$	PL30Past$_{it+2}$	PLChgOff$_{it}$	PLChgOff$_{it+1}$	PLChgOff$_{it+2}$
$P2PVolume_{it}$	2.87**	5.68***	2.13	0.38	2.39**	3.52***
	(2.049)	(3.814)	(1.385)	(0.378)	(2.308)	(3.240)
Bank Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Local Economy	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
SE clustered	Bank	Bank	Bank	Bank	Bank	Bank
R^2	0.087	0.064	0.060	0.052	0.034	0.020
$Adj.R^2$	0.0413	0.0157	0.0102	0.0049	-0.0159	-0.0328
Obs.	164,711	157,309	149,524	164,711	157,319	149,543
Number of Banks	7,758	7,683	7,569	7,758	7,683	7,569

Panel B. Small Banks (<\$300 Million Total Assets)

	(1)	(2)	(3)	(4)	(5)	(6)
	PL30Past_{it}	PL30Past_{it+1}	PL30Past_{it+2}	PLChgOff_{it}	PLChgOff_{it+1}	PLChgOff_{it+2}
$P2PVolume_{it}$	0.52	4.36**	0.15	0.27	2.81**	3.53**
	(0.275)	(2.108)	(0.069)	(0.222)	(2.086)	(2.266)
Bank Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Local Economy	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
SE clustered	Bank	Bank	Bank	Bank	Bank	Bank
R^2	0.084	0.066	0.058	0.046	0.029	0.019
$Adj.R^2$	0.0360	0.0158	0.0044	−0.0039	−0.0239	−0.0367
Obs.	116,581	111,638	106,446	116,581	111,638	106,446
Number of Banks	5,768	5,715	5,658	5,768	5,715	5,658

Panel C. Large Banks (≥\$300 Million Total Assets)

	(1)	(2)	(3)	(4)	(5)	(6)
	PL30Past_{it}	PL30Past_{it+1}	PL30Past_{it+2}	PLChgOff_{it}	PLChgOff_{it+1}	PLChgOff_{it+2}
$P2PVolume_{it}$	3.77**	3.49*	1.35	−0.44	0.34	2.08*
	(2.122)	(1.946)	(0.821)	(−0.296)	(0.241)	(1.693)
Bank Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Local Economy	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
SE clustered	Bank	Bank	Bank	Bank	Bank	Bank
R^2	0.109	0.095	0.088	0.083	0.068	0.046
$Adj.R^2$	0.0551	0.0389	0.0291	0.0282	0.0094	−0.0151
Obs.	48,022	45,574	42,986	48,022	45,584	43,005
Number of Banks	2,703	2,656	2,575	2,703	2,656	2,575

Table 10. Loan Volume Robustness to Quantitative Easing

The table presents ordinary least squares regression results in which personal loan volume is regressed on peer-to-peer loan volume, quantitative easing variables, bank characteristics, and local economy controls. The dependent variable is the natural log of one plus $PLoans$. In column (1), the full sample of banks is used and the personal loan volume is regressed on peer-to-peer loan volume, bank characteristics, and local economy controls. Columns (2) and (3) use the subsample of small (total assets <\$300 million) and large (total assets $\geq$\$300 million) banks, respectively. $P2PVolume$ is the volume of peer-to-peer loans originated in lender i's market, which is defined by its deposit-weighted geographic footprint in quarter t. $MBSActivity_t$ is the sum of mortgage-backed securities purchased by the Federal Reserve in quarter t. $TBActivity_t$ is the sum of the par amount of Treasury bonds purchased by the Federal Reserve in quarter t. $MBSHolding_{it}$ is the ratio of bank i's balance in MBS holdings to total assets in quarter t. Bank characteristic variables are winsorized at 1% and 99%. Local economic variables are state-level statistics weighted by bank i's deposit-weighted geographic footprint. See the variable appendix for further details on variable definitions and construction. The regression includes bank and year fixed effects. Standard errors are clustered at the bank level. Numbers in parentheses are t-statistics. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	$PLoans_{it}$		
	(1)	(2)	(3)
	Full	Small	Large
$P2PVolume_{it}$	−0.0093*	−0.0160**	−0.0039
	(−1.646)	(−2.129)	(−0.458)
$MBSActivity_t$	−0.00307***	−0.00288***	−0.00268***
	(−7.390)	(−5.901)	(−2.863)
$TBActivity_t$	−0.00065***	−0.00052**	−0.00119***
	(−3.012)	(−1.961)	(−2.772)
$MBSHolding_{it}$	−0.0164***	−0.0195***	−0.0073
	(−6.319)	(−6.539)	(−1.523)
$MBSActivity_t \times MBSHolding_{it}$	0.00162	−0.00066	0.00380
	(0.504)	(−0.174)	(0.586)
Bank Characteristics			
$TotalAsset_{it}$	0.00102***	0.00051	0.00059*
	(2.909)	(0.068)	(1.688)
$TotalEquity_{it}$	0.0024	0.0033	−0.0114
	(0.369)	(0.481)	(−0.642)
$NetIncome_{it}$	0.0906***	0.0910***	0.0576***
	(8.197)	(7.476)	(3.385)
$InterestExp_{it}$	−0.165***	−0.146***	−0.180***
	(−8.233)	(−5.978)	(−6.451)
Local Economy			
$PerCapitaInc_{it}$	0.0586	0.0352	0.0592
	(0.547)	(0.281)	(0.375)
$Unemp_{it}$	−0.0064	−0.0008	−0.0474*
	(−0.457)	(−0.046)	(−1.792)
$AutoDebt_{it}$	−5.04***	−3.18***	−4.77***
	(−5.751)	(−2.995)	(−3.343)
$CCDebt_{it}$	1.29	−3.41*	5.43**
	(0.779)	(−1.660)	(2.262)
$MortDebt_{it}$	−0.465***	−0.273*	−0.601***
	(−3.926)	(−1.843)	(−3.549)
$AutoDebtDelinq_{it}$	0.0088	0.0257	−0.0170
	(0.293)	(0.722)	(−0.367)
$CCDebtDelinq_{it}$	0.0556***	0.0559***	0.0445
	(2.974)	(2.654)	(1.465)
$MortDebtDelinq_{it}$	−0.0348**	−0.0508***	−0.0095
	(−2.384)	(−2.785)	(−0.466)
$Constant$	0.0608***	0.0676***	0.0491***
	(9.921)	(9.568)	(4.478)
Year FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
SE clustered	Bank	Bank	Bank
R^2	0.933	0.935	0.945
$Adj.R^2$	0.930	0.931	0.942
Obs.	164,711	116,632	48,078
Number of Banks	7,758	5,819	2,760