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

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Abstract

We show that small (rural) commercial banks lose lending volume and take on riskier borrowers in response to peer-to-peer lending encroachment. Large (urban) bank loan volumes appear to be unaffected by the increase in competition. To identify the influence of peer-to-peer (P2P) lending, we utilize time varying, state level entry restrictions on the part of P2P borrowers and P2P investors. We estimate a substantial fraction (26.7%) of peer-to-peer loan volume substitutes for small commercial bank personal loan volume. Our results highlight the changing landscape of financial intermediation and the regulatory challenges faced by financial technology (FinTech) firms.

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Technological advancement in the banking industry has 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 (FinTech) sector have allowed peer-to-peer lending platforms to rapidly enter into the traditional financial intermediation space without any geographic footprint. For example, in 2015 the largest two peer-to-peer lending platforms originated around $12 billion in personal unsecured loans, compared to the $241 billion in personal loans outstanding reported for the entire U.S. market by the Federal Reserve. Banking entry models founded on information production such as Hauswald and Marquez (2003, 2006) suggest "informationally close" non-bank lenders may be able to poach the "good" borrowers from incumbents and create adverse selection problems for traditional intermediaries. Alternatively, if technological advancements in credit modeling allow *observably* poor but actually good credit borrowers to gain access to credit, these new financial intermediaries may be expanding access to credit.

Empirical evidence on peer-to-peer lending from Butler, Cornaggia, and Gurun (2016) and De Roure, Pelizzon, and Tasca (2016) suggest that peer-to-peer lending platforms target high-risk borrowers excluded from traditional credit channels, such as commercial bank credit. If this is the case, increased peer-to-peer lending may represent marginal credit expansion for borrowers outside of the risk tolerance of commercial banks. Our main contribution is to provide empirical evidence on the impact of emerging FinTech firms on traditional financial intermediaries. To our knowledge, we are the first to examine if the increasing scope of FinTech firms like peer-to-peer lending represents credit expansion or substitution from one intermediary to another.

We use the cross-sectional heterogeneity in state level peer-to-peer lending to identify the influence of peer-to-peer origination on commercial bank lending. State banking and security regulators can create barriers to entry for peer-to-peer lenders in multiple forms such as origination rebates, licensing, reviews, etc. These prohibitions effectively deny entry to peer-to-peer lenders. In addition, these borrower restrictions and investor regulations vary from state to state and over time. Our main empirical approach uses the time series and cross-sectional variation in peer-to-peer lenders' participation in credit markets at the state level to identify the changes in commercial bank lending behavior. Still, we cannot rule out the possibility of additional omitted time varying local market conditions that may correlate with both the entrance of peer-to-peer lending and bank lending behavior which may confound our results. In support of our results, we augment our initial findings with evidence from an instrumented variables approach where we instrument the volume of peer-to-peer lending in each bank market with the aggregate fraction of the US population available to *invest* in peer-to-peer lending markets. We interview 49 state security regulators and the District of Columbia security regulator to generate the time varying fraction of the US population able to supply funds on the peer-to-peer lending platforms. The results from the IV regressions are consistent with the initial results and in most cases increase the magnitude and statistical significance of our findings. This IV approach should alleviate most endogeneity concerns connected with omitted variables and further support our initial findings.

Using the OLS approach, we observe a 1.3% decrease in the volume of personal loans across all commercial banks experiencing a standard deviation increase in peer-to-peer lending activity in their market. Our results likely represent a conservative lower bound. The personal loan sub-segment as reported to the FDIC by commercial banks is a combination of multiple consumer loans including automotive, student, and unsecured personal loans. Peer-to-peer lending is likely to compete with the unsecured personal loan portion of this segment for a variety of reasons, and according to the Federal Reserve, aggregate personal loan debt is only 9.2% of this consumer credit conglomerate.[1] We divide the flow of peer-to-peer loans into high and low-risk loans and find that the substitution at the commercial bank is most sensitive to the high-risk portion of the peer-to-peer loan flow and indifferent to lower risk peer-to-peer loan volume. This substitution result suggests that the displacement occurs most strongly among the poor credit borrowers and that higher credit quality borrowers might experience credit expansion opportunities.

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

[1] In 2015, the Federal Reserve estimated $2,597 billion in non-revolving consumer credit facilities outstanding at financial intermediaries of which $1,318 billion were student loans and $1,038 billion were motor vehicle loans leaving $241 billion in personal 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 (U.S. Treasury (2016)). Peer-to-peer loans require no collateral but are still dischargeable in bankruptcy making them most comparable to the Federal Reserve personal loan segment. If commercial banks hold a similar fraction of their personal credit facilities portfolio in unsecured personal loans relative to the aggregate Federal Reserve statistics, our results likely represent a lower bound on the impact of peer-to-peer lending.

the pressure from peer-to-peer platforms. First, we show that the loss in personal loan volume concentrates among small commercial banks with assets under $300 million, while 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 a standard deviation increase in peer-to-peer lending. One potential benefit of the expansion of peer-to-peer lending is the opportunity to provide greater access to banking services in rural areas or areas with less banking competition. However, if community banks in less competitive markets are disproportionately influenced by peer-to-peer expansion, a tension emerges between supporting the growth of new banking technology and maintaining the existing brick and mortar access to financial services. We show an additional layer of heterogeneity that banks in less competitive markets such as rural counties experience a 2.0% decline in personal loan volume for a standard deviation increase in peer-to-peer lending while banks with geographic footprints in more competitive environments appear unaffected. Finally, we provide evidence that while peer-to-peer lending platform competition is burdensome to small/rural lenders, the strategic switch on the part of peer-to-peer platforms in 2013 that allowed commercial banks to participate as investors seems to have stymied the majority of volume losses among small banks. Hauswald and Marquez (2006) suggest that intermediaries optimally merge when faced with competitors that invest in information production technology to reduce the overinvest problems. In this light, the choice to partner and specialize (origination, servicing, underwriting, etc.) appears to be an interesting alternative strategy.

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 standard deviation increase in peer-to-peer lending appears to drive a 3.9% increase in quarterly charge-off rates. While the increase in delinquency and charge-off rates may be evidence of an adverse selection problem (Hauswald and Marquez (2006)), it is possible that the reverse causal story may also explain this association. For example, if banks in an area with 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. In the robustness section, we repeat the above analysis using the population fraction instrument and find that the initial results strengthen significantly. We also find additional evidence in elevated 30-90 (90+) day delinquency measures. As a whole, these provide strong evidence that in addition to suffering volume losses 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 also note that the deterioration of borrower quality helps alleviate reverse causal concerns in the loan volume results, i.e., the regulatory arbitrage story where banks are choosing to decrease personal loan issuances because of increased capital requirements which creates a vacuum that encourages peer-to-peer entry.

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 (rural) commercial banks appear to shoulder the loan volume (quality) losses. This substitution appears to be driven by lower credit quality loans while our results indirectly point to greater credit opportunities for higher credit quality borrowers. Given the initial narrow focus of peer-to-peer lending platforms in unsecured personal 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 space.[2] Using the small bank subsample, we can 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 paper contributes to both the emerging financial technology (FinTech) literature and the established works of financial intermediation. The majority of the peer-to-peer lending (FinTech) literature focuses on individual investor behavior and borrower characteristics. For example, there are multiple papers that show rational and irrational herding behavior among individual investors (Lin, Sias, and Wei (2015), Kim and Viswanathan (2016), Zhang and Liu (2012), and Duarte, Siegel, and Young (2012)) and the ability of investors to glean private information on borrowers from geography or textual analysis of the loan application (Agrawal, Catalini, and Goldfarb (2011), Iyer,

[2]Sofi, a platform connecting institutional investors with student loan borrowers, entered the student loan market in 2012. While Sofi has experience rapid growth, originating a total loan volume of $4-5 billion in 2015, this represents less than 50 basis points of the overall $1.3 trillion market for student loans.

Khwaja, Luttmer, and Shue (2016), Senney (2016), and Ramcharan and Crowe (2013)). Other work has focused on the network of investors that group together to fund loans/projects. Hildebrand, Puri, and Rocholl (2017) show that investors irrationally follow group leaders on the personal loan peer-to-peer lending site Prosper yielding lower returns and higher defaults. Another strand of peer-to-peer lending literature looks at borrower characteristics that influence funding outcomes. Lin, Prabhala, and Viswanathan (2013) show that social connections on Prosper increase the probability of a borrower being successfully funded, but Freedman and Jin (2017) show that such social ties do not perform better ex-post. Butler et al. (2016) show that the concentration of local commercial banking activities influences the interest rate caps set by borrowers. They show 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 interest rates on the loans. They provide evidence this is particularly true of small loans and poor credit borrowers suggesting peer-to-peer lending platforms might provide credit expansion for the marginal borrower. In contrast to the above, 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 three strands of the traditional financial intermediation literature. The first strand includes banking competition models founded on informational differences among lenders due to geographic breadth or technology. Models such as Hauswald and Marquez (2003, 2006), Chiesa (1998), and Almazan (2002) based on informational advantages would suggest peer-to-peer lenders might steal volume and create adverse selection problems for incumbent commercial lenders. Empirically there are multiple examples of the role that information production plays in financial intermediation. For example, Petersen and Rajan (2002) and Filomeni, Udell, and Zazzaro (2016) identify shifts in commercial and industrial lending at commercial banks driven by screening technology improvements. Loutskina and Strahan (2011) show evidence that commercial banks adjust their lending strategy based on the private/soft information in residential real estate markets. In the automotive loan segment, Einav, Jenkins, and Levin (2013) show that the use of credit scoring models in automotive financing largely takes the place of soft information and levels the playing field among lenders.

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 where commercial banks with increasing capital requirements compete with non-bank intermediaries with less liquid liabilities. In their model, the shadow banks engage in regulatory arbitrage and capture a higher fraction of the banking activity due to the capital constraints of the regulated commercial bank system. Buchak, Matvos, Piskorski, and Seru (2017) empirically show mixed evidence of this regulatory shift in the residential real estate market. They show less non-bank participation in counties with tightening capital constraints but more non-bank growth in counties with more exposure to fair lending lawsuits and enforcement actions following the financial crisis. Additionally, evidence of indirect influence through monetary policies such as quantitative easing (Chakraborty, Goldstein, and MacKinlay (2016)) suggests lenders adjust their portfolio of loans in response to regulatory actions. We take care to control for such shifting regulatory burdens in the main regressions and show our results are independent of monetary policy shifts in the robustness section. While it is likely that regulatory policy plays a role in the changing landscape, our results identify the role technological progress plays in the changing role of commercial banking activities.

Finally, we view peer-to-peer lending as an extreme version of the originate-to-distribute (OTD) strand of literature where the originator distributes some fraction of the assets it originates (Berndt and Gupta (2009), Parlour and Plantin (2008)). Rajan, Seru, and Vig (2010) model the changing incentives for intermediaries to collect private information in OTD markets during the subprime financial crisis and later provide empirical support in Rajan, Seru, and Vig (2015). Their work suggests that originators eventually hit a threshold where it is more efficient to stop investing in costly technology to identify bad loans and simply hold them in their portfolio and take the default losses. In their current state, peer-to-peer lending platforms pass on all of their loans which would suggest that peer-to-peer platforms do not have a strong incentive to price loans accurately by generating private information on the borrowers.

Three recent papers examine FinTech lending and imply some competition with commercial banks. In a contemporaneous paper, De Roure et al. (2016) examine German peer-to-peer lending on Auxmoney and also conclude that peer-to-peer lending serves 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 for both the internet's role in the expansion and weak banking competition. Our paper is most similar to Buchak et al. (2017) who examine the growth of shadow banks, and particularly FinTech shadow banks, in the residential mortgage market. They suggest that both regulatory burdens and improved technology account for the growth in shadow banking in that market.

Our paper differs from these in three key dimensions. First, while Havrylchyk et al. (2017) and Buchak et al. (2017) show evidence higher participation rates of shadow banks/FinTech in low banking competition counties, we examine the issue of peer-to-peer lending from the perspective of the commercial bank and directly estimate the change in lending activity of the bank as a result of peer-to-peer lending. Our paper directly estimates this substitution away from commercial banks toward the peer-to-peer lending platforms and can rule out expansionary credit explanations of shadow bank growth. We also provide direct evidence of the particularly influential role riskier loans play in this substitution while lower risk loan contracts appear to have little influence on commercial bank loan activity. This lack of influence uniquely suggests that credit expansion may still occur amongst the high-quality credit borrowers. 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 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 banking lending by using the differences in state openness to peer-to-peer lending on the borrower side and regulatory barriers on the investor side. It also allows us to rule out reverse causal 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. These cross-sectional differences are particularly informative as the peer-to-peer markets evolve in the time series to include commercial banks as investors.

1 Peer-to-peer Market Background

Technology improvements in the 2000's produced a wave of crowdfunding ventures that have disrupted the financial intermediation market. The term crowdfunding encompasses many forms of capital accumulation: reward-based platforms like Kickstarter and Indiegogo, debt based platforms like SoFi and LendingClub, non-profit sourcing of funds like Kiva, and more recently equity-based platforms like SeedInvest and Wefunder with the passage of Regulation Crowdfunding (Freedman and Nutting (2015)). Out of this emerging 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, referred to as peer-to-peer platforms,[3] have emerged in the U.S. and originate the majority of loans in the unsecured personal debt lending segment. Both founded in 2006, LendingClub and Prosper provide a mechanism to match borrowers' demand for credit with investors looking to supply credit. Borrowers apply for a loan online through the platform which performs some screening based on hard information like credit score and outstanding debt. Loans are then posted on the peer-to-peer platform to be funded by investors. Investors can fractionally fund the loan in \$25 increments over a 30-day window.[4] Once the pledge volume reaches a certain threshold, for example, 70% funded, the loan will execute at expiration. Fully funded loans may execute before the conclusion of the 30-day window. Borrowers then receive their funds and investors receive a security tied to the principal and interest payments of the borrower.

Because the peer-to-peer platforms are issuing consumer credit, they are required to navigate financial intermediation regulations in all 50 states and the District of Columbia. To allow state residents to borrow on the platform, intermediaries must typically obtain licensing at the state level which can vary in level of intensity and fee structure. We observe at least ten states that experience droughts in peer-to-peer platform origination over the sample window. LendingClub fails

[3]In a recent U.S. Department of Treasury white paper, unsecured personal peer-to-peer lending is referred to as marketplace lending to reflect the shifting base of investors that now includes both institutional investors and individuals.

[4]After Sept. 2012 (LC)/ April 2013 (Prosper), the platforms created a second market for institutional investors allowing the purchase of the whole loan. 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. LC announcement - http://blog.lendingclub.com/investor-updates-and-enhancements/. Prosper announcement - https://www.sec.gov/Archives/edgar/data/1416265/000114036113032671/form10q.htm.

to issue loans in the states of Iowa, Idaho, Maine, North Dakota, and Nebraska for more than three calendar quarters in our sample period. The LendingClub platform initiates lending part way through the sample in Indiana, Mississippi, North Carolina, and Tennessee. Before its "quiet period"[5] LendingClub issued loans in all 50 states except North Dakota. Prosper does not issue loans in the states of 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. Before its quiet period, Prosper issued loans in all of these excluded states. While it is possible that the peer-to-peer platforms fail to originate loans in these state-quarters due to local demand, we find multiple large marketplaces such as Indiana and North Carolina are among the initially omitted states. We also note the cessation of loan issuance in states like Pennsylvania, on only one of the platforms, runs counter to local demand arguments.

Additionally, we find evidence that regulatory stances may prevent peer-to-peer lenders from participating in these states. 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. As a result, no borrowers in the state of Iowa have received loans from Prosper and only three borrowers from LendingClub over the 25 quarters we examine.[6] Given the above evidence, we assume the lack of origination by peer-to-peer platforms to be driven by regulatory hurdles at the state level.[7] These cross-sectional differences provide an empirical design to test for differences in local bank response to the encroachment, or lack of encroachment of peer-to-peer lending. We further address this issue in the robustness section through an instrumented variables approach.

[5]LendingClub ceased selling securities to investors 4/7/08 and filed for federal security registration in June 2008. Their federal registration was approved in October 2008 at which time they resumed investor participation on 10/14/2008. Thus LendingClub's quiet period extends from April 2008 to October 2008. Prosper filed a federal registration in October 2007 and ceased selling notes 10/15/2008. Prosper resumed issuing notes 7/13/2009 when it received federal registration approval from the SEC. See the Appendix Section B for more detail.

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

[7]We attempt to verify this in all of the omitted states. In some cases like the state of Maine, regulators suggest no such barriers exist while other states like Pennsylvania cannot comment on regulatory hurdles for specific firms for confidentiality reasons.

2 Hypothesis Development

We draw our formal hypothesis tests 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. They introduce the idea of informational distance where 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 their model, informationally close lenders can poach customers from rivals. This setup is similar to other information production models such as Chiesa (1998), Almazan (2002) and Hauswald and Marquez (2003). However, if instead, the technological innovation behind FinTech firms such as LendingClub and Prosper focuses on a particular segment of borrowers such as those that are informationally distant, peer-to-peer lending expansion may represent credit expansion. That is, 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, may gain incremental access to credit (Hauswald and Marquez (2006)). This tension leads us to our first two hypotheses:

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

Hypothesis 2. *Personal loan volume at the commercial bank will decrease more with peer-to-peer loan origination among good credit quality borrowers ($H2_A$) than peer-to-peer loan origination among poor credit quality borrowers ($H2_0$).*

The second consequence of this informational advantage is the increase in adverse selection faced by rivals. Competitors that are less informed must select from the pool of borrowers after the informed intermediary rejects low-quality borrowers and face higher adverse selection costs. Our third testable hypothesis derived from this is:

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

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

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 includes 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 publicly available from the FDIC. SOD data is available annually as of June 30 and provides branch level detail on location and deposits. We use the SOD data to generate a dynamic geographic footprint for each commercial bank. Later we use the deposit information to weight 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 is also available on the FDIC website. A unique identifier assigned by the Federal Reserve (rssdid) links the SOD and the Call Report data. 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 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, loans 90+ days delinquent and still accruing interest, charge-offs).[8] In some of the robustness tests, we also utilize mortgage loan volume,

[8]We parallel the analysis presented for commercial bank credit card facilities. Results are available upon request.

MBS holdings, and commercial and industrial loan information. The Appendix contains variable definitions, and the associated Call Report ID's. As noted by Kashyap and Stein (2000), reporting requirements change throughout the sample period and we are careful to form consistent times series for the personal loans, mortgage loan volume, and MBS holdings.

We gather peer-to-peer lending information from two of the largest peer-to-peer lending platforms, Prosper Marketplace Inc. and LendingClub Corporation. These two platforms comprise the majority of the peer-to-peer lending market for unsecured personal loans although other smaller platforms exist for personal debt and similarly sized platforms for student loan refinancing.[9,10] Loan volume on the platforms combined to be more than $6 billion in 2014 and $12 billion in 2015.[11] 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 the average loan size of $11,225 on Prosper and $12,475 on LendingClub. We graph the quarterly aggregate peer-to-peer loan volume in Figure 1. Both platforms provide historical loan information on successfully funded loans to the SEC which includes a wealth of information on the borrowers including geography, loan amount, interest rates, credit scores, etc. We use this information to aggregate loan issuance volume in each state-quarter for the combination of the peer-to-peer lenders. To better measure the amount 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. Our weighting scheme implicitly assumes that demand for personal loan volume is local and that banks draw most of their loan assets from the geographic footprint of their branches. In a contemporaneous paper by Carbo-Valverde and Perez-Saiz (2016), they show that the probability of holding a credit card or line of credit from a bank increases by more than 60% when a bank

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.

[9]Upstart (founded in 2014) had extended less than $200 million in loans as of 2015Q3. Upstart is only available to accredited investors compared to Prosper and LendingClub which allow non-accredited investors in 49 of the 50 states.

[10]SoFi (https://www.sofi.com/) extends refinancing options of student loans online. According to their investor fact sheet, Sofi began in 2011 and issued $5.2 billion in student loan refinancing in 2015. Unlike Prosper and LendingClub, Sofi is only available to accredited investors.

[11]Prosper 2015 loan volume of $3.6 billion (http://www.altfi.com/article/1639_prospers_2015_in_numbers) and LendingClub volume of $8.4 billion (https://www.lendingclub.com/info/statistics.action) compared to $1.6 billion and $4.4 billion respectively in 2014.

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. Our approach is similar to Chakraborty et al. (2016) who examine real estate originations by commercial banks and seems reasonable given the type of loan product we examine (unsecured personal loans).[12] 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 and as a result, no borrowers in the state of Iowa have received loans from Prosper and only three borrowers from LendingClub over the 25 quarters we examine. The weighting scheme used above will thus help 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, presumably due to regulatory issues.

Finally, we obtain local economic factors to help control for cross-sectional difference in the demand for loans similar to those used in Butler et al. (2016). State level annual data on income per capita, unemployment, auto debt, credit card debt, mortgage debt, automotive debt delinquencies, credit card delinquencies, and mortgage delinquencies comes 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. 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 presents summary statistics for each of the variables above. The average commercial bank in the sample has $494 million in total assets ($TotalAsset$) and $342 million in to-

[12] To give an 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 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 PNC Bank's deposits are not equally distributed among these state. 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.

tal loans ($TotalLoans$). Commercial banks have an average of \$21.2 million in personal loans ($PersonalLoans$), which includes loans for automotive purchases, student loans, and personal unsecured loans. Personal loans account for an average of 3.17% of the commercial bank total assets. For the personal loans, the average bank volume of loans delinquent 30-89 days ($PL30Past$) is \$248,700 or 5.9 BP of total assets. The average volume of personal loans 90+ days delinquent ($PL90Past$) is \$87,600 or 0.8 BP of total assets and the average volume of charge-off activity ($PLChgOff$) each quarter is \$49,800 or 0.8 BP of total assets. The average bank holds approximately 11.1% of total capital as equity ($TotalEquity$) and reports net income ($NetIncome$) of 0.39% of total capital. Banks compete against an average of \$17 million in peer-to-peer loans in their weighted geographic area each quarter ($P2Pvolume$). Summary statistics for sub-samples based on bank size are found in Table 1 Panel B. We employ multiple state level control variables that are also weighted by lender geographic area. As reported in Panel C, the weighted average per-capita income is \$42,548 ($PerCapitaInc$), unemployment rate 7.07% ($Unemp$), automotive debt \$3,351 ($AutoDebt$), credit card debt \$2,724 ($CCDebt$), and mortgage debt \$28,833 ($MortDebt$). State level delinquency measures average 3.69% for automotive debt ($AutoDelinq$), 9.15% for credit card debt ($CCDelinq$) and 3.93% for mortgage debt ($MortDelinq$).

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 increased peer-to-peer lending activity has no effect on 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 lending. However, if we find a negative relation between peer-to-peer lending and commercial bank loan levels ($H1_A$), this would suggest individuals are at least partially substituting away from traditional commercial bank products. To ease interpretation, the dependent variable is presented as the natural log of one plus the loan volume as a fraction of total assets. We use the following specification,

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

As personal loans tend to be unsecured, riskier loan products, we control for cross-sectional differences in bank risk preference using bank equity capital fraction, and net income. Note 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)) and 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) to include market level controls for personal income, unemployment, debt levels (auto, credit card, mortgage), and delinquencies (auto, credit card, mortgage).

There may still be persistent unobservable bank characteristics that influence loan portfolio selection and correlate with peer-to-peer volume. These unobservable omitted characteristics would bias the coefficient estimates. To address such concerns, we include bank fixed effects to eliminate such time-invariant omitted variables connected with bank structure, risk tolerance, etc. 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)-(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 the level of 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 -0.010. The coefficient magnitude suggests a decline in total personal credit facilities of 1.0% ($0.010 \times 0.0314/ln(1+0.0332) = .0096$) of total assets for a standard deviation increase in peer-to-peer volume although the coefficient is indistinguishable from zero at the 10% level of significance. We repeat the exercise for the sub-segment personal loans. The coefficient on $P2PVolume$ in the personal loan regression in column (2) is statistically significant at the 5% level with a magnitude of -0.013. This coefficient suggests that a one standard deviation increase in peer-to-peer lending activity reduces the relative fraction of the bank's personal loan segment by 1.3%. As noted before, commercial banks report three types of loans in the personal loan category; student loans, automobile loans, and unsecured personal 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 non-dischargeable, and automotive loans are typically collateralized. Thus it is extremely likely our results understate the degree of substitution felt by commercial banks in the personal loan sub-segment. The results in columns (1)-(2) reject the null hypothesis for $H1$ suggesting that commercial banks experience loan losses as a result of peer-to-peer lending encroachment.

More profitable banks associate with having a higher volume of personal credit facilities according to the coefficient estimates. 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% ($0.097 \times 0.0078/ln(1 + 0.0332) = 0.0232$) increase in the volume of personal credit. Bank size also appears to be positively associated with personal credit volume. As local levels of automotive and mortgage debt increase, lenders appear to curtail personal loan lending. Surprisingly, average local credit card debt levels do not appear to influence personal credit facility lending volume among banks. However, credit card delinquencies appear to increase personal loan lending, suggesting borrowers may use personal loans as a vehicle for debt consolidation activities. Higher unemployment levels appear to be associated with a lower fraction of personal credit facilities.

Evidence from the prior literature implies that areas with a high concentration of banking activity cause peer-to-peer borrowers to demand cheaper credit, suggesting peer-to-peer lenders compete with banks on price (Butler et al. (2016)). The Butler et al. (2016) results are most sensitive for low credit score borrowers which suggest that these borrowers gain more from the increase in competition from credit suppliers and may be most inclined to substitute away from the commercial banks. However, Freedman and Jin (2011) suggest 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. To better understand if a particular part of the commercial bank's portfolio is being influenced, we split the flow of peer-to-peer lending by high ($P2PHighRating$) and low credit grade ($P2PLowRating$) and report the results in columns (3)-(4).[13] 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 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 total consumer credit volume by 3.5% and personal loan volume by 3.3%. 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 the Butler et al. (2016) findings. Thus we fail to reject the null hypothesis $H2_0$. Interestingly, the coefficient on $P2PHighRating$ implies that as peer-to-peer lending increases in a bank's market, total consumer credit facilities increased by 2.9% for a standard deviation increase in $P2PHighRating$. We later investigate the time series variation in peer-to-peer lending volume in Section 4.2 to explain why an increase in high credit quality loans on the peer-to-peer platform might cause commercial banks to increase their holdings of personal credit facilities.

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 the personal loan activity, commercial banks may address this increased competition in other ways that need not alter the segment size of their lending portfolio. Lenders may compete on the price of the loan by lowering the interest rate (Butler et al. (2016)). Commercial banks have the ability to adjust contractual features of the loan such as collateral or loan term. Additionally, banks could alter the quality of borrowers accepted to maintain loan volume. The alteration of the quality

[13] We use the platform credit designation as a sufficient statistic for the riskiness of the loan. The platform credit 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/low for the two platforms using average interest rate information per credit grade.

of borrowers in the pool may be competitor driven if peer-to-peer lending investors target borrowers of a particular quality and leave poor quality borrowers for the less competitive commercial banks as in Hauswald and Marquez (2006). We attempt to identify such changes in borrower quality by examining the volume of delinquent loans using the following specification,

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

We analyze three delinquency measures: late by 31-90 days and accruing interest, late 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 in seven out of the nine specifications. The late payment measure in column (1) is statistically significant at the 10% level and implies an increase of 1.7% in 30-89 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 and imply an increase in charge-off activity of 3.9% to 4.4%. The increase in delinquency measures suggests we reject the null Hypothesis 3 ($H3_0$) for 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 the geography of demand to emphasize certain areas. Second, we repeat the OLS analysis above in the robustness section instrumenting for peer-to-peer loan volume and find the results strengthen. 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 indicate that there are 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 an unsecured personal loan during financial distress than other debt contracts. 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 consumer default behavior for unsecured 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, it appears that banks with a high cost of deposits carry higher levels of past due personal loans and experience higher charge-off levels. The higher charge-off levels may suggest that the higher cost of capital may be passed on to consumers who then may experience increased default activity.

The results in Table 2 show personal loan volume does appear to fall with increased pressure from peer-to-peer loan activity. In Table 3 we show there is also clear evidence of elevated delinquency and charge-off activity for personal credit facilities. It is possible that banks differ among 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 or if their ability to set competitive interest rates is associated with market competitiveness, we may observe different responses to peer-to-peer lending among commercial banks. In the next section, we analyze how the heterogeneity in bank size and market competitiveness may lead 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 or have 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 into size based on the bank's total assets and then repeat the analysis on loan volume (Table 4) and loan quality (Table 5) to formally test Hypotheses 4 and 5.

In Table 4, we show the different subsamples of commercial bank size with total assets under $300 million in columns (1)-(2) and larger commercial banks in columns (3)-(4). The total consumer credit facilities regression in column (1) suggests that small commercial banks experience a decrease in volume as peer-to-peer lending activity increases in their market. The coefficient on peer-to-peer lending remains negative in column (2) for the personal loan segment and is stronger in statistical and economic significance than the aggregate bank sample. The coefficient suggests a 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 low credit rating loan volume appears to drive this result. Turning to the large commercial banks in columns (3)-(4), the coefficient on peer-to-peer lending is negative although statistically indistinguishable from zero at the 10% level of significance. The coefficient suggests that the aggregate results in Table 2 may be driven by small commercial banks while large commercial banks may be relatively unaffected by peer-to-peer encroachment. Thus we reject the null hypothesis $H4_0$ that asserts bank loan levels are uniformly impacted by peer-to-peer lending volume encroachment. The results in Table 4 are robust to alternative size thresholds ($161 million (median), $1 billion). We also perform a Chow test and verify 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 where a bank has a geographic footprint in only one state. Using this filter removes 3,002 observations from the small bank sample in columns (1)-(2) but allows us to calculate the average number of banks per market-quarter. We repeat the regression from column (2) this time with the unscaled personal loan volume and report the results in column (9). We find that a standard deviation increase in peer-to-peer lending in a market (state), causes an average decrease of $86,783 in personal loans per bank. Since we have limited the banks to 51 markets (states) over 25 quarters, there is an average

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

of 89.1 banks per market $(113,630/(51 \times 25) = 89.1)$. The average number of banks suggests a one standard deviation increase in peer-to-peer lending (\$28.9 million) in a market (state) causes a decrease in personal loan volume of \$7.7 million ($\$86,783 \times 89.1 = \$7.7$ million) among small banks. Thus roughly 26.7% of the peer-to-peer loan volume in a market-quarter appears to be a direct substitution away from small commercial bank lending.

One potential benefit of peer-to-peer lending expansion is that areas with less access to financial services 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 services 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 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. 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 competition) results in columns (5)-(6) of Table 4 and the results for below median index banks (high competition) in columns (7)-(8). 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 suggests 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 would seem to lend credence to concerns that policymakers should be mindful of the substitution that occurs in rural areas when encouraging non-bank growth.

The results in Table 4 are consistent with the foreign bank competition model of Dell'Ariccia and Marquez (2004) where 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 personal 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.[15] Since 2010 both platforms set the interest rate 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, etc. in the decision to fund a loan. The results in Table 4 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 might expect to observe deterioration in loan quality across bank size. We repeat the personal loans analysis in Table 5 dividing the lenders in each panel based on bank size.

In Table 5 Panel A, the small bank sample again shows some signs of borrower quality deterioration with increased peer-to-peer loan competition. In column (8) the next period scaled charge off activity appears to increase 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 only one is statistically significant at the 5% level. For example, the results in column (6) indicate a 9.5% increase in 90 days past due loan volume two quarters in the future. Based on the results in Table 5 we again reject the null Hypothesis 5 ($H5_0$) that suggests a homogeneous deterioration in credit quality among commercial banks.

[15] https://www.prosper.com/about-us/2016/10/30/banks-marketplace-platforms-perfect-match/?bid=2&bname=Blog

The sub-sample results reveal a heterogeneous impact of peer-to-peer lending on the commercial banking sector. As these non-banks enter into markets, small commercial banks appear to yield loan volume in the personal loan segment. While the OLS results above only provide weak evidence of an increase in the risk character of small bank personal loans, the robustness section below shows that these results significantly strengthen when we attempt to instrument for peer-to-peer loan volume. Thus, small banks in our sample appear to lower their borrower quality threshold to further stop volume loss. Large commercial banks appear relatively unaffected by this encroachment, appearing to yield no loan volume. There is some weak evidence of increased riskiness in the facilities issued in either sector by large commercial banks, but later in the robustness section, these results are more mixed.

4.2 Time Series Variation in P2P Strategy

The previous section identifies the heterogeneous impact of peer-to-peer lending encroachment on the cross-section of commercial banks. Small and rural banks appear to disproportionately lose personal loan volume and are forced to lower lending quality standards. Anecdotal evidence suggests that these types of commercial banks had been struggling to participate in these segments as larger competitors were able to capture customers. In the second quarter of 2013, both peer-to-peer lending platforms made a strategic shift in their investor base, allowing institutional investors greater access to the investment side of the platform. LendingClub specifically identifies the first commercial bank participation on the investment side in the second quarter of 2013.[16] Prosper also opened a "Whole Loan Market" specifically for institutional investors in April 2013.[17] With the ability to invest on the peer-to-peer platforms, banks struggling to originate personal credit facilities could begin to obtain loan assets in the personal credit facility segment, although still foregoing the origination fees.

For example, a bank identified in the Wall Street Journal,[18] BankNewport, signed a deal with LendingClub to purchase personal unsecured loans through their institutional investor platform be-

[16] LendingClub S-1 filing dated 8/27/14, pg.46
https://www.sec.gov/Archives/edgar/data/1409970/000119312514323136/d766811ds1.htm

[17] https://www.sec.gov/Archives/edgar/data/1416265/000114036114014832/form10k.htm

[18] https://www.wsj.com/articles/lending-club-and-smaller-banks-in-unlikely-partnership-1435015121

ginning the second quarter of 2015. Figure 2 shows the dramatic shift in personal loan volume carried by BankNewport following the partnership to purchase loans through the LendingClub platform. We may find that the losses suffered by small and rural banks shrink if commercial banks become able to purchase loans on the platforms and hold them as loan assets. We repeat the analysis from Table 4 with an additional indicator for the period after 2013 when institutional investors like commercial banks become able to invest on the platform. We interact the $Post$ indicator with $P2PVolume$ and use the following specification,

$$\begin{aligned} ln(1 + LoanVolume_{it}) = &\beta_1 \cdot P2PVolume_{it} + \beta_2 \cdot Post_t + \beta_3 \cdot (P2PVolume_{it} \times Post_t) \\ &+ \pi_1 \cdot Bank_{it} + \pi_2 \cdot Macro_{it} + \pi_3 \cdot Bank_i + \pi_4 \cdot Year\text{-}Quarter_t \\ &+ Error_{it} \end{aligned} \tag{3}$$

Table 6 reports the results from OLS regressions in Equation (3). The results show a substantial mitigation of the influence of peer-to-peer lending in the post period. The reduction emerges in both the full sample, columns (1) and (2), as well as the small commercial bank sample in columns (3) and (4). Larger commercial bank personal loan volume, reported in columns (5)-(6), continues to appear unaffected. The results indicate that the ability of small banks to purchase loans on the platform appears to minimize a majority of the influence of peer-to-peer lending platforms as competitors.

5 Robustness Tests

The results in Table 2 and Table 3 suggest peer-to-peer loans compete with a commercial bank's ability to issue personal credit facilities. Commercial bank response can take multiple forms ranging from loan volume loss in some segments to expanding the acceptable range of borrowers. Thus far our identification strategy relies on a geographic 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 this 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. There is also some concern that the results could be driven by reverse causality which would bias our coefficient estimates and cast doubt on our initial findings. To further alleviate these concerns, we use the regulatory environment on the *investor* side of peer-to-peer lending to create instrumental variables for peer-to-peer lending volume and improve identification.

We use the quarterly average fraction of the U.S. population able to invest on each peer-to-peer platform as an instrument for the peer-to-peer volume in each market. Following the quiet period for each platform in 2009, both LendingClub and Prosper Marketplace began to federally register each borrower dependent note (BDN).[19] Normally, federal registration of a security is accompanied with the ability to issue the security to investors throughout the United States without additional state level registration. However, because these borrower dependent notes do not trade on a national market system exchange, they do not qualify for a blue sky exemption that frees the issuer of additional registration requirements.[20] Thus following their quiet periods, peer-to-peer platforms were forced to seek approval from each state and the District of Columbia individually so that residents of the state could invest on the platform. Prosper Marketplace and the North America Securities Administrators Association (NASAA) negotiated a settlement during the Prosper quiet period where Prosper gave notice of their intent to adhere to state level registration requirements.[21] While no action was brought against LendingClub by the NASAA, interviews with the state security regulators and the United States Government Accountability Office (2011) report would seem to indicate that LendingClub was required to seek similar state level registration.

We interview securities regulators in 49 states and the District of Columbia to collect effective

[19] 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 $3500 loan. The loan had 92 investors with notes ranging from $25-350 in principal.

[20] While each state has its own security registration laws, state level registration laws are generically referred to as "Blue Sky Laws". To be considered a federally covered security, and thus blue sky law exempt, peer-to-peer lending platforms must meet the section 18(b) of the Securities Act of 1933 requiring the securities, or a more junior security, to trade on the national market system (a registered exchange). See the Appendix Section B for additional details.

[21] http://www.nasaa.org/5622/prosper-marketplace-inc-enters-settlement-with-state-securities-regulators-over-sales-of-unregistered-securities/

registration dates for both platforms.[22] Security registration at the state level often involves a renewal process, and multiple lapses in registration occur for both platforms.

Figure 3 (Figure 4) shows the daily dollar investment on Prosper (LendingClub) compared to the population able to invest on the platforms. The figures show substantial volatility in the actual registration status of the platforms, while the level of investment appears less sensitive to the current status of registration. We also graph in each figure the quarterly average fraction of US population that resides in states that at any point in time have granted registration status to a platform regardless of the registration status is current ($AssumedPopLC$ and $AssumedPopPR$). From the graphs, it appears likely that the platforms ignore the dynamic status of state level registration. We confirm this using data collected from Prosper sales reports registered with the SEC and Prosper investor profile pages.[23] In light of this, we use the fraction of 2008 US population granted access to each platform at any point in time ($AssumedPopLC$ and $AssumedPopPR$) as instruments for peer-to-peer lending volume and re-estimate Equation (1).[24,25]

Table 7 reports the results of the instrumented loan volume regressions and Table 8 reports the loan quality results. In Table 7 Panel A, we show that the instruments pass the relevancy test as both

[22] We were able to obtain effective registration dates from state security regulators for all states except Tennessee.

[23] Prosper filed sales report supplements with the SEC for each of their borrower payment dependent note (BPDN) series from 7/10/2009 until 4/15/2013. During that time period, the identity of the investors is disclosed, as a screenname, for each BPDN. This provides a list of investors in each security issued by Prosper during that time period. Prosper also provides basic information for each screenname that is publicly available. For example, in the sales report supplement dated July 20, 2009, (`https://www.prosper.com/published/sec/sales/2009/sales_20090720-1211.htm`) the first BPDN (series 416275) was a loan for $3,500 issued on 7/13/2009. The sixth investor "fotep-financial" resides in Utah according to her/his profile page (`https://www.prosper.com/groups/member_home.aspx?screen_name=fotep-financial`). However, Prosper did not secure state level registration in Utah until 12/27/12. Using the transactions collected from the sales report supplements, we generate a list of unique traders and collect location information for 30,909 investors on the platform. Using the registration dates collected via interviews with state regulators, we marked 1,142,212 trades that occurred outside effective registration. These trades occur in 36 states and include approximately 44% of the investors on the Prosper platform. That is to say, nearly half of all investors on Prosper invest in securities at some point in time when they are likely to be outside of effective registration status.

[24] Note that to be a valid instrument the variable need only meet the exclusion and relevancy criteria. We would argue both versions of the investor population (Actual vs. Assumed) should be free of confounding omitted variable correlation, and thus the relevancy of both can be observed in the first stage of the regression. The IV's in both cases are statistically significant but we note that the assumed population investing tends to have the greater statistical significance

[25] To capture the increased access to both Prosper and LendingClub platform while avoiding potential problem in the first stage caused by the high correlation between these two instruments, we orthogonalize $AssumedPopLC$ by taking the residuals from the regression of $AssumedPopLC$ on $AssumedPopPR$. We then use this orthogonalized $AssumedPopLC$ to replace the original $AssumedPopLC$ in the instrumented regression. The second stage results are unaffected by this manipulation and the results are qualitatively similar in the just identified cases when only one instrument is used.

variables are significant in the first stage as presented in column (1). 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 columns (2)-(3).[26] However, splitting the sample by commercial bank size as in Table 4, the results for small commercial banks in Panel B again suggest a loss in personal loans. A one standard deviation increase in peer-to-peer lending suggests a decrease of 21 BP or 6.3% 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 is positive and significant at the 5% level. It is possible this increase in personal loan volume is driven by the latter half of the sample once institutional investors were allowed to participate on the platform as suggested by the results in Table 6.

Turning to the loan quality regressions, we report the results for personal loans in Table 8. 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 and statistically significant for eight of the nine specifications. Splitting the sample by lender size in Panels B and C, the increase in delinquencies and charge-off activity appears to be present in both large and small commercial banks. As is common for instrumented regressions, the coefficient size on peer-to-peer volume are substantially larger indicating economic magnitudes of increased delinquencies and charge-off activity. For example, the contemporaneous charge off activity implied by the coefficient in Panel B (C) column (7) is an increase of 126% (59%).

The IV results are broadly consistent with the OLS results in Table 4 and Table 5. 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 suggest little change in borrower quality at large commercial banks while the IV results suggest some increase in delinquency and charge-off activity.

In a contemporaneous working paper, Chakraborty et al. (2016) show that commercial banks

[26] Because the instruments $AssumedPopLC$ and $AssumedPopPR$ are quarterly measures, they are collinear with the year-quarter fixed effects. To continue to remove any potential macro period effects, we instead include a year fixed effect.

substitute away from commercial and industrial loans for more mortgage origination activity to take advantage of the Federal Reserve's quantitative easing (QE) program. 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 causing our results to be spurious. We repeat the OLS analysis from Table 2 including the Federal Reserve mortgage-backed security ($MBSActivity$) and Treasury bond purchasing activity ($TBActivity$) measures and lender sensitivity measure ($MBSHolding$) from Chakraborty et al. (2016). Table 9 reports the results from this exercise. The results for the loan volume in Table 2 and Table 4 are robust to such concerns.

6 Conclusion

Peer-to-peer lending and other forms of crowdfunding are an emerging area of non-bank activity competing with traditional deposit-taking lenders. Their rate of growth has been extremely rapid and largely 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 show that small (rural) commercial banks lose 1.8% (2.0%) of their personal loan volume for a standard deviation increase in aggregate peer-to-peer lending in addition to increases in loan delinquency and charge-off measures. Because the personal loan segment as reported to the FDIC includes automotive and student loans, which are three to four times the size of the personal loan segment (each), this would appear to be a lower bound on the volume of substitution at small commercial banks. Surprisingly, this volume loss appears to be most sensitive to the inroads of lower credit grade peer-to-peer loans. We also show evidence that large commercial banks above $300 million in total assets appear to maintain loan volume. Loan quality also deteriorates among the largest commercial banks despite their ability to maintain volume with increased competition from peer-to-peer lending. While small commercial banks appear to struggle to compete against peer-to-peer lending encroachment, the provision of access to the peer-to-peer lending platform investment process appears to alleviate most of the volume loss among small commercial banks. While we cannot observe loan level data at the commercial bank, it is likely that the ability to access a geographically broad set of borrowers may provide additional benefits in diversification (geographic, occupational, etc.) which would be particularly valuable for commercial lenders unable to reach these broader markets.

We anticipate the current shift toward broader inclusion of non-bank intermediaries by way of regulatory policy should encourage greater encroachment by peer-to-peer lenders. The peer-to-peer advance might include additional peer-to-peer platforms focused on personal loan products but also other debt contracts such as student loans, automotive loans, commercial and industrial loans, and even real estate. Indeed, large traditional financial intermediaries have begun to enter the space previously occupied by just LendingClub and Prosper.[27] Our results highlight the heterogeneous impact of increased competition. We highlight the detrimental effect on loan volume and loan quality for small/rural commercial banks as a result of increasing peer-to-peer expansion but also the benefit of increased access if commercial lenders can participate as investors. As more commercial bank segments become targets for non-bank expansion, our results emphasize the need for careful policy selection.

[27] https://www.wsj.com/articles/goldman-sachs-joins-the-fintech-fray-with-marcus-1476368800

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.)
$TotalLoans_{it}$ (in \$B)	Bank i's total loans and leases, net of unearned income in quarter t. (RCON2122)
$C\&ILoans_{it}$ (in \$B)	Bank i's commercial and industrial loans in quarter t. (RCON1766)
$RealLoans_{it}$ (in \$B)	Bank i's loans secured by real estate in quarter t. (RCON1410)
$AllConsumerLoans_{it}$ (in \$B)	Bank i's loans to individuals in quarter t. (RCONB538 +RCONB539)
$PersonalLoans_{it}$ (in \$B)	Bank i's personal loans to individuals in quarter t. (RCONB539) from 2009Q2 until 2010Q4. From 2011Q1 onward is (RCONB539 + RCONK137 + RCONK207)
$PL30Past_{it}$ (in \$M)	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). (RCONB578 until 2010Q4 and then RCONK213 + RCONK216 for 2011Q1 onwards)
$PL90Past_{it}$ (in \$M)	Bank i's personal loans that have become past due with the minimum payment not made for 90 days or more. (RCONB579 until 2010Q4 and then RCONK214 + RCONK217 for 2011Q1 onwards)
$PLChgOff_{it}$ (in \$M)	Bank i's personal loans charged off against the allowance for personal loan in quarter t. Note banks report the cumulative amount for each calendar year. We use the quarterly change from $t-1$ to t. (RIADB516 until 2010Q4 and then RCONK215 + RCONK218 for 2011Q1 onwards)

Bank Characteristics

$TotalAsset_{it}$ (in \$B)	Bank i's total asset in quarter t. (RCON2170)
$TotalEquity_{it}$	Bank i's total equity capital (RCON3210) scaled by its total asset in quarter t.
$NetIncome_{it}$	Bank i's net income (RIAD4340) scaled by its total asset in quarter t.
$InterestExp_{it}$	Bank i's interest on deposits (RIAD4073) scaled by its total deposits (RCON2200) in quarter t.
$Competition_{it}$	Equal weighted average Herfindahl index across bank i's branches in period t. Herfindahl index is calculated for each county based on branch deposits.

Economy Controls[28]

$PerCapitaInc_{it}$ (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.

[28]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

$AssumedPopPR(LC)_t$ (in %)	Population granted access to Prosper (LendingClub) for lending in quarter t. $AssumedPopPR(LC)_t = \frac{1}{\#\, of\ days\ in\ quarter\ t} \sum_{d \in t} AssumedPopPR(LC)_d$, where $AssumedPopPR(LC)_d = \sum_k \left[\mathbb{1}_{\{if\ registered\}} \times population_{kd} \right] /$ $US\ population\ in\ 2008$. $\mathbb{1}_{\{if\ registered\}}$ is 1 if Prosper (LendingClub) has ever been registered in state k prior to 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.
$MBSHolding_{it}$[29]	Bank i's balance in MBS (Mortgage-backed security) holdings scaled by its total asset in quarter t. MBS holdings are the sum of 1) MBS held for trading, 2) MBS held not for trading, and 3) MBS for sale.

[29] 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.

Appendix B. Security Creation Mechanism

The security creation mechanism underpinning the peer-to-peer lending market has evolved since its original structure in 2006-2007. Included here is a summary of some of the applicable details, but the interested reader should consult the U.S. Government Accountability Office (GAO) Report to Congressional Committees (2011) for more details.

When the peer-to-peer lending platforms were founded in 2006, after matching up borrowers with a pool of investors, peer-to-peer platforms would create and purchase a set of promissory notes from the borrower that by construction corresponded to the funds loaned by investors. For example, if three investors equally funded a \$3,000 loan, the platform would create three separate promissory notes with face value \$1,000 tied to the principal and interest payments of that borrower. The platform would sell the promissory notes to investors retaining origination and servicing fees throughout the process. Two problems emerged with this structure. As Rigbi (2013) explains, the lending platforms were not registered commercial banks which forced them to curtail the interest rates charged on the loans according to the usury laws accorded by the borrower's state of residence. Thus, if the state of New York had a usury cap of 16%, investors could not charge a New York borrower an interest rate commiserate with their level of risk if it exceeded this cap. Naturally, this caused investors to restrict the supply of funds in that state. After some initial operations, both platforms addressed this first problem through some structural changes in the spring of 2008. At that time, both Prosper and LendingClub entered an arrangement with an industrial bank in Utah to originate loans produced on the online platform in exchange for a servicing fee. Because these loans were issued by a state chartered banking institution, they allowed for the exporting of the usury caps in the bank's home state which was at the national limit of 36%. After this change, the platforms would purchase a single promissory note issued by the state chartered bank within days of its creation and simultaneously issue a new set of securities to the platform investors. We refer to these securities generically as borrower dependent notes (BDN). The platforms would continue to retain the initial promissory note issued by the borrower. However, this altered structure created a second issue. According to the U.S. GAO report (2011), the SEC considers the BDN issued by both platforms to be securities under section 2(a)(1) of the Securities Act of 1933. This implies that the BDN required security registration to issue. Both platforms ceased selling the loans to investors during a federal security registration quiet period. After the SEC had approved the federal security registration applications, the platforms resumed sales of the notes to investors. Although following the quiet period both platforms began to federally register the BDN with the Securities and Exchange Commission (SEC), the BDN were not traded on a national market system exchange. According to the Securities Act of 1933, this is one of the standard tests to receive an exemption from state level registration, and so the BDN were still subject to state level registration requirements before residents of a state could invest on the platform.

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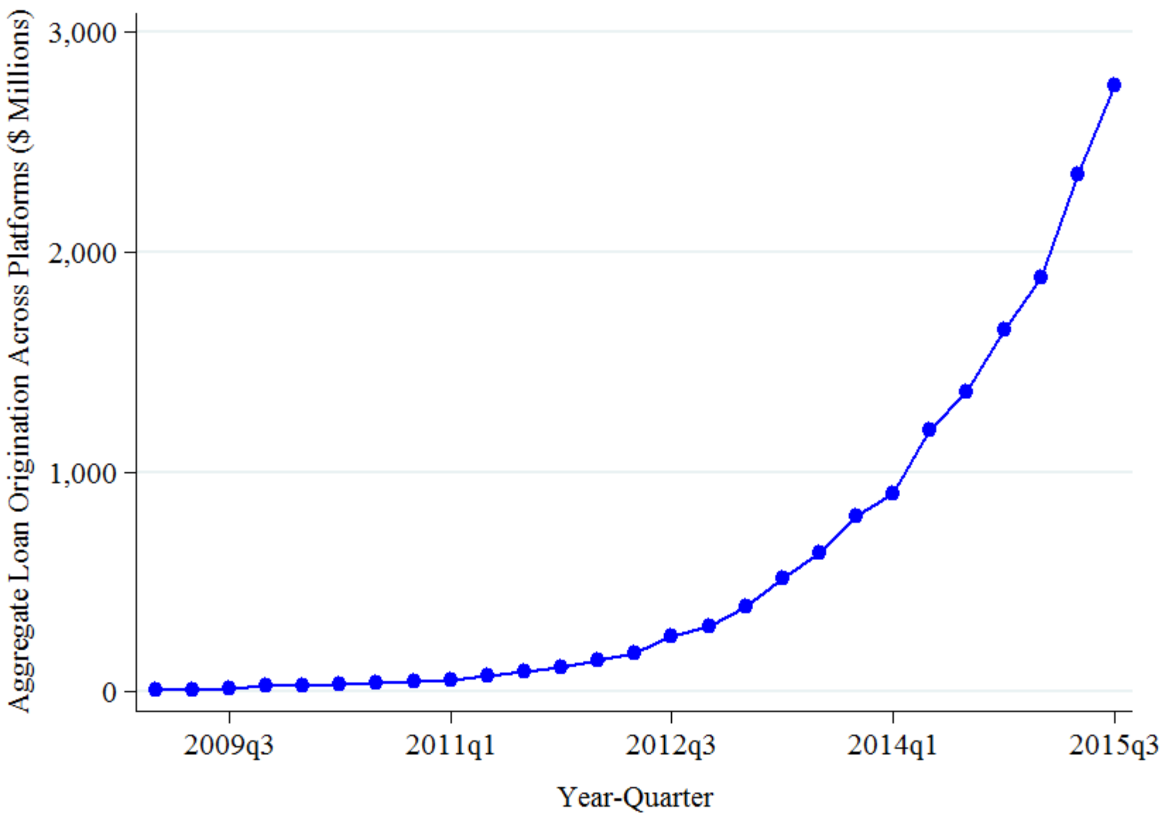

Figure 1. Average Quarterly Peer-to-peer Loan Volume

The figure above shows the aggregate loan volume in $ millions originating from peer-to-peer marketplace platforms Prosper Marketplace and LendingClub Corporation in each quarter.

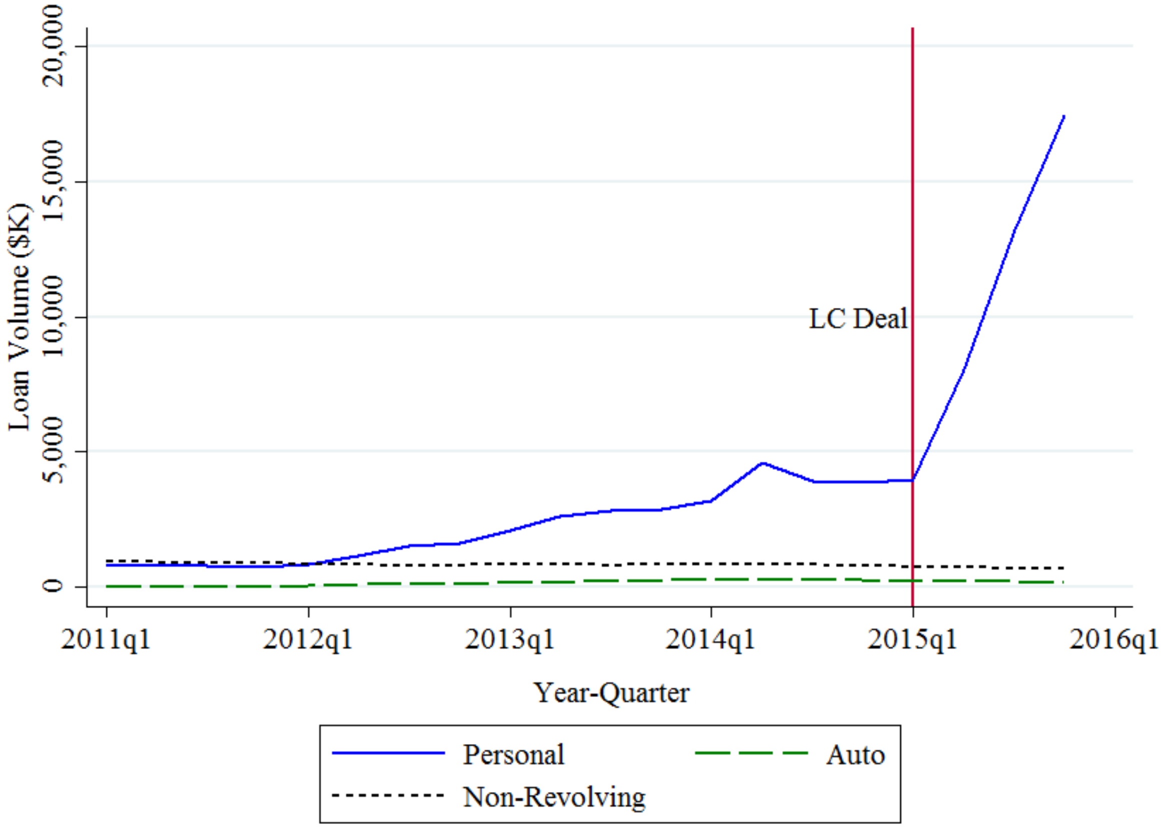

Figure 2. BankNewport Personal Loan Sub-segments before and after LendingClub Partnership

The figure above shows the quarterly loan volume for BankNewport as reported to the FDIC for each personal credit sub-segment in $ thousands. The three sub-segments, Personal (Student, Unsecured Personal), Auto, and Non-revolving, are shown before and after the deal with LendingClub announced in 2015Q2 to allow BankNewport to purchase loans on the LendingClub platform.

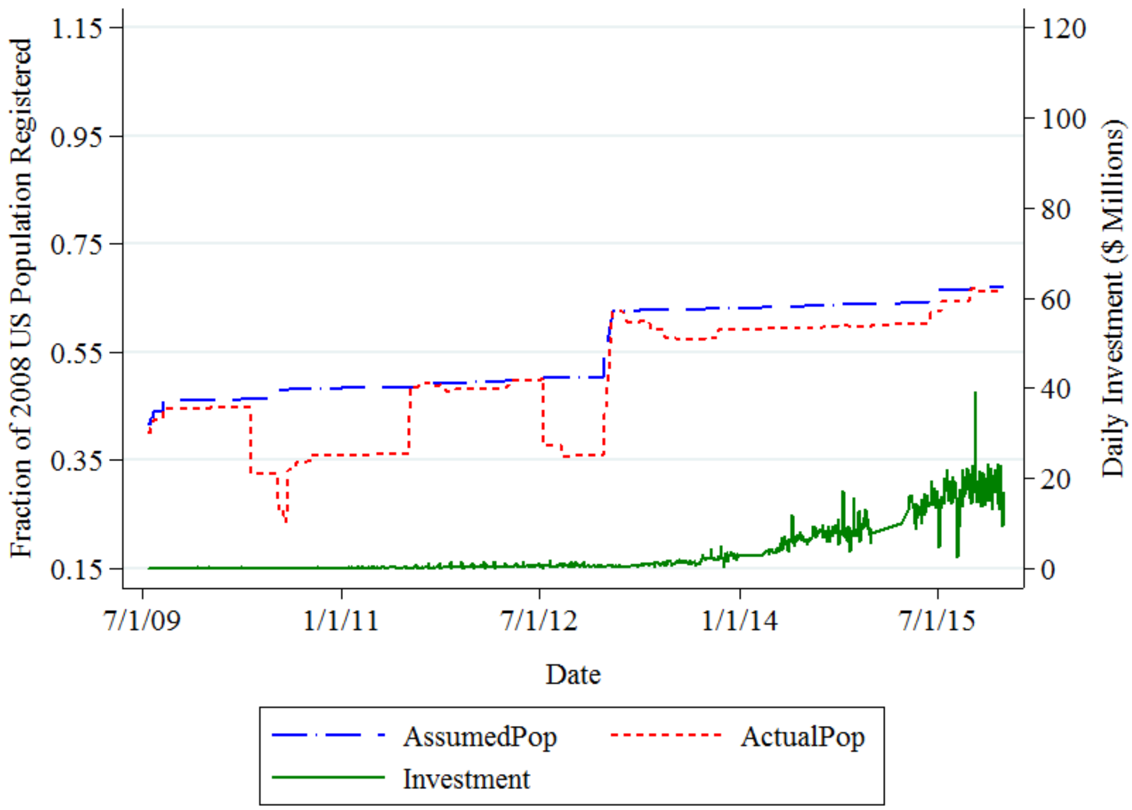

Figure 3. Daily Investment and Fraction of US Population Residing in States Registered to Purchase Securities on the Prosper Marketplace Platform

The figure above graphs the fraction of the US population able to invest on Prosper according to state security regulator interviews. The actual registration incorporates registration lapses while the assumed registration does not. Daily investment volume on Prosper is graphed on the secondary axis.

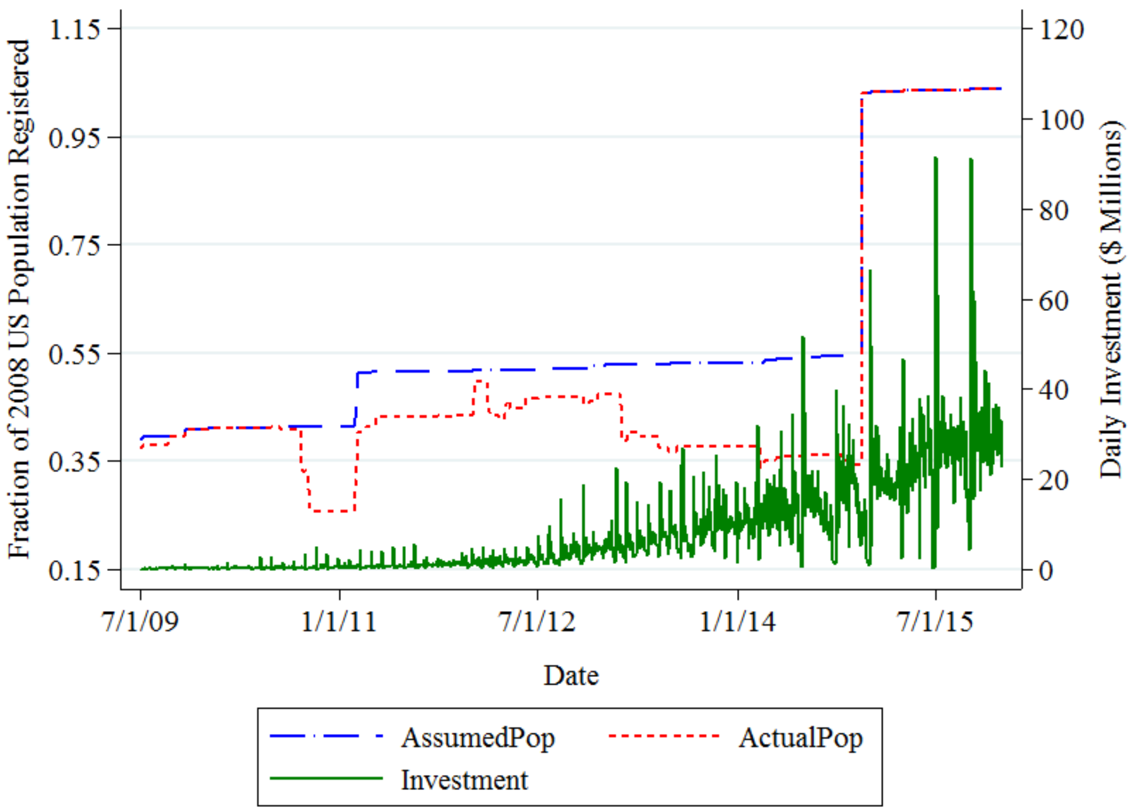

Figure 4. Daily Investment and Fraction of US Population Residing in States Registered to Purchase Securities on LendingClub Corporation Platform

The figure above graphs the fraction of the US population able to invest on LendingClub according to state security regulator interviews. The actual registration incorporates registration lapses while the assumed registration does not. Daily investment volume on LendingClub is graphed on the secondary 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.

Table 1. Summary Statistics

Reported are the number of observations, mean, and distribution of the main variables used in the analysis. Panel A presents summary statistics for the full sample while Panel B.1 and B.2 present summary statistics for the small and large commercial bank subsamples. Panel C presents summary statistics for the local and macro economy.

Panel A. Full Sample

Variable Name	N	Mean	Std. Dev.	P25	P50	P75
P2Pvolume ($B)	164,711	0.0170	0.0314	0.0007	0.0037	0.0182
P2PLowRating ($B)	164,711	0.0024	0.0049	0.0001	0.0006	0.0025
P2PHighRating ($B)	164,711	0.0155	0.0323	0.0006	0.0030	0.0152
TotalLoans ($B)	164,711	0.3416	1.7078	0.0451	0.0994	0.2266
C&ILoans ($B)	164,711	0.0476	0.2982	0.0038	0.0102	0.0273
RealLoans ($B)	164,711	0.2337	0.9290	0.0293	0.0727	0.1737
AllConsumerLoans ($B)	164,711	0.0426	1.0809	0.0013	0.0031	0.0075
PersonalLoans ($B)	164,711	0.0212	0.3191	0.0012	0.0030	0.0072
PL30Past ($M)	164,711	0.2487	3.5132	0.0000	0.0240	0.1020
PL90Past ($M)	164,711	0.0876	4.1448	0.0000	0.0000	0.0030
PLChgOff ($M)	164,711	0.0498	0.7223	0.0000	0.0010	0.0140
TotalAsset ($B)	164,711	0.4935	1.6688	0.0799	0.1607	0.3499
TotalEquity	164,711	0.1109	0.0423	0.0900	0.1034	0.1224
NetIncome	164,711	0.0039	0.0078	0.0016	0.0039	0.0074
InterestExp	164,711	0.0063	0.0058	0.0023	0.0044	0.0084
MBSHolding	164,711	0.0798	0.0988	0.0021	0.0470	0.1199
AllConsumerLoans/TA	164,711	0.0332	0.0392	0.0089	0.0218	0.0428
PLLoans/TA	164,711	0.0317	0.0356	0.0083	0.0210	0.0418
PL30Past/TA	164,711	0.0006	0.0012	0.0000	0.0001	0.0006
PL90Past/TA	164,711	0.0001	0.0003	0.0000	0.0000	0.0000
PLChgOff/TA	164,711	0.0001	0.0002	0.0000	0.0000	0.0001
C&Iloans/TA	164,711	0.0815	0.0647	0.0376	0.0672	0.1080
RealLoans/TA	164,711	0.4495	0.1741	0.3279	0.4612	0.5776

Panel B.1. Small Banks (i.e., Banks with Total Assets<$300M)

Variable Name	N	Mean	Std. Dev.	P25	P50	P75
TotalLoans ($B)	116,632	0.0764	0.0532	0.0331	0.0646	0.1101
C&ILoans ($B)	116,632	0.0100	0.0112	0.0027	0.0064	0.0132
RealLoans ($B)	116,632	0.0565	0.0447	0.0205	0.0453	0.0826
AllConsumerLoans ($B)	116,632	0.0040	0.0068	0.0010	0.0023	0.0048
PersonalLoans ($B)	116,632	0.0039	0.0061	0.0010	0.0023	0.0047
PL30Past ($M)	116,632	0.0750	0.2181	0.0000	0.0180	0.0740
PL90Past ($M)	116,632	0.0119	0.1335	0.0000	0.0000	0.0020
PLChgOff ($M)	116,632	0.0106	0.0519	0.0000	0.0000	0.0070
TotalAsset ($B)	116,632	0.1228	0.0744	0.0616	0.1081	0.1747
TotalEquity	116,632	0.1127	0.0455	0.0902	0.1043	0.1246
NetIncome	116,632	0.0038	0.0079	0.0014	0.0038	0.0074
InterestExp	116,632	0.0063	0.0056	0.0024	0.0045	0.0084
MBSHolding	116,632	0.0730	0.0986	0.0001	0.0352	0.1088

Panel B.2. Large Banks (i.e., Banks with Total Assets≥$300M)

Variable Name	N	Mean	Std. Dev.	P25	P50	P75
TotalLoans ($B)	48,079	0.9850	3.0660	0.2612	0.3891	0.7022
C&ILoans ($B)	48,079	0.1389	0.5408	0.0222	0.0449	0.0981
RealLoans ($B)	48,079	0.6636	1.6404	0.1984	0.2994	0.5394
AllConsumerLoans ($B)	48,079	0.1362	1.9976	0.0031	0.0088	0.0216
PersonalLoans ($B)	48,079	0.0632	0.5884	0.0028	0.0082	0.0201
PL30Past ($M)	48,079	0.6701	6.4745	0.0030	0.0520	0.2340
PL90Past ($M)	48,079	0.2713	7.6657	0.0000	0.0000	0.0050
PLChgOff ($M)	48,079	0.1448	1.3296	0.0000	0.0100	0.0480
TotalAsset ($B)	48,079	1.3927	2.8958	0.4006	0.5879	1.0749
TotalEquity	48,079	0.1067	0.0332	0.0897	0.1015	0.1177
NetIncome	48,079	0.0044	0.0077	0.0019	0.0042	0.0075
InterestExp	48,079	0.0064	0.0062	0.0022	0.0044	0.0084
MBSHolding	48,079	0.0964	0.0974	0.0212	0.0724	0.1406

Panel C. Local and Macro Economy

Variable Name	N	Mean	Std. Dev.	P25	P50	P75
PerCapitaInc ($)	164,711	42,548	5,617	38,438	42,164	45,862
Unemp (%)	164,711	7.0729	2.0603	5.5	6.9	8.4712
AutoDebt ($)	164,711	3,351	682	2,860	3,190	3,672
CCDebt ($)	164,711	2,724	425	2,410	2,680	2,990
MortDebt ($)	164,711	28,833	9,399	22,980	25,050	33,970
AutoDebtDelinq (%)	164,711	3.6876	1.4487	2.62	3.47	4.47
CCDebtDelinq (%)	164,711	9.1472	2.6686	7.11	8.76	10.56
MortDebtDelinq (%)	164,711	3.9268	2.8954	2.1845	3.20	4.51
MBSActivity ($B)	164,711	0.1159	0.1022	0.0067	0.0909	0.2008
TBActivity ($B)	164,711	0.1017	0.0836	0.0360	0.1320	0.1350
AssumedPopLC	164,711	0.5557	0.1804	0.4139	0.5204	0.5330
AssumedPopPR	164,711	0.5478	0.0785	0.4825	0.5020	0.6325

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

Ordinary least squares regression results from Equation (1) where total consumer loan volume and personal loans are regressed on peer-to-peer loan volume, bank characteristics, and local economy controls. $P2PVolume$ 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. $P2PLowRating$ is the volume of low credit rating 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. $P2PHighRating$ is the volume of high credit rating 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. $TotalAsset$ is the total assets of lender i in quarter t. $TotalEquity$ is the ratio of bank i's equity to total assets in quarter t. $NetIncome$ is the ratio of bank i's net income to total assets. $InterestExp$ is bank i's net interest expense over total deposits in quarter t. Bank characteristic variables are winsorized at the 1% and 99%. Local economy controls are state level statistics weighted by bank i's deposit-weighted geographic footprint. The regression includes bank fixed effects and year-quarter fixed effects. Standard errors are clustered at the bank level. Numbers in parenthesis are t-statistics. ***, **, and * represent 1%, 5%, and 10% significance respectively.

	(1)	(2)	(3)	(4)
	All Consumer Loans	Personal Loans	All Consumer Loans	Personal Loans
$P2Pvolume_{it}$	−0.010	−0.013**		
	(−1.63)	(−2.14)		
$P2PLowRating_{it}$			−0.226***	−0.200***
			(−2.72)	(−2.63)
$P2PHighRating_{it}$			0.028*	0.022
			(1.83)	(1.58)
Bank Characteristics				
$TotalAsset_{it}$	0.001*	0.001***	0.001*	0.001***
	(1.94)	(3.04)	(1.94)	(3.04)
$TotalEquity_{it}$	0.010	0.002	0.010	0.002
	(1.09)	(0.38)	(1.09)	(0.38)
$NetIncome_{it}$	0.097***	0.091***	0.097***	0.092***
	(7.86)	(7.98)	(7.87)	(8.00)
$InterestExp_{it}$	−0.068*	−0.106***	−0.071*	−0.109***
	(−1.74)	(−3.35)	(−1.84)	(−3.46)
Local Economy				
$PerCapitaInc_{it}$	0.115	0.161	0.096	0.146
	(0.85)	(1.32)	(0.70)	(1.19)
$Unemp_{it}$	−0.017	−0.011	−0.014	−0.008
	(−0.99)	(−0.69)	(−0.83)	(−0.50)
$AutoDebt_{it}$	−5.452***	−5.230***	−5.506***	−5.293***
	(−5.63)	(−5.90)	(−5.67)	(−5.96)
$CCDebt_{it}$	2.535	1.809	2.360	1.616
	(1.42)	(1.09)	(1.33)	(0.98)
$MortDebt_{it}$	−0.437***	−0.479***	−0.427***	−0.470***
	(−3.19)	(−4.02)	(−3.12)	(−3.95)
$AutoDebtDelinq_{it}$	0.010	0.005	0.010	0.005
	(0.29)	(0.17)	(0.30)	(0.15)
$CCDebtDelinq_{it}$	0.070***	0.056***	0.078***	0.063***
	(3.43)	(2.98)	(3.90)	(3.46)
$MortDebtDelinq_{it}$	−0.041**	−0.036**	−0.041**	−0.035**
	(−2.45)	(−2.44)	(−2.47)	(−2.42)
$Constant$	0.052***	0.054***	0.052***	0.054***
	(7.01)	(8.33)	(7.01)	(8.35)
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

Ordinary least squares regression results from Equation (2) where 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 30-89 days delinquent. In columns (4)-(6) the dependent variable is the volume of personal loans 90+ days delinquent. In columns (7)-(9) 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. $TotalAsset$ is the total assets of lender i in quarter t. $TotalEquity$ is the ratio of bank i's equity to total assets in quarter t. $NetIncome$ is the ratio of bank i's net income to total assets. $InterestExp$ is bank i's net interest expense over total deposits in quarter t. Bank characteristic variables are winsorized at the 1% and 99%. Local economy controls are state level statistics weighted by bank i's deposit-weighted geographic footprint. The regression includes bank fixed effects and year-quarter fixed effects. Standard errors are clustered at the bank level. Numbers in parenthesis are t-statistics. ***, **, and * represent 1%, 5%, and 10% significance respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$PL30Past_t$	$PL30Past_{t+1}$	$PL30Past_{t+2}$	$PL90Past_t$	$PL90Past_{t+1}$	$PL90Past_{t+2}$	$PLChgOff_t$	$PLChgOff_{t+1}$	$PLChgOff_{t+2}$
$P2Pvolume_{it}$	0.369*	0.447**	0.557**	0.131	0.166	0.279*	0.360***	0.430***	0.483***
	(1.68)	(1.97)	(2.33)	(0.92)	(1.13)	(1.79)	(3.32)	(3.82)	(4.06)
Bank Characteristics									
$TotalAsset_{it}$	0.022**	0.021**	0.020**	0.014**	0.013**	0.012**	0.001	0.004	0.002
	(2.45)	(2.35)	(2.43)	(2.16)	(2.19)	(2.15)	(0.10)	(0.70)	(0.47)
$TotalEquity_{it}$	−0.472**	−0.563***	−0.569***	−0.118	−0.133	−0.096	−0.566***	−0.462***	−0.515***
	(−2.56)	(−3.10)	(−2.91)	(−1.02)	(−1.12)	(−0.78)	(−5.61)	(−4.51)	(−5.03)
$NetIncome_{it}$	0.803*	0.570	0.864*	1.963***	1.240***	1.504***	−1.554***	−0.563**	−1.327***
	(1.71)	(1.21)	(1.86)	(6.90)	(4.20)	(5.07)	(−5.32)	(−2.07)	(−5.03)
$InterestExp_{it}$	3.139***	3.465***	3.044***	0.499	−0.629	−0.301	1.951***	2.044***	1.721***
	(2.69)	(3.08)	(2.81)	(0.66)	(−0.90)	(−0.43)	(2.72)	(3.27)	(2.87)
Local Economy									
$PerCapitaInc_{it}$	−2.784	−3.101	−4.420	3.718	4.218	2.330	3.649	3.649	1.964
	(−0.63)	(−0.70)	(−1.00)	(1.24)	(1.40)	(0.76)	(1.54)	(1.52)	(0.84)
$Unemp_{it}$	2.902***	2.241***	1.918***	0.761	0.547	0.306	2.199***	1.756***	1.460***
	(4.49)	(3.44)	(2.93)	(1.61)	(1.16)	(0.64)	(6.14)	(4.87)	(4.08)
$AutoDebt_{it}$	−154.341***	−143.922***	−123.851***	−118.186***	−120.353***	−112.813***	−33.709*	−20.371	−9.597
	(−4.43)	(−4.12)	(−3.46)	(−5.00)	(−5.21)	(−4.81)	(−1.80)	(−1.10)	(−0.52)
$CCDebt_{it}$	155.056**	173.411***	197.499***	24.184	19.430	21.130	47.710	72.814**	90.297***
	(2.52)	(2.87)	(3.30)	(0.56)	(0.47)	(0.52)	(1.49)	(2.31)	(2.93)
$MortDebt_{it}$	−17.262***	−15.180***	−11.234***	−2.777	−1.628	−0.957	−7.175***	−6.311***	−4.060*
	(−3.96)	(−3.56)	(−2.69)	(−0.98)	(−0.59)	(−0.34)	(−3.01)	(−2.74)	(−1.81)
$AutoDebtDelinq_{it}$	−0.423	−0.172	0.649	−2.551***	−2.205***	−1.799**	0.250	0.691	0.568
	(−0.37)	(−0.15)	(0.56)	(−3.13)	(−2.76)	(−2.24)	(0.39)	(1.10)	(0.92)
$CCDebtDelinq_{it}$	1.367*	1.381*	0.914	1.365***	1.234**	1.186**	2.289***	2.062***	1.783***
	(1.87)	(1.92)	(1.25)	(2.77)	(2.55)	(2.38)	(5.77)	(5.25)	(4.54)
$MortDebtDelinq_{it}$	−1.046**	−0.835*	−0.780	−0.407	−0.304	−0.129	−0.934***	−0.702**	−0.572**
	(−2.09)	(−1.70)	(−1.58)	(−1.17)	(−0.89)	(−0.37)	(−3.31)	(−2.52)	(−2.03)
$Constant$	1.750***	1.683***	1.399***	0.524***	0.505***	0.475***	0.166	0.098	−0.071
	(6.83)	(6.65)	(5.53)	(3.04)	(3.02)	(2.79)	(1.21)	(0.72)	(−0.54)
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE clustered	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank
R^2	0.786	0.789	0.791	0.624	0.629	0.633	0.560	0.563	0.565
$Adj.R^2$	0.775	0.778	0.780	0.605	0.610	0.613	0.538	0.540	0.542
Obs.	164,711	157,384	149,638	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	7,758	7,758	7,683

Table 4. Cross-Sectional Variation in Loan Volume Based on Lender Size and Market Competitiveness

Ordinary least squares regression results from Equation (1) where total consumer loan volume and personal loans are regressed on peer-to-peer loan volume, bank characteristics, and local economy controls. In columns (1)-(2) we use the subsample of small commercial banks with $TotalAsset$ less than \$300 million, while columns (3)-(4) contain the subsample of large commercial banks with $TotalAsset$ greater than \$300 million. In columns (5)-(6) we use the subsample of banks with branches in below median competition areas, while columns (7)-(8) contain the subsample of banks with branches in above median competition areas. $P2PVolume$ 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 characteristic variables include $TotalAsset$, $TotalEquity$, $NetIncome$, and $InterestExp$ and are winsorized at the 1% and 99%. Local economy controls are state level statistics weighted by bank i's deposit-weighted geographic footprint that include $PerCapitaInc$, $Unemp$, $AutoDebt$, $CCDebt$, $MortDebt$, $AutoDebtDelinq$, $CCDebtDelinq$, and $MortDebtDelinq$. The regression includes bank fixed effects and year-quarter fixed effects. Standard errors are clustered at the bank level. Numbers in parenthesis are t-statistics. ***, **, and * represent 1%, 5%, and 10% significance respectively.

	Small		Large		Low Competitiveness		High Competitiveness		Small-Single
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All Consumer Loans	Personal Loans	All Consumer Loans	Personal Loans	All Consumer Loans	Personal Loans	All Consumer Loans	Personal Loans	Personal Loans (unscaled)
$P2Pvolume_{it}$	-0.021^{**}	-0.021^{***}	-0.004	-0.006	-0.014	-0.016^{**}	-0.010	-0.011	-0.003^{**}
	(-2.50)	(-2.70)	(-0.42)	(-0.69)	(-1.64)	(-2.09)	(-0.91)	(-1.15)	(-2.40)
Bank Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Local Economy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE clustered	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank
R^2	0.932	0.934	0.946	0.945	0.932	0.932	0.944	0.947	0.934
$Adj.R^2$	0.929	0.931	0.943	0.942	0.928	0.928	0.941	0.944	0.931
Obs.	116,632	116,632	48,078	48,078	82,313	82,313	82,398	82,398	113,630
Number of Banks	5,819	5,819	2,760	2,760	4,545	4,545	4,839	4,839	5,691

Table 5. Cross-Sectional Variation in Personal Loan Quality based on Lender Size

Ordinary least squares regression results from Equation (2) where late payment status variables are regressed on peer-to-peer loan volume, bank characteristics, and local economy controls. Panel A presents the results for the subsample of small commercial banks with $TotalAsset$ less than \$300 million, while Panel B 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 90+ days delinquent. In columns (7)-(9) 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 characteristic variables include $TotalAsset$, $TotalEquity$, $NetIncome$, and $InterestExp$ and are winsorized at the 1% and 99%. Local economy controls are state level statistics weighted by bank i's deposit-weighted geographic footprint that include $PerCapitaInc$, $Unemp$, $AutoDebt$, $CCDebt$, $MortDebt$, $AutoDebtDelinq$, $CCDebtDelinq$, and $MortDebtDelinq$. The regression includes bank fixed effects and year-quarter fixed effects. Standard errors are clustered at the bank level. Numbers in parenthesis are t-statistics. ***, **, and * represent 1%, 5%, and 10% significance respectively.

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$PL30Past_t$	$PL30Past_{t+1}$	$PL30Past_{t+2}$	$PL90Past_t$	$PL90Past_{t+1}$	$PL90Past_{t+2}$	$PLChgOff_t$	$PLChgOff_{t+1}$	$PLChgOff_{t+2}$
$P2Pvolume_{it}$	0.337	0.312	0.312	−0.114	−0.108	−0.032	0.447***	0.496***	0.536***
	(1.10)	(0.97)	(0.92)	(−0.56)	(−0.51)	(−0.14)	(3.00)	(3.19)	(3.26)
Bank Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Local Economy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE clustered	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank
R^2	0.769	0.771	0.773	0.607	0.612	0.615	0.517	0.520	0.522
$Adj.R^2$	0.757	0.758	0.760	0.586	0.590	0.592	0.492	0.494	0.494
Obs.	116,632	111,731	106,540	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	5,819	5,808	5,752

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$PL30Past_t$	$PL30Past_{t+1}$	$PL30Past_{t+2}$	$PL90Past_t$	$PL90Past_{t+1}$	$PL90Past_{t+2}$	$PLChgOff_t$	$PLChgOff_{t+1}$	$PLChgOff_{t+2}$
$P2Pvolume_{it}$	0.089	0.253	0.453	0.193	0.298	0.448**	0.093	0.151	0.163
	(0.29)	(0.80)	(1.40)	(1.00)	(1.57)	(2.34)	(0.57)	(0.91)	(0.93)
Bank Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Local Economy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE clustered	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank
R^2	0.846	0.848	0.852	0.729	0.735	0.744	0.724	0.729	0.735
$Adj.R^2$	0.837	0.838	0.842	0.712	0.718	0.727	0.707	0.711	0.717
Obs.	48,079	45,653	43,098	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	2,760	2,735	2,687

Table 6. Loan Origination Volume Post Institutional Investor Expansion

Ordinary least squares regression results from Equation (1) where total consumer loan volume and personal loans are regressed on peer-to-peer loan volume, an indicator of institutional investor involvement, bank characteristics, and local economy controls. In columns (1)-(2) we use the full sample of commercial banks. In columns (3)-(4) we use the subsample of small commercial banks with $TotalAsset$ less than \$300 million, while columns (5)-(6) contain the subsample of large commercial banks with $TotalAsset$ greater than \$300 million. $P2PVolume$ 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. $Post$ is an indicator that equals one if the quarter is equal to or after the introduction of whole-loan markets in 2013Q2. Bank characteristic variables include $TotalAsset$, $TotalEquity$, $NetIncome$, and $InterestExp$ and are winsorized at the 1% and 99%. Local economy controls are state level statistics weighted by bank i's deposit-weighted geographic footprint that include $PerCapitaInc$, $Unemp$, $AutoDebt$, $CCDebt$, $MortDebt$, $AutoDebtDelinq$, $CCDebtDelinq$, and $MortDebtDelinq$. The regression includes bank fixed effects and year-quarter fixed effects. Standard errors are clustered at the bank level. Numbers in parenthesis are t-statistics. ***, **, and * represent 1%, 5%, and 10% significance respectively.

	Full		Small		Large	
	(1)	(2)	(3)	(4)	(5)	(6)
	All Consumer Loans	Personal Loans	All Consumer Loans	Personal Loans	All Consumer Loans	Personal Loans
$P2Pvolume_{it}$	-0.065^{***}	-0.067^{***}	-0.099^{***}	-0.094^{***}	-0.023	-0.031
	(-3.99)	(-4.52)	(-4.81)	(-4.90)	(-0.89)	(-1.33)
$P2Pvolume_{it} \times Post_t$	0.051^{***}	0.051^{***}	0.073^{***}	0.068^{***}	0.018	0.023
	(4.03)	(4.57)	(4.78)	(4.88)	(0.86)	(1.31)
$Post_t$	-0.006^{***}	-0.007^{***}	-0.011^{***}	-0.011^{***}	-0.001	-0.004
	(-3.22)	(-4.32)	(-5.91)	(-6.21)	(-0.42)	(-1.59)
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	0.932	0.934	0.932	0.934	0.946	0.945
$Adj.R^2$	0.929	0.931	0.929	0.931	0.943	0.942
Obs.	164,711	164,711	116,632	116,632	48,079	48,079
Number of Banks	7,758	7,758	5,819	5,819	2,760	2,760

Table 7. Robustness Tests Using Instrument Variables - Loan Volume

IV regression results from instrumenting $P2PVolume$ with $AssumedPopLC$ and $AssumedPopPR$, the fraction of US population assumed to be able to invest on the LendingClub platform and Prosper platform respectively. The table shows Equation (1) where total consumer loan volume and personal loans are regressed on peer-to-peer loan volume, bank characteristics, and local economy controls. Panel A presents the results for the full sample. Panel B presents the subsamples by bank size. $P2PVolume$ 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. $TotalAsset$ is the total assets of lender i in quarter t. $TotalEquity$ is the ratio of bank i's equity to total assets in quarter t. $NetIncome$ is the ratio of bank i's net income to total assets. $InterestExp$ is bank i's net interest expense over total deposits in quarter t. Bank characteristic variables are winsorized at the 1% and 99%. Local economy controls are state level statistics weighted by bank i's deposit-weighted geographic footprint. The regression includes bank fixed effects and year fixed effects. Standard errors are clustered at the bank level. Numbers in parenthesis are t-statistics. ***, **, and * represent 1%, 5%, and 10% significance respectively.

Panel A. Full Sample

	(1)	(2)	(3)
	P2PVolume	All Consumer Loans	Personal Loans
$AssumedPopLC$	0.033***		
	(27.43)		
$AssumedPopPR$	0.030***		
	(3.03)		
$P2Pvolume_{it}$		−0.022	−0.009
		(−0.79)	(−0.38)
Bank Characteristics			
$TotalAsset_{it}$	0.001*	0.001**	0.001***
	(1.94)	(1.99)	(3.09)
$TotalEquity_{it}$	−0.018***	0.009	0.003
	(−2.62)	(1.09)	(0.40)
$NetIncome_{it}$	−0.069***	0.094***	0.092***
	(−5.63)	(8.12)	(8.54)
$InterestExp_{it}$	−0.188***	−0.141***	−0.158***
	(−6.76)	(−6.26)	(−8.17)
Local Economy			
$PerCapitaInc_{it}$	5.504***	0.101	0.083
	(33.53)	(0.47)	(0.46)
$Unemp_{it}$	−0.612***	−0.019	−0.007
	(−39.70)	(−0.79)	(−0.34)
$AutoDebt_{it}$	−15.326***	−5.438***	−5.010***
	(−9.32)	(−5.19)	(−5.47)
$CCDebt_{it}$	26.770***	2.513	1.521
	(10.14)	(1.30)	(0.87)
$MortDebt_{it}$	−0.716***	−0.423***	−0.460***
	(−3.60)	(−3.12)	(−3.91)
$AutoDebtDelinq_{it}$	−0.548***	0.006	0.010
	(−11.79)	(0.17)	(0.32)
$CCDebtDelinq_{it}$	−1.295***	0.050	0.057*
	(−42.24)	(1.26)	(1.69)
$MortDebtDelinq_{it}$	−0.090***	−0.043***	−0.036**
	(−4.27)	(−2.61)	(−2.50)
Year FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
SE clustered	Bank	Bank	Bank
R^2	0.752	0.121	0.140
$Adj.R^2$	0.752	0.078	0.098
Obs.	164,711	164,711	164,711
Number of Banks	7,758	7,758	7,758

Panel B. Subsamples by Bank Size ($300 Million Total Assets)

	Small		Large	
	(1)	(2)	(3)	(4)
	All Consumer Loans	Personal Loans	All Consumer Loans	Personal Loans
$P2Pvolume_{it}$	-0.065^{*}	-0.072^{**}	0.036	0.068^{**}
	(−1.81)	(−2.08)	(0.72)	(1.99)
Bank Characteristics	Yes	Yes	Yes	Yes
Local Economy	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
SE clustered	Bank	Bank	Bank	Bank
R^2	0.163	0.174	0.049	0.056
$Adj.R^2$	0.119	0.130	−0.008	−0.001
Obs.	116,581	116,581	48,022	48,022
Number of Banks	5,768	5,768	2,703	2,703

Table 8. Robustness Tests Using Instrument Variables - Personal Loan Quality

IV regression results from instrumenting $P2PVolume$ with $AssumedPopLC$ and $AssumedPopPR$, the fraction of US population assumed to be able to invest on the LendingClub platform and Prosper platform respectively. The table reports Equation (2) where late payment status variables are regressed on peer-to-peer loan volume, bank characteristics, and local economy controls. 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 90+ days delinquent. In columns (7)-(9) 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 characteristic variables include $TotalAsset$, $TotalEquity$, $NetIncome$, and $InterestExp$ and are winsorized at the 1% and 99%. Local economy controls are state level statistics weighted by bank i's deposit-weighted geographic footprint that include $PerCapitaInc$, $Unemp$, $AutoDebt$, $CCDebt$, $MortDebt$, $AutoDebtDelinq$, $CCDebtDelinq$, and $MortDebtDelinq$. The regression includes bank fixed effects and year fixed effects. Standard errors are clustered at the bank level. Numbers in parenthesis are t-statistics. ***, **, and * represent 1%, 5%, and 10% significance respectively.

Panel A. Full Sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	PL30Past_t	PL30Past_{t+1}	PL30Past_{t+2}	PL90Past_t	PL90Past_{t+1}	PL90Past_{t+2}	PLChgOff_t	PLChgOff_{t+1}	PLChgOff_{t+2}
$P2Pvolume_{it}$	3.162*	12.060***	10.680***	−1.870	3.372***	1.606**	7.724***	8.767***	8.793***
	(1.85)	(10.21)	(10.12)	(−1.53)	(4.17)	(2.18)	(6.09)	(10.80)	(12.00)
Bank Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Local Economy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE clustered	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank
R^2	0.086	0.013	0.019	0.018	0.007	0.012	−0.015	−0.037	−0.038
$Adj.R^2$	0.041	−0.038	−0.033	−0.031	−0.044	−0.041	−0.065	−0.090	−0.094
Obs.	164,711	157,309	149,524	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	7,758	7,683	7,569

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	PL30Past$_t$	PL30Past$_{t+1}$	PL30Past$_{t+2}$	PL90Past$_t$	PL90Past$_{t+1}$	PL90Past$_{t+2}$	PLChgOff$_t$	PLChgOff$_{t+1}$	PLChgOff$_{t+2}$
$P2Pvolume_{it}$	1.532	15.910***	13.222***	−3.622*	4.752***	1.815	11.024***	11.171***	11.034***
	(0.56)	(8.98)	(8.37)	(−1.80)	(3.87)	(1.64)	(5.38)	(9.34)	(10.15)
Bank Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Local Economy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE clustered	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank
R^2	0.083	−0.010	0.009	0.013	0.002	0.013	−0.053	−0.054	−0.050
$Adj.R^2$	0.036	−0.065	−0.047	−0.038	−0.052	−0.043	−0.108	−0.112	−0.110
Obs.	116,581	111,638	106,446	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	5,768	5,715	5,658

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	PL30Past$_t$	PL30Past$_{t+1}$	PL30Past$_{t+2}$	PL90Past$_t$	PL90Past$_{t+1}$	PL90Past$_{t+2}$	PLChgOff$_t$	PLChgOff$_{t+1}$	PLChgOff$_{t+2}$
$P2Pvolume_{it}$	4.920***	4.495***	5.438***	−0.310	0.537	0.516	4.288***	4.239***	4.212***
	(3.15)	(3.76)	(5.12)	(−0.35)	(0.74)	(0.73)	(3.78)	(4.78)	(5.74)
Bank Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Local Economy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE clustered	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank
R^2	0.097	0.087	0.064	0.024	0.020	0.016	0.037	0.027	0.017
$Adj.R^2$	0.043	0.031	0.004	−0.035	−0.042	−0.047	−0.021	−0.033	−0.046
Obs.	48,022	45,574	42,986	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	2,703	2,656	2,575

Table 9. Loan Volume Robustness to Quantitative Easing

Ordinary least squares regression results from Equation (1) where personal loan volume is regressed on peer-to-peer loan volume, quantitative easing variables, bank characteristics, and local economy controls. $P2PVolume$ 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. $MBSActivity_t$ 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. $TotalAsset$ is the total assets of lender i in quarter t. $TotalEquity$ is the ratio of bank i's equity to total assets in quarter t. $NetIncome$ is the ratio of bank i's net income to total assets. $InterestExp$ is bank i's net interest expense over total deposits in quarter t. Bank characteristic variables are winsorized at the 1% and 99%. Local economic variables are state level statistics weighted by bank i's deposit-weighted geographic footprint. The regression includes bank fixed effects and year fixed effects. Standard errors are clustered at the bank level. Numbers in parenthesis are t-statistics. ***, **, and * represent 1%, 5%, and 10% significance respectively.

	Full	Small	Large
	(1)	(2)	(3)
	Personal Loans	Personal Loans	Personal Loans
$P2Pvolume_{it}$	-0.009^{*}	-0.016^{**}	-0.004
	(-1.65)	(-2.13)	(-0.46)
$MBSActivity_t$	-3.068^{***}	-2.879^{***}	-2.680^{***}
	(-7.39)	(-5.90)	(-2.86)
$TBActivity_t$	-0.653^{***}	-0.516^{**}	-1.188^{***}
	(-3.01)	(-1.96)	(-2.77)
$MBSHolding_{it}$	-0.016^{***}	-0.019^{***}	-0.007
	(-6.32)	(-6.54)	(-1.52)
$MBSActivity_t \times MBSHolding_{it}$	1.617	-0.658	3.801
	(0.50)	(-0.17)	(0.59)
Bank Characteristics			
$TotalAsset_{it}$	0.001^{***}	0.001	0.001^{*}
	(2.91)	(0.07)	(1.69)
$TotalEquity_{it}$	0.002	0.003	-0.011
	(0.37)	(0.48)	(-0.64)
$NetIncome_{it}$	0.091^{***}	0.091^{***}	0.058^{***}
	(8.20)	(7.48)	(3.39)
$InterestExp_{it}$	-0.165^{***}	-0.146^{***}	-0.180^{***}
	(-8.23)	(-5.98)	(-6.45)
Local Economy			
$PerCapitaInc_{it}$	0.059	0.035	0.059
	(0.55)	(0.28)	(0.37)
$Unemp_{it}$	-0.006	-0.001	-0.047^{*}
	(-0.46)	(-0.05)	(-1.79)
$AutoDebt_{it}$	-5.042^{***}	-3.176^{***}	-4.772^{***}
	(-5.75)	(-2.99)	(-3.34)
$CCDebt_{it}$	1.288	-3.411^{*}	5.430^{**}
	(0.78)	(-1.66)	(2.26)
$MortDebt_{it}$	-0.465^{***}	-0.273^{*}	-0.601^{***}
	(-3.93)	(-1.84)	(-3.55)
$AutoDebtDelinq_{it}$	0.009	0.026	-0.017
	(0.29)	(0.72)	(-0.37)
$CCDebtDelinq_{it}$	0.056^{***}	0.056^{***}	0.044
	(2.97)	(2.65)	(1.46)
$MortDebtDelinq_{it}$	-0.035^{**}	-0.051^{***}	-0.010
	(-2.38)	(-2.78)	(-0.47)
$Constant$	0.061^{***}	0.068^{***}	0.049^{***}
	(9.92)	(9.57)	(4.48)
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