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The expansion of the peer-to-peer lending and barriers to entry

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Abstract

Peer-to-peer (P2P) lending platforms are online intermediaries that match lenders with borrowers. We use data from the two leading P2P lending platforms on the US consumer credit market, Prosper and Lending Club, to explore the main drivers of the expansion of demand for P2P credit. We exploit the heterogeneity in local credit markets at the county level to test three main hypotheses: 1) global financial crisis; 2) competition and barriers to entry; and 3) learning costs. We find that P2P lending platforms have partly substituted for banks in counties that were more affected by the financial crisis. High market concentration and high branch density appear to deter the entry and expansion of the P2P lending. Finally, we find a positive impact of variables that are correlated with lower learning costs, such as education, population density, high share of young population, as well as important spatial interactions.

JEL codes: G21, G23, G01, O33, D40

Keywords: peer-to-peer lending, market structure, barriers to entry, financial crisis, information and communication technologies

"Banking is necessary; banks are not"

Bill Gates, 1990

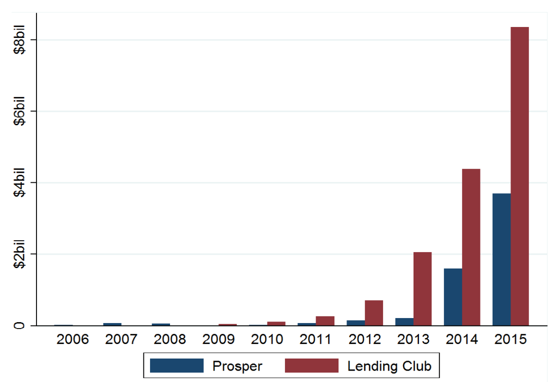
"Is information technology going to disrupt finance? My first response is: please. My second response is: yes."

Martin Wolf, 2016

1. Introduction

Information and communication technologies have enabled new business models of financial intermediation, such as peer-to-peer (P2P) lending platforms. First P2P lending platforms (Zopa, Prosper and Lending Club) have been launched in 2005-2007 in the UK and the US. As the market expanded, a large part of loans has been funded not by individual lenders, but institutional investors. Hence, in the US, the term P2P lending has evolved into marketplace lending. In this paper, we continue to use the term of P2P lending because we study the emergence of this new business model. The volume of P2P lending has been growing rapidly (see figure 1) and, in 2015, the flow of P2P/marketplace consumer credit was equivalent to 11% of traditional consumer lending in the US (Wardrop et al., 2016).[1]

Figure 1: P2P consumer lending growth in the US (in billions of dollars)



Source: Websites of the Lending Club and Prosper Marketplace

P2P lending platforms perform the brokerage function of financial intermediaries by matching lenders' supply and borrowers' demand of funding. Although platforms do not technically perform risk and maturity transformation, there is an ongoing experimentation with different business models that could allow them to perform bank-like functions in the future (Havrylchyk and Verdier, 2018). Firstly, many platforms allow lenders to automate their lending process by setting their lending criteria (risk, maturity, etc), which lowers their transaction costs and permits diversification. Secondly, platforms use credit scoring to assign a risk band to every borrower and effectively play the role of a delegated monitor insofar as

[1] Consumer credit is also provided by balance sheet lenders, which represent another Fintech business model. In 2015, it was equivalent to 1% of traditional consumer lending (Wardrop et al., 2016).

lenders delegate to them due-diligence. Thirdly, platforms provide liquidity services when they create secondary markets on which lenders can sell their loans to other investors

From the borrower perspective, there are no fundamental differences between a credit obtained from a bank or via a P2P lending platform. This is why the emergence of online platforms has sparked a lively debate about their ability to disrupt traditional banking (Morse, 2015, Phillipon, 2016; Nash and Beardsley, 2015; Deloitte, 2016; The Economist, 2015; Wolf, 2016; Citi, 2016). Philippon (2015) demonstrates that the cost of financial intermediation in the US has remained unchanged since the 19 century, which is surprising in the context of the rapid progress in the communication and information technologies. Hence, the entry of new FinTech players could be needed to improve the efficiency of financial services. Indeed, online lenders claim that their operating expenses are much lower than those of brick-and-mortar banks due to the extensive use of new technologies as well as absence of legacy problems and costly branch networks. Haldane (2016) suggests that the entry of new FinTech players could diversify the intermediation between savers and borrowers, which would make the financial sector more stable and efficient and could ensure greater access to financial services.

In this paper, we explore the main drivers behind the rapid expansion of demand for credit from P2P online platforms. Platforms are entering a banking market that is dominated by large incumbent banks and that is characterized by monopolistic competition due to high barriers to entry (Claessens and Laeven, 2004). Since US banks have the monopoly on credit, P2P lending platforms do not have the right to originate loans and need to have a partnership with a bank to do so, representing an important regulatory barrier to entry. P2P lending was forbidden in several states during the period of our study. Structural barriers, such as high switching costs (Shy, 2002; Kim et al., 2003) as well adverse selection in lending markets (Dell'Ariccia et al., 1999) could be particularly significant. Literature about emerging markets has shown that banks lose their informational advantage during periods of financial instability, hence facilitating the entry of new players (Althammer and Haselmann, 2011; Havrylchyk and Jurzyk, 2011). In the past, banks have strategically overinvested in their branch network to make the entry of new banks unprofitable (Adams and Amel, 2016). Importantly, the entry of the P2P lending platforms has coincided with the Global Financial Crisis and its rapid expansion has happened as the banking sector was deleveraging, consolidating, reducing its credit supply and cutting costs by closing branches, while regulation and supervision of banks was strengthened.

In light of this discussion, we outline three main hypotheses to explain the demand for P2P credit. Our *first hypothesis* explores the idea that P2P lending platforms could substitute bank credit by targeting borrowers underserved by incumbent banks in the wake of the global financial crisis. In other words, we test whether banks' deleveraging reduces barriers to entry because creditworthy borrowers are searching for new lenders. Our *second hypothesis* is related to the structure of the banking markets, characterized by high concentration and branch networks that could serve as strategic barriers to entry. Our *third hypothesis* links the speed of the development of the P2P lending to borrowers' search costs, proxied by population density, education, age, as well as spatial interaction variables. Besides these main hypotheses, we control for credit demand, Internet access, as well as other borrower and market characteristics.

Sorting out the above competing hypotheses is difficult because the expansion of the P2P lending has coincided with the post-crisis period, increased concentration of the banking sector and closing of banking branches. To address this problem, our identification strategy relies on the exploration of the geographic heterogeneity of the P2P lending at the county level. To undertake this empirical analysis, we aggregate data for the two leading P2P consumer lending platforms in the US - Prosper and Lending Club. We measure their expansion by aggregating the volume and number of loans provided by these two online lenders. As early as 2007, 1183 counties had P2P borrowers, and their number has increased to 2609 in 2013.

The expansion of the P2P lending could be explained by spatial network effects due to human interactions, that lower search costs and facilitate the diffusion of technologies (Comin et al., 2012). Notwithstanding the online nature of the P2P lending, geography might still play a crucial role in its adoption. Indeed, our data exhibits a an important pattern of spatial correlation, as P2P lending per capita is higher in counties that are close to California, New York and Florida. Hence, our econometric approach relies incorporating a spatial lag variable in our model that enables us to measure how the demand for P2P lending in a given county is impacted by the demand for P2P lending in neighboring counties.[2]

This paper contributes to the nascent literature on the P2P lending and, more generally on Fintechs. The largest strand of this literature explores how borrower characteristics affect loan outcomes and how lenders on P2P platforms mitigate informational frictions (see the literature review by Morse, 2015).[3] Several papers have started to explore the determinants of entry and expansion of FinTechs. Rau (2017) studies drivers of the development of crowdfunding, including P2P lending, at the global level and finds that the quality of regulation, financial development, and ease of internet access are all positively related to crowdfunding volume while the ease of doing business is negatively associated. Buchak et al. (2017) argue that regulatory arbitrage has driven the expansion of US Fintechs that provide mortgage financing. Importantly, they analyze Fintechs that have adopted the business model of balance sheet lenders (or shadow banks), while our paper focuses on Fintechs that are P2P/marketplace lending platforms. Haddad and Hornuf (2016) find that FinTech startups are created in countries where the latest technology is readily available and people have more mobile telephone subscriptions. Butler et al. (2014) explore how borrowers choose between traditional and alternative sources of finance and show that borrowers who reside in areas with good access to bank finance request loans with lower interest rates on P2P lending platforms.

By focusing on the expansion of a new technology, our paper is also related to the literature on the diffusion of innovation (Bass, 1969; Rogers, 2003).[4] The literature on financial innovation is scarce and focuses on the new products and the distribution channels in the traditional banking (Frame and White, 2009). Most of these studies have focused on users' incentives to adopt innovations according to their individual characteristics. DeYoung et al. (2007) and Hernando et al. (2007) analyze the impact of the adoption of online banking on banks' profitability and find that the Internet channel is a complement to rather than a substitute for physical branches. Damar (2009) finds that payday lenders may be complements to banks since they locate in low-income neighborhoods with large number of banks. A few papers try to relate the diffusion of financial innovations to the market structure. Hannan and McDowell (1987) identify a positive role of peers' adoption in ATM diffusion which diminishes in more concentrated markets. He (2015) finds that rival banks' adoption of mobile apps encourages potential adoption more in concentrated markets.

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2 This hypothesis is different from but related to the study by Agrawal et al. (2011) who find that crowdfunding largely overcomes the distance-related economic frictions as the average investor is not in the local market but is 3,000 miles away. Our hypothesis that the expansion of the P2P lending exhibits spatial correlation does not contradict the fact that investors could be located far away.

3 Morse (2015) provides a literature survey of papers that study how P2P lending mitigates information frictions by relying on real world social connections (Freedman and Jin, 2014; Everett, 2010), textual analysis of successful funding bids (Mitra and Gilbert, 2014), psychology text mining techniques to uncover deception (Gao and Lin, 2012), identity claim methodology to identify trustworthy and hardworking borrowers (Sonenshein and Dholakia, 2011) as well as discrimination (Ravina, 2012; Pope and Sydnor, 2011; Duarte et al., 2012).

4 Rogers (2003) argues that the more people that use a technology, the more non-users are likely to adopt.

The paper is structured as follows. In section 2, we describe the institutional environment in which P2P lending platforms evolve, including regulatory barriers to entry. In section 3, we develop our main hypotheses and explain our identification strategy. In section 4, we describe how we assemble our data set, provide data sources and variable definition. Section 5 reports our empirical finding and Section 6 concludes.

2. Institutional environment of P2P lending platforms in the US

Online lenders connect individuals or businesses wishing to obtain a loan with individuals and institutions willing to fund this loan. Online lenders encompass P2P lending platforms, which offer lending-based crowdfunding for consumers and small businesses (Lending Club, Prosper, Funding Circle) and balance sheet lenders (e.g., SoFi, OnDeck Capital, Kabbage).[5] In our paper, we focus on P2P lending platforms, on which multiple lenders lend small sums of money online to consumers or small businesses with the expectation of periodic repayment.

Prosper Marketplace and Lending Club launched the first online P2P lending platforms in the US, respectively in 2006 and 2007, followed by other companies such as Upstart, Funding Circle, CircleBack Lending or Peerform. At the end of 2008, the Securities and Exchange Commission (SEC) issued a "cease and-desist" order against Prosper since the sale of unregistered securities represented a violation of Section 5 of the Securities Act of 1933. A month earlier, Lending Club registered its loans as securities with the SEC and induced the latter to impose such registration on all other platforms (Mariotto, 2016). Lending Club took advantage of the period during which Prosper and the other platforms were inactive while registering the loans as securities, and conquered the majority of the American market share. In December 2014, Lending Club became the first publicly traded online P2P lending platform in the US, after its Initial Public Offering on the New York Stock Exchange. As of September 2017, Lending Club has intermediated $28 billion of loans, while Prosper issued $10 billion of loans, about one third of its rival's volume.

Consumer loan amounts vary between a minimum loan of $1,000 for Prosper and $500 for Lending Club and a maximum loan of $35,000 for both platforms ($300,000 for businesses). They fund various types of projects ranging from credit card debt consolidation to home improvement, short-term and bridge loans, vehicle loans or engagement loans.[6] Despite such similarities, Mariotto (2016) documents that Prosper lends to riskier clients, at higher interest rates, but lower average amounts.

As in many other two-sided markets (Rysman, 2009), online lending marketplaces try to attract two different groups of users, namely borrowers and investors, by choosing an appropriate structure of fees that depends on the magnitude of cross-network externalities. On the borrower side of the market, both companies compete with banking institutions, credit unions, credit card issuers and other consumer finance companies. They also compete with each other and with other online marketplaces such as Upstart or Funding Circle. Platforms claim that their prices are lower on average than the ones consumers would pay on outstanding credit card

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[5] Other types of crowdfunding include donation or reward-based crowdfunding.

[6] Consumer lending does not include credit for purchase of a residence or collateralized by real estate or by specific financial assets like stocks and bonds.

balances or unsecured installment loans funded by traditional banks.[7] Online marketplaces perform the traditional screening function of banks by defining various criteria that must be met by borrowers. Any U.S. resident aged at least 18 with a U.S. bank account and a social security number may apply and request a credit, provided that the platform is authorized in her/his state. Platforms collect online some information about the applicant (i.e., FICO score, debt-to-income ratio, credit report…), which is used to compute a proprietary credit score. Some additional enquiries may also be performed offline (e.g., employment verification). Consumers are divided into several rating segments, which correspond to different fixed interest rates ranging from 6% to 26% for Lending Club in 2014. Origination fees paid to the platform depend on the consumer's level of risk.

On the investor side, investment in online loans on P2P platforms faces potential competition from investment vehicles and asset classes such as equities, bonds and commodities. Prosper claims to offer an asset class that has attractive risk adjusted returns compared to its competitors. Investors can be divided into two different populations: individuals and institutions. Both populations are subject to different requirements. Individual investors must be U.S. residents aged at least 18, with a social security number, and sometimes a driver's license or a state identification card number. Institutional investors must provide a taxpayer identification number and entity formation documentation. Investors' annual income must exceed a floor defined by platforms' rules. Prosper and Lending Club issue a series of unsecured Notes for each loan that are sold to the investors (individual or institutional), and recommend that each investor diversifies his/her portfolio by purchasing small amounts from different loans.[8] Each investor is entitled to receive pro-rata principal and interest payments on the loan, net of a service charge paid to the platform. In addition to the "Note Channel", Prosper has designed specifically a "Whole Loan Channel" for accredited investors (according to the definition set forth in Regulation D under the Securities Act of 1933), which must be approved by the platform. Accredited Investors can purchase a borrower loan in its entirety directly from Prosper.

The lending market in the United-States is subject to many regulations, which are changing continuously (e.g., State Usury Laws, State Securities Laws, Dodd-Frank Wall Street Reform and Consumer Protection Act, Truth-in-Lending Act…). Online lending platforms need to obtain a license to operate in a given state and comply with all existing regulations on consumer lending. For example, currently, Lending Club does not facilitate loans to borrowers in Idaho, Iowa, Maine, Nebraska and North Dakota, but has obtained a license in all other jurisdictions. Furthermore, state and local government authorities may impose additional restrictions on their activities (such as a cap on the fees charged to borrowers) or mandatory disclosure of information. In some states, platforms are opened to borrowers but not to investors, or vice versa. Authorizations can also differ for Prosper and Lending Club.

Unlike in other countries (e.g., UK, France), P2P lending platforms do not have the right to originate loans and need to have a partnership with a bank to do so. Prosper and Lending Club rely on a partnership with WebBank, an FDIC-insured, Utah-chartered industrial bank that originates all borrower loans made through their marketplaces.

An important issue is the potential violation of states' usury laws. The interest rates charged to

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[7] This view is confirmed by a study conducted by Demyanyk and Kolliner at the Federal Reserve Bank of Cleveland. They offer time-series evidence that, on average, marketplace loans carry lower interest rates than credit cards and perform similarly.

[8] Notes can be viewed as debt-back securities.

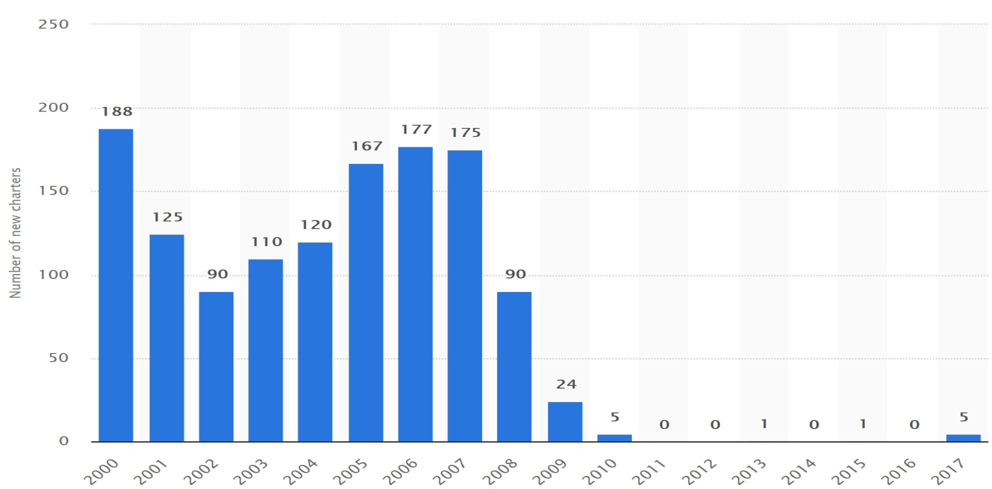
borrowers are based upon the ability under federal law of the issuing bank that originates the loan (i.e., WebBank) to “export” the interest rates of its jurisdiction (i.e., Utah) to other states. This enables the online marketplace to provide for uniform rates to all borrowers in all states in which it operates. Therefore, if a state imposes a low limit on the maximum interest rates for consumer loans, some borrowers could still borrow at a higher rate through an online marketplace since the loan is originated in Utah.[9] Some states have opted-out of the exportation regime, which allows banks to export the interest rate permitted in their jurisdiction, regardless of the usury limitations imposed by the borrower’s state.

3. Hypothesis development and the identification strategy

A. Hypothesis development

Dell’Ariccia et al. (1999) highlight the problems of asymmetric information in lending between incumbent banks and new entrants and show that the resulting adverse selection could be a significant barrier to entry. However, Althammer and Haselmann (2011) suggest that incumbent banks might lose their informational advantage in times of crises. They model an emerging market where domestic banks possess more soft information, while foreign banks have a superior screening technology that allows to screen borrowers using hard information. This model implies that foreign banks increase their market share when credit market conditions deteriorate because, which was confirmed by empirical evidence (Havrylchyk and Jurzyk, 2011).

Figure 2. Number of new FDIC-insured commercial bank charters in the US



Source: Statista

It might be that a similar scenario has been played out in the US after the global financial crisis. Total consumer credit significantly decreased in the years 2008-2011, partly due to the

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[9] Of the forty-six jurisdictions whose residents may obtain loans in the United-States, only seven states have no interest rate limitations on consumer loans (Arizona, Nevada, New Hampshire, New Mexico, South Carolina, South Dakota and Utah), while all other jurisdictions have a maximum rate less than the maximum rate offered by WebBank through online marketplaces.

deleveraging of insolvent banks. This should have forced creditworthy borrowers to search for new lenders, reducing problems related to adverse selection. However, the post-crisis period has been characterized by the plummeting of new FDIC-insured commercial bank charters (Figure 2) and the emergence of P2P lending (Figure 1). Koetter and Blaseg (2015) show that bank instability in Germany has pushed businesses to use equity crowdfunding as a source of external finance. Atz and Bholat (2016) attribute this to the tightening of the banking regulation and the spreading mistrust in the banks. On the credit supply side, as interest rates approached zero, retail lenders entered the market, attracted by the higher return (and risk) available from the exposure to P2P assets.

If mistrust of the banks is the main driving factor behind the growth of P2P lending, then the impact of the crisis could be long-term. In the survey of UK borrowers, in response to the question about the main advantages of borrowing from a P2P lending platform, 54% of Funding Circle's borrowers responded that it is 'Not my bank'.[10] The only response that was more popular was 'speed of securing finance' (58%). This suggests that the choice to use P2P lending platforms could be permanent even when banks deleverage and pick-up their credit supply.

Hypothesis 1: Financial crisis. P2P lending platforms expanded faster in markets that were more affected by the Global Financial Crisis.

The entry P2P lending platforms could also be related to the nature of the market structure.[11] Location models show that incumbent banks have an incentive for branch proliferation to such an extent that an entry with an additional network would become unprofitable (Vives 1991). There is abundant empirical evidence that market entry is lower in more concentrated banking markets and in markets with an extensive branch network (Hanweck, 1971; Rose, 1977; Adams and Amel, 2016). Branches are a form of advertising for banks and branch density could play an important role in the bank's advertising strategy to develop brand loyalty (Dick, 2007). Dick (2007) provides plenty of anecdotal evidence on how banks hope to attract customers using their branches, usually with stylish merchandising and customer service. For example, banks become more visible to consumers by putting clocks outside their branches. Dick (2007) shows that banks open branches mostly in response to their own market targets, as opposed to their existing customers' needs.

It is important to note that in the literature on the market structure and entry in the banking sector, entry is represented by new charter creation and branch expansion. Given the fact that P2P lending is done via a web-page, the entry into new markets is not physical and simply reflects a borrower's decision to ask credit from a P2P lending platform. Hence, the model of Vives (1991) does not apply. In this context, the measures of market concentration and branch density at the county level would proxy strategic barriers to entry related to advertising and brand loyalty .

Hypothesis 2: Market structure. P2P lending platforms expanded faster in areas with low

[10] Funding Circle is the largest P2P lending platform to small business, headquartered in the UK.
[11] The existing literature finds weak conclusions on the relationship between innovation and market structure (see the survey of Cohen and Levin, 2010). A number of theoretical studies (e.g., Gilbert, 2006) show that the competition innovation is monotonic only under restrictive conditions. On the one hand, innovation incentives should be lower in more concentrated markets because of the replacement effect identified by Arrow (1962). On the other hand, innovation incentives should be lower in more competitive environments because aggregate industry profits are lower. Aghion et al. (2005) demonstrate that the relationship between competition and innovation should have a nonlinear inverted U-pattern. Other studies include measures of entry and exit in the market (Geroski, 1989).

market concentration and branch density, which is related to strategic barriers to entry.

Finally, we need to look at learning costs that are borne by borrowers to use online platforms. Learning costs include search costs, cognitive effort, emotional costs, psychological risk, and social risk associated with the understanding of the new business model of P2P lending and building trust in it. They represent a part of switching costs, which are notoriously high in the banking sector (Honka, 2014; Stango and Zinman, 2016; Shy, 2002). Customer surveys find that despite being unsatisfied with their bank (negative net promoter score), the switching rates remain very low. If bank customers wanted to switch to an online platform, they would need to incur learning costs about P2P lending, as well as transaction costs to set up their profile and describe their loan (a task that is performed by their credit officer in a bank). Since our study is done in the homogeneous institutional environment in the context of switching to one of the two very similar lending platforms, financial and administrative switching costs should be similar across counties. However, learning and psychological switching costs could depend on local country level characteristics.

To proxy learning costs, we rely on educational attainment, population density and age, which have been shows to correlate with switching costs. Indeed, survey evidence shows that younger and more educated individuals were more likely to adopt electronic banking in the 90s, reflecting lower learning costs (Kennickell and Kwast, 1997; Tesfom and Birch, 2011). The same survey shows that the most popular source of information for saving and borrowing decisions is calling around friends, relatives, and colleagues. Hence spatial effects could reflect human interactions that lower learning and psychological costs and speed up technological diffusion.

Finally, concentrated markets could also be a sign of high psychological switching costs due to brand loyalty. Indeed, customers living in counties with only one bank might be less exposed to advertising from rival banks and be less familiar with people who are customers at other banks. This might develop strong brand loyalty because bank customers are less familiar with other alternatives and have lower incentives to search for an alternative to their bank.

Hypothesis 3: learning costs. The expansion of the P2P lending platforms is faster in countries with more educated, urban and young population, which is related to lower learning and psychological switching costs.

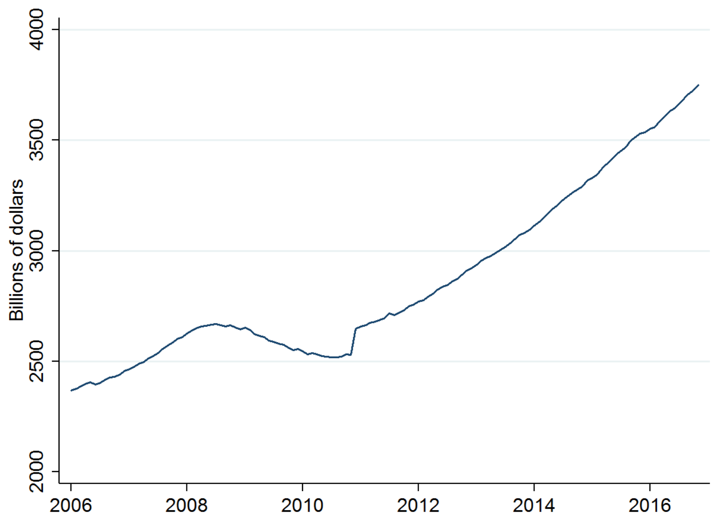
Importantly, our study explores barriers to entry that operate at the county level. Legal and regulatory barriers will be captured by state dummies. Structural barriers, such as scale and scope economies that operate at the platform level cannot be explored in our study.

B. Identification strategy

Identifying between the above three hypotheses is very difficult for at least two reasons. First, the data show very little annual variation in the market concentration and branch density before the crisis. Socio-demographic variables that are correlated with learning costs are also fairly constant over time. Moreover, their measurement is based on survey data and due to limited number of annual observations, to obtain reliable data at the county level we need to average data over several years.

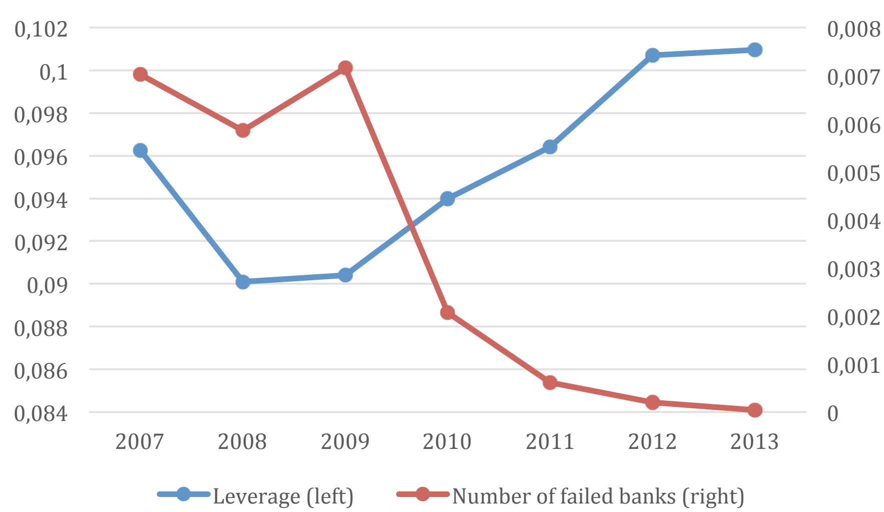
Second, the Global Financial Crisis has been the most influential force during the last decade and the variation in many of our variables of interest is related to it. The number of failed banks peaked in 2007-2009 and has fallen virtually to zero afterwards (see Figure 3). The leverage ratio has collapsed during 2008-2009 and has only recovered after massive banks' recapitalizations (see Figure 3). The stock of consumer loans originated by banks has fallen for a number of years, before starting to pick up at the end of 2011 (see Figure 2). In reaction to the crisis, the US banks have engaged in a wave of mergers and acquisitions, as less stable firms were acquired by those that were better prepared to withstand the crisis (see Figure 4). Also, the need to increase cost-efficiency has forced banks to close bank branches. Branch density has been stable before the crisis but has been falling steadily since 2009 (see Figure 4).

Figure 2: Total consumer loans in the USA in billions of dollars



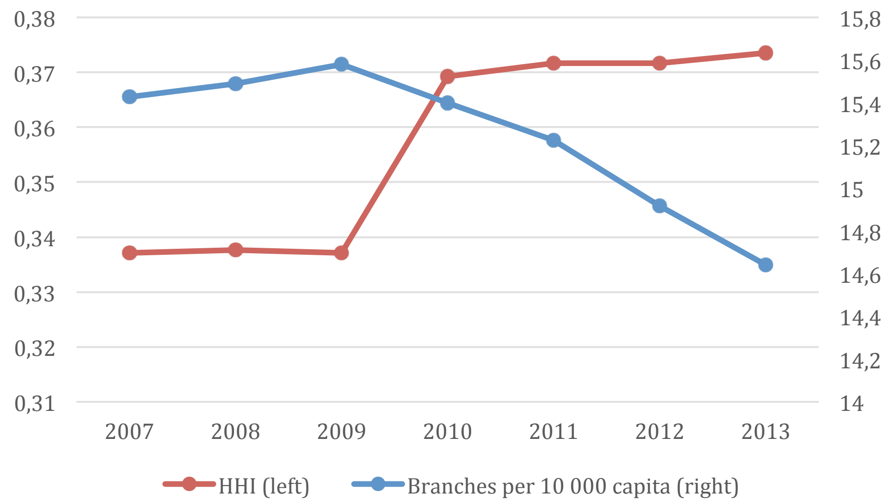
Source: Federal Reserve Bank of Saint Louis

Figure 3. Leverage ratio and number of failed banks



Source: Call reports and authors' calculations.

Figure 4. Market concentration and branch density



Source: Call reports and authors' calculations.

In this context, our identification strategy cannot rely on the time variation of our variables. Instead, we will explore the geographic variation at the county level. The county unit is the standard definition of the local banking market in the literature (e.g., Hannan and Prager, 1998; Berger, Demsetz, and Strahan, 1999; Rhoades, 2000; and Black and Strahan, 2002). Our choice to use cross-sectional analysis is further justified by our interest in the long-term impact of the Global Financial Crisis.

Since P2P lending activity happens online, one might think that the geographic location of borrowers does not matter anymore. However, human interactions lower learning costs, which is crucial for the diffusion of any new technology (Comin et al., 2012). Borrowers from P2P lending platforms need to acquire knowledge about their existence, as well as to build trust in their reliability. This often comes from interactions with other agents and the frequency and success of these interactions is likely to be shaped by geography, leading to spatial correlation in the P2P lending expansion. Our data allows us to explore local banking markets at the county level. Figure 5 attests to the importance of spatial correlation by showing that borrowing from P2P lending platforms is clustered regionally.

Model specification: a spatial autoregressive model

To test our three hypotheses on the adoption of P2P lending in the presence of spatial correlation at the county level, we specify the following Spatial Autoregressive Model with Autoregressive Disturbances (SARAR) (See Anselin, 1988):

$$y_i = \beta_0 + \lambda \mathrm{W} y_j + \beta_1 * market\ structure_i + \gamma_1 * crisis_i + \delta_1 * learning\ costs_i + \alpha * X_i + \mathrm{u}_i;$$

where

$$\mathrm{i}, \mathrm{j} = 1, \dots, \mathrm{n};$$

and

$$u_i = \rho W u_j + \varepsilon_i, \qquad \text{with } \varepsilon_i \sim \mathrm{N}(0, \sigma^2 \mathrm{I}).$$

In the equation above, i and j represent the n counties; y_i is the log of our observed dependent variable, that is the logarithm of the average for the years 2006-2013 of the volume of P2P lending (or the number of P2P loans) per county per capita; W= $\sum_{j=1}^{n} w_{ij}\, y_j$ is a weighted average of our dependent variable, known as a spatial lag, in which the weights are determined by an N × N spatial weights contiguity matrix where w_{ij} the coefficient of line i and column j expresses the degree of spatial proximity between county i and county j[12]; λ is the unobserved spatial autoregressive coefficient; β_1 is the coefficient of our variables regarding market structure; γ_1 is the coefficient of our independent variables regarding the banking crisis; δ_1 is the coefficient of our independent variables regarding the learning costs; α is the coefficient for other socio-economic and demographic variables that could capture demand for P2P lending (See Table 1 for the detailed list of observed independent variables); ρ is the unobserved spatial autoregressive coefficient as, in our model, we allow the error term to be affected by the disturbances of neighbors; ε_i and u_i are unobserved error terms.

Thus, this model specification accounts not only for spatial correlation of the dependent variable, but also for spatial correlation within the error terms, which could be affected by unobservable factors such as regional economic cycles, or because of a boundary mismatch problem, that is when the economic notion of a market does not correspond well with the county boundaries (Rey and Montouri, 1999). Ignoring spatial relation, in this case, could potentially lead to inconsistency in the standard errors. To compute our cross-sectional spatial regressions, we use the Maximum-Likelihood Estimator method, as the OLS estimation will be biased and inconsistent due to simultaneity bias. As a matter of fact, the spatial lag term must be treated as an endogenous variable since the volumes of loans in contingent counties are simultaneously impacting one another (See Anselin, 2003 and LeSage and Pace, 2009 for a theoretical explanation on why MLE solves the simultaneity bias).[13]

Our main coefficients of interest are β, γ ,δ and α that measure the short-term impact of market structure, crisis variables, learning costs, as well as other socio-economic and demographic variables on the adoption of P2P lending in each county. Finally, λ measures whether the adoption of P2P lending in a given county positively impacts neighbour counties. If this coefficient is significantly greater than 0, we can conclude that there is a positive correlation between the adoption of the P2P lending between neighbouring counties.

4. Data, maps and descriptive statistics

To construct variables about the diffusion of P2P lending, we rely on loan book data from Lending Club and Prosper Marketplace. For Lending Club we have 376 261 observation points, corresponding to a total volume of funded loans equal to \$3.2 billion, starting from January 2007 to December 2013. This amounts to 99.25% of the Lending club portfolio. For Prosper we have 88 988 observation points, corresponding to a total volume of originated loans equal to \$662 million, starting from January 2006 to 30 October 2013. This amounts to 100% of the total Prosper portfolio. There are 313 counties with zero P2P loans in our final dataset.

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[12] The matrix W we use is a "minmax-normalized" matrix, where the $(i,j)^{th}$ element of W becomes $w_{ij} = \frac{\mathrm{wij}}{m}$, where $m = \{max_i(\mathrm{r}_i), max_i(\mathrm{c}_i)\}$, being $max_i(\mathrm{r}_i)$ the largest row sum of W and $max_i(\mathrm{c}_i)$, the largest column sum of W. We also use the inverse-distance matrix composed of weights that are inversely related to the distances between the units, and we obtain similar results in our regression. Obtaining similar results with an inverse-distance and a contiguity matrix is consistent with the findings of LeSage and Pace, 2010.

Our analysis ends in 2013, because platforms stopped providing city names afterwards to allegedly avoid racial discrimination. This allows us to focus on the initial years of the P2P lending expansion, avoiding an endogeneity problem related to reverse causality or simultaneity bias.

Since loan book data provide information on each borrower's city, we can assign a county name to each borrower by matching with an official data containing US States, cities and counties.[14] Due to missing values and mistakes in city names, we lose 4.8% of the volume of funded loans in the Lending Club dataset and 10% from the Prosper dataset. Next, for the purpose of descriptive statistics, we aggregate this data at the year-county level to construct a measure of P2P lending diffusion: volume of P2P lending per capita. For large cities belonging to multiple counties, we split the total data between counties weighted by total income per county.

Table 1 shows the total volume of funded loans, the number of counties and the total number of loans that we have in our dataset. The decline in activity of the Prosper in 2009 is due to the "cease and-desist" order issued by the SEC, as it is explained in Section 2. This is also another reason to avoid the use of temporal dimension of the data and to focus on the geographic heterogeneity.

Table 1: Our dataset (loan volumes, number of counties and loans)

Lending Club	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**
Volume (in mln $)	0	2	13	46	116	257	718	2064
N. of counties	0	110	379	676	987	1359	1836	2384
N of. loans	0	246	1488	4500	10594	19861	49811	137824

Prosper	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**
Volume (in mln $)	29	81	69	9	27	75	154	217
N. of counties	673	1175	1377	631	1029	1397	1739	1721
N. of loans	6145	11592	11683	2118	5864	11508	20054	21990

Data source: Lending Club and Prosper loan books

We can now map the depth of the P2P development at the county level for each year (see figure 5). As early as 2007, 1183 counties had P2P borrowers, and their number increased to 1881 in 2010 and to 2609 in 2013. Visual map exploration allows us to observe the importance of spatial interactions.

For cross-sectional regressions, we aggregate annual data for each county and, then, merge our dataset with other datasets that contain our explanatory variables. Our specification accounts for a large number of county characteristics that could influence the expansion of the P2P lending.

Crisis variables

To measure the effects of the financial crisis on the adoption of the P2P lending, we rely on two measures. First, we compute the share of deposits in each county affected by bank failures

[14] We use the Americas Open Geocode (AOG) database. Source: http://www.opengeocode.org/download.php.

during the analyzed period. To do this, we merge FDIC Failed Bank List with the data on branches of these banks in each county from the FDIC Summary of Deposits. This is an exhaustive database about all branches of deposit taking institutions in the US, providing data on the amount of deposits at the branch level. We then compute the share of deposits held by failed banks in a county *i* in the total amount of deposits held by all banks in a county *i* as of 31 December, 2013. As shown by Aubuchon and Wheelock (2010), there is a wide geographic heterogeneity with respect to bank failures in the US and it is possible that customers from counties that have been the most affected by the crisis have relied more on alternative credit providers. If our *crisis-related hypothesis* is confirmed, we expect a positive sign on this variable.

Our second measure of the depth of the financial crisis takes into account banks' solvency. To do so, we use Call Reports' data that reports solvency ratios at the consolidated level and then weight this data by the share of each bank's branches present in each county from the FDIC Summary of Deposits. This measure is based on the assumption that banks' capital management is performed at the consolidated level (De Haas and van Lelyveld, 2010). We rely on two measures of solvency (unweighted leverage ratio and risk-weighted Tier 1 capital ratio) calculated at the peak of the crisis, 2009-2010[15]. Solvency ratio of a county *i* is computed as an average capital ratios of banks present in a county *i* weighted by deposits of their branches in county *i*. If our *crisis-related hypothesis* is confirmed, we expect a negative sign on this variable.

Measuring market structure and entry barriers

The FDIC Summary of Deposits allows us to calculate a number of market structure variables that are used as proxies for entry barriers. In particular, we compute branch density per 10000 population, HHI and C3 indices for deposits at the country level. To avoid endogeneity problems related to reverse causality (i.e. financial crisis has led to a more concentrated market structure), we calculate these variables for 2007. We also measure the entry of other alternative credit providers, such as pay-day lender, which could be a proxy for entry barriers. To do so, we use County Business Patterns to construct the ratio of non-bank establishments that are related to consumer lending and credit intermediation per capital (Bhutta, 2013).

Socio-demographic characteristics to control for learning costs

To measure socio-demographic characteristics of the population, we rely on 5-year averages (2009-2013) from the American Community Survey, the only data available at the county level. Due to lower learning costs, we expect that counties with higher educational attainment, higher population density and higher proportion of young people, should have higher levels of P2P lending penetration because human capital and network effects of urban areas are significant predictors of the technological diffusion.

Measuring openness to innovation and new communication and informational technologies

To proxy for openness to innovation, we use U.S. Patent and Trademark Office data to calculate the number of patents per capita. This measure is often used as a measure of innovation and, as such, it has a number of shortcomings, since some innovations are not patented and patents differ enormously in their economic impact. Nonetheless, our objective is

[15] We define these two years as crisis years because bank capital ratios and loan growth were at the lowest and bank failures and credit-card delinquencies at the highest during this period. This allows us to capture the severity of the crisis.

not to measure innovation per se, but rather to account for a local culture that has a high propensity to generate innovative ideas and, hence, accept innovative ideas of others. Such culture could be more open to new forms of financing though P2P lending. To measure internet penetration at the county level, we rely on the NTIA's State Broadband Initiative that allows us to compute the percent of county population with access to optical fiber technology.[16] Since these data are available from a survey, it is computed as an average between 2010 and 2013, the only data available at the county level. We expect these variables to have a positive sign, reflecting the fact that P2P lending is part of the revolution in the information and communication technologies.

Other variables

To account for the credit demand, we control for the average income per capita, unemployment rates, poverty rate and race. We have no theoretical priors about the direction of the relationship. The demand of racial minorities for online lending could be higher because race identification is no longer possible on P2P lending platforms.[17] Racial identification was possible during earlier years of the P2P lending when borrowers had the possibility to post a picture. This has led to the well-documented discrimination of racial minorities on the Prosper lending platform (Pope and Sydnor, 2011; Ravina, 2012; Duarte et al., 2012). Consequently, platforms have removed the possibility of posting a photo, which has made the identification of borrowers' race impossible. This could have incentivized racial minorities to turn to the P2P platforms to avoid discrimination that occurs in traditional credit markets (see a literature review by Pagern and Shepherd, 2008).

We introduce state level dummies to control for differences in state-level regulation of consumer lending and P2P lending platforms, as well as other state characteristics that are not captured by our county-level variables. These dummies account for the fact that Iowa was closed for borrowers from both Lending Club and Prosper platforms, while Maine and North Dakota were closed for Prosper platform.

Overall, we have sufficient cross-sectional data for 3,060 out of 3,144 counties and county equivalents. Table 2 provides exact definitions of all variables, Table 3 provides summary statistics and Table 4 provides the correlation matrix.

5. Empirical results

The SARAR model estimates cannot be interpreted as partial derivatives like in the typical regressions, because a unit change in the explanatory variable is likely to affect the dependent variable in all neighboring regions too (see Le Sage and Pace, 2009). Hence, we first discuss the short-run impacts of a change in the explanatory variables on the volume of P2P lending per capita in each county. Then, we compute the average direct impact, the average indirect impact and the average total impact, which is the sum of the direct and indirect impacts. We also consider their economic significance.

Short run results

[16] We also computed a share of the population that have access to broadband technology, Mobile Wireless (Licensed) technology, as well as various measures of internet speed, such as percent of county population with access to upload speed 50 mbps or higher.

[17] However, the platforms have removed the possibility of posting the photo, which has made the identification of borrowers' race impossible.

In Table 5 and Table 6, we present our empirical findings for the adoption of P2P lending (in terms of volume and number of loans respectively) as a function of different county characteristic. First of all, we note that the estimates for the coefficients ρ and λ are significantly different from zero, pointing to the existence of strong spatial effects. In other words, a higher level of P2P lending in one county leads to a higher level of P2P lending in the contingent counties. Hence, our choice to use SARAR model was correct and ordinary least-squares would have led to inconsistent estimations.[18]

Our findings show that in all specifications, the leverage ratio is statistically significant and has a negative effect on P2P lending expansion. These results support our *Financial Crisis Hypothesis* that P2P lending platforms enter countries that are more affected by the Global Financial Crisis and have more undercapitalized banks. However, other proxies for the depth of the financial crisis are not statistically significant. Neither the share of deposits affected by failed banks nor the Tier 1 capital ratios during the crisis had an impact on the diffusion of P2P lending. The lack of significance for the risk-weighted Tier 1 capital adequacy is consistent with the idea that a weighted capital ratios appear to be worse predictors of future banks' performance than unweighted measures (Blundell-Wignall and Roulet, 2013; Haldane, 2011a, 2012). This is because risk weights are inconsistent and subject to frequent manipulations (Mariathasan and Merrouche, 2014; Le Leslé and Avramova, 2012; Haldane 2012; FSA, 2010).

Turning our attention to the market structure, we find that high market concentration (C3 and HHI) and high branch outreach of traditional banks appear to deter the adoption of the P2P credit. As explained earlier, the presence of branches could be considered as an advertisement strategy that increases brand loyalty to banks. This supports our *Barriers to Entry Hypothesis* (H2) and is also in line with earlier literature on the entry of new banks. Importantly, branch density could also measure financial isolation or the outreach of the financial sector in terms of access to banks' physical outlets (Benfratello et al., 2008; Beck et al., 2007). Hence, its negative impact would also be consistent with the idea that P2P lending platforms are used by customers that are underserved by traditional banks. We additionally test the contestability hypothesis by looking at the impact of the alternative consumer credit providers, such as payday loans. The evidence that P2P lending is diffused in counties with a higher number of payday loan establishments is not robust across specifications and need to be explored further.

As expected, among socio-demographic variables that could impact learning costs, we find that the expansion of the P2P lending is faster in counties with higher population density, higher educational attainment and higher share of young population. The positive effect of the higher educational attainment is consistent with the fact that human capital is a significant predictor of the technological diffusion and could diminish learning costs. A positive effect of population density reflects the existence of network effects in urban areas that is another well-known predictor of the diffusion of new technologies. Similarly, the presence of young population could also reflect a higher willingness to adopt new technologies. Our results are in line with our *Learning Costs Hypothesis*.

Among other socio-economic variables, lower levels of poverty and income per capita, as well as higher unemployment rates and share of Hispanic minorities increase the expansion of the P2P lending. The direction of the impact of these economic variables reflects different credit

[18] If we estimate the OLS regression model and compare these estimates to the output from our SARAR model, we realize that OLS estimates are mostly biased up-words as in Lesage (2008). Results are available upon request.

demand and supply factors. Our finding that the expansion of the P2P lending is faster in counties with higher share of Hispanic minorities could be a sign of higher demand from these areas to escape discrimination in traditional credit markets. However, we do not see this effect for Black minorities. A higher share of P2P lending in counties with Hispanic minorities could also reflect the fact that informal lending markets are widely spread among this minority and that P2P lending could be an opportunity to switch from informal to formal P2P lending.

We now turn our attention to variables that capture the geographic heterogeneity in terms of innovation, measured by the quality of Internet connection and by the number of patents issued by each county. None of these variables is a statistically important driver for the entry of the P2P lending platforms. This is an interesting result because it means that the entry of the P2P lending is not a technological phenomenon, but rather an economic one.

Sensitivity analysis

As it was discussed earlier, Prosper Marketplace was the first platform to enter the US credit market and a large part of the Prosper's lending in our sample has been done in 2006-2008. It has then experienced a sharp decline in 2008-2009 due to the regulatory uncertainty about its legal status, followed by a slow expansion since 2010 and losing market share to the Lending Club. As discussed earlier, two platforms appear to have slightly different development strategies and target different clients (Mariotto, 2016).

In this context, we estimate our preferred specification in column 2 separately for Prosper Marketplace and Lending Club (Table 7). The development of two P2P lending platforms could be explained by different local characteristics for at least two reasons. First, two platforms might pursue different strategies and target different borrowers. Second, different drivers could be important at the early and later stages of the P2P development. To further account for the time dimension, we estimate the model separately for every year (Table 8). This is important because in the context of the exponential growth of the P2P lending, loans extended in 2013 represent almost 60% of the total lending since 2007 (Table 5).

Our results in Tables 7-8 show that a large part of our findings holds for both platforms and for all years. In particular, we find that market concentration play a similar negative role for the expansion of the two P2P lending platforms and throughout the whole analyzed period. The impact of the population density, education, poverty, unemployment also does not change.

At the same time, some salient differences are documented. Some of the drivers are only important for Prosper and their significance disappears with time. For example, banks' leverage impacts the adoption of P2P lending via Prosper, but not via Lending Club (Table 7). This could be due to the fact that Prosper entered the market at the peak of the crisis when banks were cutting their credit supply due to high leverage and, hence, Prosper was able to target clients excluded from the banking credit. This is confirmed by year-by-year estimations in Table 8 that show that leverage was an important driver of the P2P lending during the initial years, but its impact weakened and has completely disappeared in 2013. A similar pattern is exhibited by the share of the young population, which could be a sign that young people were more enthusiastic about the new technology at the beginning, but the impact of age disappears as the knowledge about the technology becomes mainstream. P2P lending via Prosper has also expanded faster in counties with higher share of payday loans and lower income, which might reflect a riskier target group (Mariotto, 2016).

Other factors have become statistically significant only at the later stage. For example, low branch density has become an important factor starting in 2010. This is consistent with the idea that the diffusion of new technologies could be slower in more isolated counties, even though it is the most useful in these areas. But, once the new technology becomes general knowledge, customers in counties underserved by banks make use of it.

In Section 3, we have argued that the use of panel data is not appropriate for our analyses due to endogeneity problems related to the fact that market structure and branch density have been profoundly affected by the financial crisis of 2007/2008. However, due to transparency concerns, we report results of the fixed effects panel model in Table 9. The results suggest that an increase in bank leverage ratio reduces the adoption of P2P lending, which is consistent with our earlier findings in cross-sectional models. At the same time, panel results show that there is a positive relationship between market structure and the adoption of P2P lending. This is in contrast to our cross-sectional results, but the lack of robustness was expected. As explained earlier, counties that have witnessed increased market concentration and market density are also those that have suffered the most from the financial crisis. Hence, panel data results that show that an increase in market concentration is associated with higher P2P lending volumes could be interpreted in support of the Financial Crisis Hypothesis. Please, note that panel data model excludes variables that are proxies for learning costs, because these data comes from surveys that are not available at an annual level.

Marginal effects

Following the method proposed by Drukker et al. (2013) and LeSage and Pace (2008), we compute the average direct impact, average indirect impact and average total impacts of the explanatory variables on the volume of the P2P lending using the reduced-form predictors coming from the SARAR regression.

The Average Direct effect – averaged over all *n* counties provides a summary measure of the impact arising from changes in the *i*th observation of variable x. For example, if the solvency of county *i*'s banking sector increases, what will be the average impact on the P2P lending volume in county *i*? This measure will take into account feedback effects that arise from the change in the *i*th county's banking leverage on the P2P lending volumes of neighboring counties in the system of spatially dependent counties. The Average Indirect effect could be used to measure the impact of increased banks' leverage in all other counties on the P2P lending volumes of an individual county, again averaged over all counties. Finally, the Average Total effect is a sum of the Average Direct effect and Average Indirect effect. This measure has two interpretations. According to the first interpretation, if banks' leverage in all counties increases, what will be the average total impact on P2P lending of a typical county? This total effect will include both the average direct impact plus the average indirect impact. According to the second interpretation, it measures the total cumulative impact arising from an increase of the banks' leverage in one county on P2P lending volumes of all other counties (on average).

The results reported in Table 10 and Table 11 show that while around 77% of the average total impact is direct, the indirect impact is still very important at around 23% of the total impact. Hence, taking into account spatial correlations is crucial to have unbiased results.

To calculate the economic impact, we can consider the impact of one standard deviation change in our variables of interest. For example, an increase of one standard deviation in branch density, HHI and banks' leverage produces, respectively, an average total effect of 29%, 48% and 17% on the P2P lending volumes. Hence, the impact of these factors is not only statistically significant but also economically relevant.

6. Concluding remarks

This paper is a first attempt to explore the drivers of the entry and early expansion of P2P lending platforms in the US. We have proposed three hypotheses related to (1) competition and barriers to entry, (2) the consequences of the financial crisis and (3) learning costs. We also account for spatial effects and socio-economic and demographic characteristics. Our findings are broadly consistent with the idea that P2P lending platforms have made inroads into counties that are underserved by banks and that their entry has been constrained by entry barriers and learning costs.

Having controlled for demand factors, we find that borrowers from counties with lower leverage ratios are likely to borrow more from P2P lending platforms. This finding is consistent with the hypothesis that P2P lending platforms have partly substituted banks that have cut their credit supply. Importantly, we show that the impact of the low leverage at the peak of the crisis was long-term and has only disappeared in 2013.

We also find that the entry of P2P lending is constrained by the high market concentration and branch density of incumbent banks. This has been interpreted in the earlier literature as entry barriers. Lower branch density could also be a measure of the financial exclusion, reflecting the fact that borrowers that live far away from a brick and mortar bank branch or have a poor branch experience due to long waiting times are more likely to turn to online lenders.

We document that counties with higher population density, as well as a higher share of educated and young people experience higher growth of P2P lending. Despite the online nature of the P2P lending, spatial effects play a crucial role, which could be another indication that learning costs are lowered by social interactions that allow to build trust in online markets.

Interestingly, although P2P lending platforms require access to internet, we do not find any robust impact of Internet penetration on the expansion of the P2P lending. Neither do we find that openness to innovation, measured by number of patents per capita, is significant associated with P2P lending. Hence, our results suggest that P2P lending is not a niche market, driven by new technology, but could be a substitute to banks' lending.

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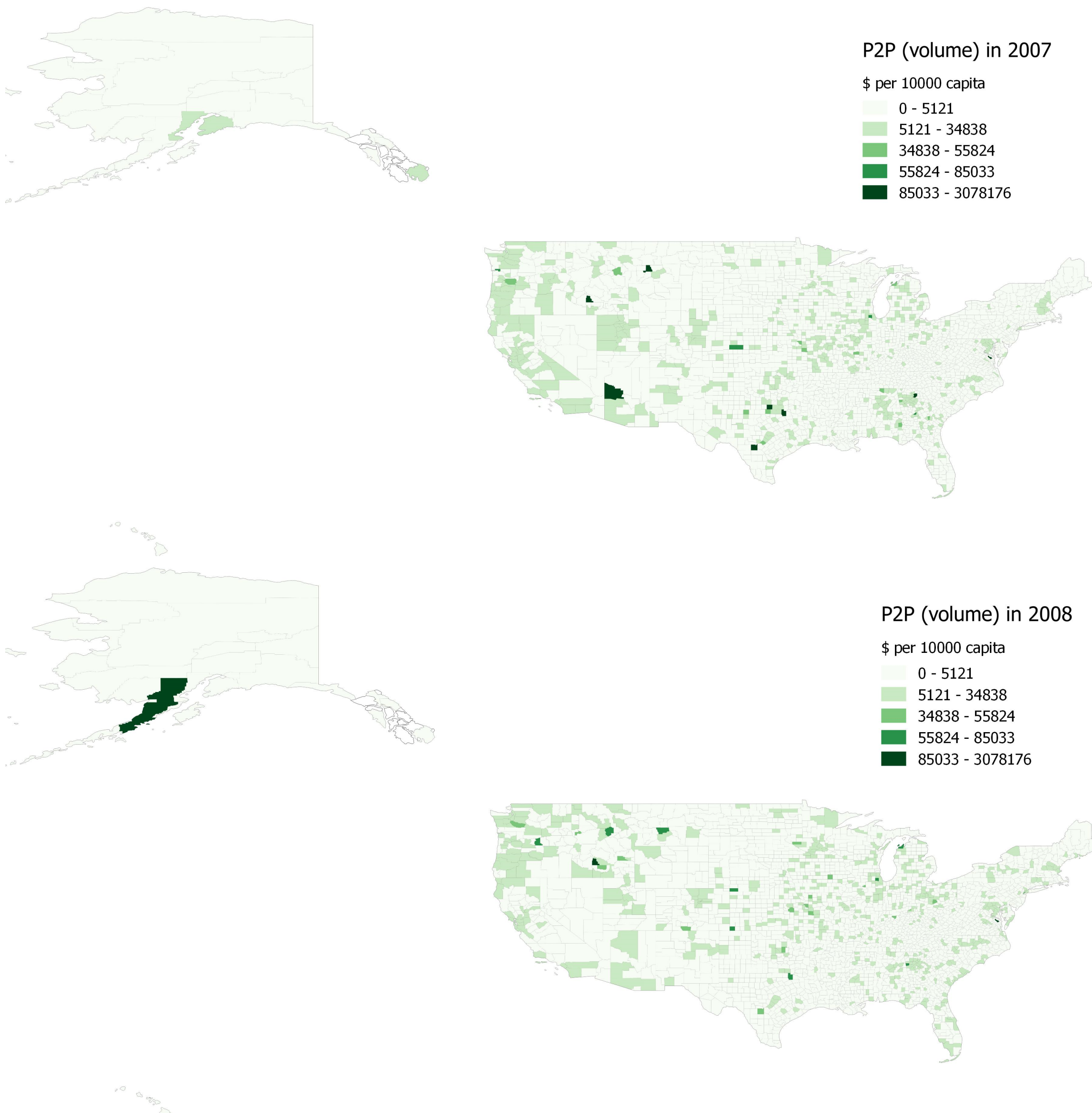
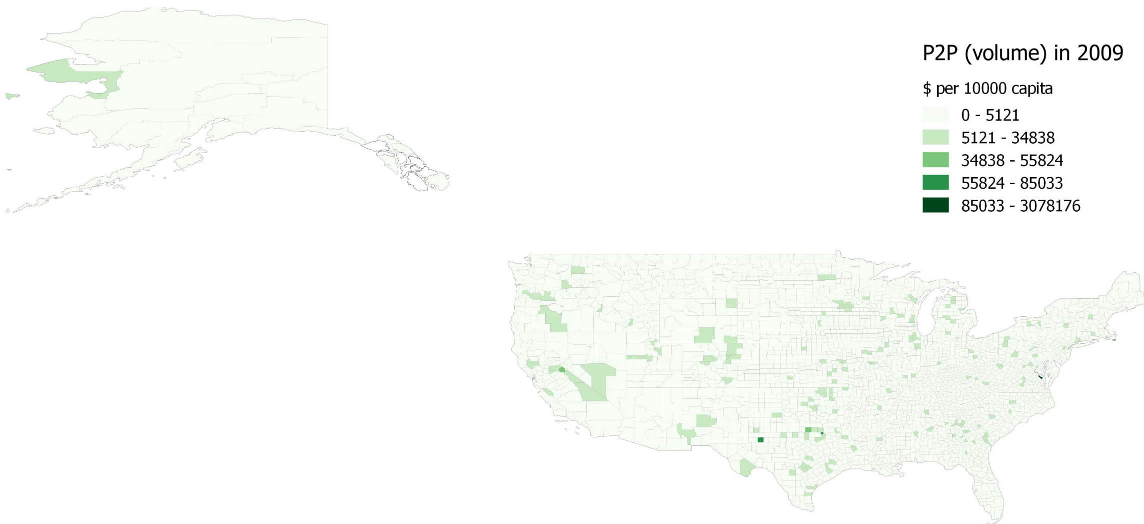
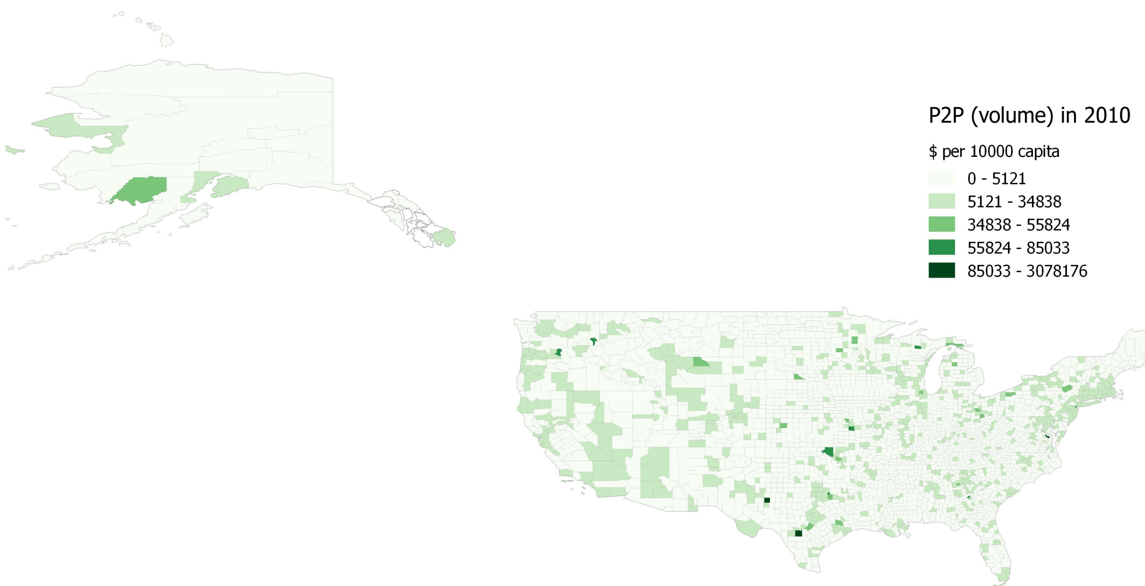
Figure 5: Depth of the P2P development at the county level during 2007-2013




P2P (volume) in 2009
$ per 10000 capita
0 - 5121
5121 - 34838
34838 - 55824
55824 - 85033
85033 - 3078176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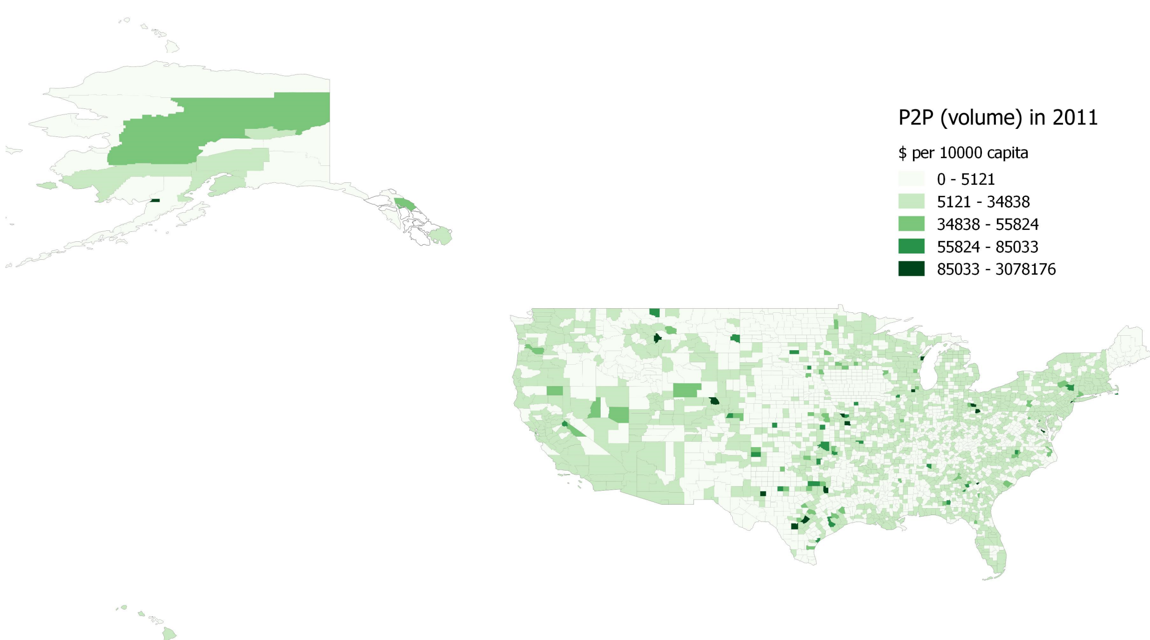
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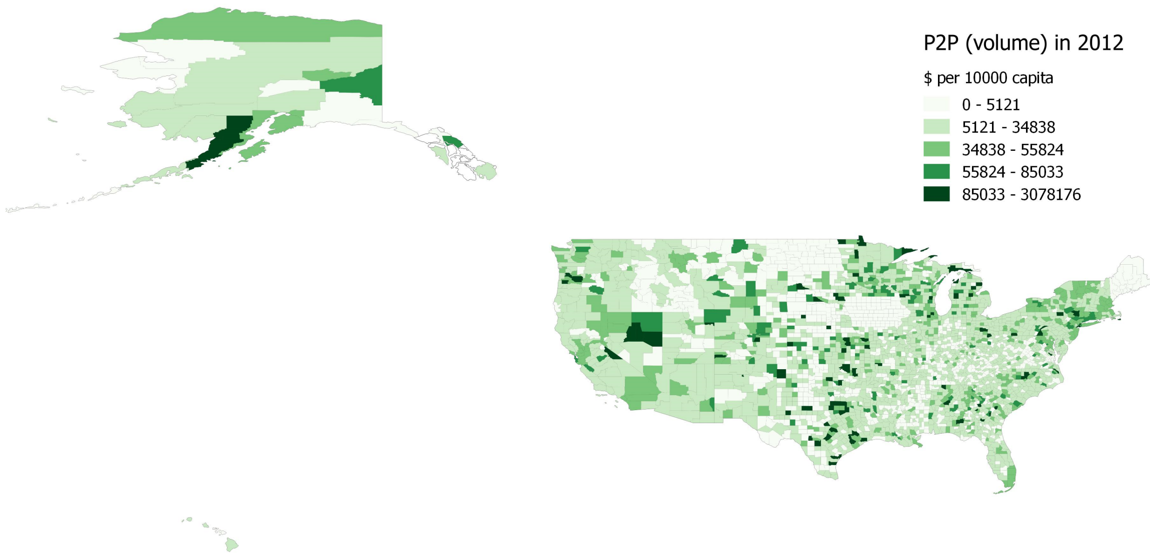
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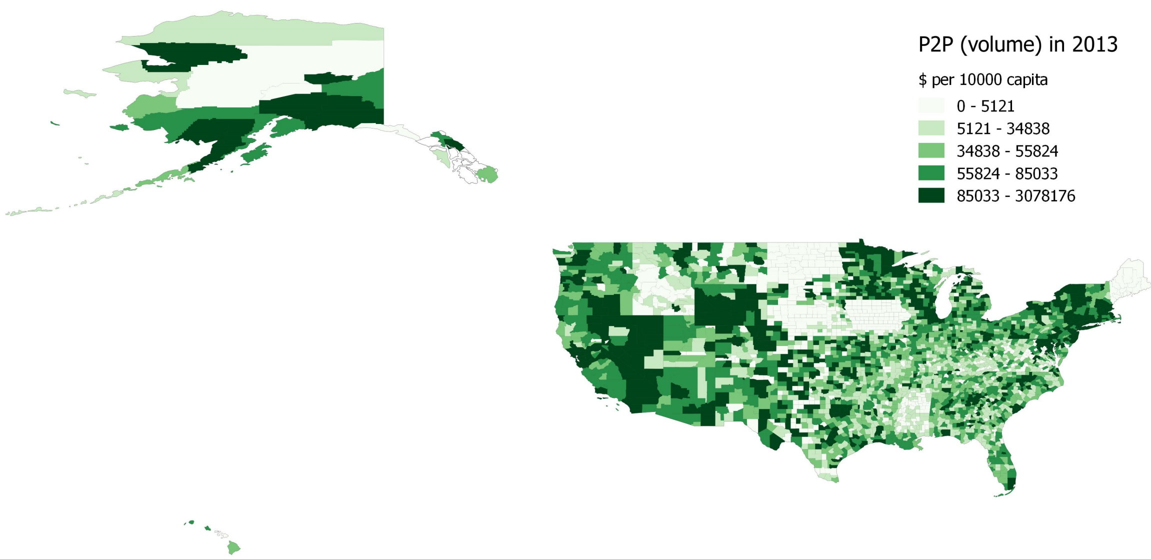
P2P (volume) in 2013
$ per 10000 capita
0 - 5121
5121 - 34838
34838 - 55824
55824 - 85033
85033 - 3078176

Table 2. Variable definitions and data sources

Variable	Definition and data source	Expected sign
Dependant variables		
P2P (volume)	Logarithm of the sum of lending from Prosper and Lending Club aggregated for the period 2006-2013 at the county level per 10 000 population Sources: Prosper and Lending Club	
P2P (number)	Logarithm of the sum of the number of loans from Prosper and Lending Club aggregated for the period 2006-2013 at the county level per 10 000 population Sources: Prosper and Lending Club	
Crisis, financial inclusion and market structure variables		
HHI	Herfindahl-Hirschmann index, computed in terms of deposits Source: FDIC Summary of Deposits	? -
C3	The share of deposits of the three largest deposit taking institutions in a county Source: FDIC Summary of Deposits	? -
Branches per capita	Number of branches in a county divided per 10 000 population Source: FDIC Summary of Deposits	-
Pay Day loans	Number establishment divided by 10 000 population. Non-depository consumer lending (NAICS: 522291) Other activities related to credit intermediation (NAICS 522390) Source: County Business Patterns	?
Leverage	The average leverage ratio of deposit taking institutions present via branches in a county weighted by the deposit share of their branches in a county, calculated during crisis years of 2008-2009. Source: FDIC Call Reports, Summary of Deposits	-
Tier 1 capital	The average Tier A capital ratio of deposit taking institutions present via branches in a county weighted by the deposit share of their branches in a county, calculated during crisis years of 2008-2009. Source: FDIC Call Reports, Summary of Deposits	-
Failed	% of deposits affected by bank failures in a county during the whole period. Source: FDIC Failed Bank List	-
Other variables		
Patents	Number of patents per 10 000 population Source: U.S. Patent And Trademark Office	+
Optical Fiber	% of county population with access to any broadband technology (excluding satellite) Source: NTIA's State Broadband Initiative	+
Young	The share of the population between 20-34 years Source: American Community Survey 5-year average (2009-2013)	+
Density	Logarithm of the population number divided by area in sq. m. in a county Source: Bureau of Economic Analysis for the population and United States Census Bureau (2013 TIGER/Line Shapefiles) for the area in sq.m.	+
Bachelor	% of county population with at least bachelor education Source: American Community Survey 5-year average (2009-2013)	+
Income	Logarithms of the average income per capita	?
Poverty	% of county population below poverty line Source: American Community Survey 5-year average (2009-2013)	?
Black	% of Afro-Americans in the county population Source: American Community Survey 5-year average (2009-2013)	?
Hispanic	% of Hispanic population in the county population Source: American Community Survey 5-year average (2009-2013)	?

Table 3. Summary statistics

Variable	Obs	Mean	Std.Dev.	Min	Max
P2P (volume)	3060	10.2928	3.294692	0	15.62018
P2P (number)	3060	1.38062	0.909318	-2.49955	6.112221
Crisis and market structure					
Leverage	3060	.090194	.0153371	.0405	.3255
Capital	3060	.1446588	.0502291	.0589	1.906835
Tier1	3060	.1434987	.0780078	.0580676	3.989462
Failed	3060	.0271653	.0933649	0	1
Branches per capita	3060	15.67731	17.17924	0	216.7444
HHI	3060	.3148341	.207403	.0533844	1
C3	3060	.7723359	.1865374	.2780705	1
Payday	3060	1.069424	1.314348	0	15.12859
Other variables					
Patents	3060	1.427546	1.235019	-1.535732	6.042779
Internet	3060	.1005509	.2101428	0	1
Poverty	3060	.1676631	.0617531	.032	.501
Income	3060	10.42882	.22329	9.608138	11.97169
Unemployment	3060	7.58592	2.508063	1.714286	25.51429
Density	3060	-1.802359	1.681683	-7.923973	5.594537
Bachelor	3060	.1667143	.0770384	.0382	.6025
Black	3060	.0882268	.1442539	0	.8523
Hispanic	3060	.0515506	.052103	.0025	.3627
Young	3060	.1868046	.0204911	.1103	.3412

Table 4: Correlation matrix

	P2P	Branches	HHI	C3	Payday	Leverage	Capital	Tier1
Branches	0.0713	1.0000						
HHI	-0.3165	-0.2599	1.0000					
C3	-0.2932	-0.3317	0.7815	1.0000				
Payday	0.1193	-0.0135	-0.1886	-0.1527	1.0000			
Leverage	-0.1308	0.0623	0.1094	0.1181	-0.0604	1.0000		
Capital	-0.0287	0.0722	0.0669	0.0614	-0.0193	0.6534	1.0000	
Tier 1	-0.0012	0.1007	0.0267	0.0308	0.0050	0.4110	0.8742	1.0000
Failed	0.0101	-0.0819	0.0666	0.0260	-0.0387	-0.1353	-0.0851	-0.0197
Patents	0.1955	0.3442	-0.3711	-0.4910	-0.1144	-0.1068	-0.0488	0.0000
Density	0.3521	0.4530	-0.5862	-0.6207	0.2144	-0.1308	-0.0313	0.0195
Internet	-0.0447	0.2044	-0.0301	-0.0509	-0.0584	0.0575	0.0549	0.0662
Poverty	-0.0538	-0.1756	0.2160	0.2840	0.3305	0.0249	0.0305	0.0276
Income	-0.0179	0.4301	-0.2062	-0.3038	-0.1913	0.0198	0.0138	0.0220
Unemployment	0.1946	-0.0945	-0.0102	0.0459	0.1933	-0.0933	-0.0365	-0.0168
Bachelor	0.1530	0.4171	-0.2692	-0.4215	-0.0481	-0.0946	-0.0304	0.0087
Black	0.0386	0.0381	0.0108	0.0496	0.3737	-0.0113	0.0087	0.0239
Hispanic	0.1404	0.0688	-0.0636	-0.1401	0.0856	-0.0392	0.0262	0.0421
Young	0.1814	-0.0051	-0.2131	-0.1936	0.2917	-0.0772	-0.0332	-0.0026

	Failed	Patents	Density	Internet	Poverty	Income	Unemployment	Bachelor
Patents	-0.0226	1.0000						
Density	-0.0188	0.4535	1.0000					
Internet	-0.0249	0.1285	0.0518	1.0000				
Poverty	0.0320	-0.4789	-0.0900	-0.1397	1.0000			
Income	-0.0955	0.4868	0.1570	0.2561	-0.6752	1.0000		
Unemployment	0.0784	-0.1723	0.2010	-0.2040	0.5270	-0.5361	1.0000	
Bachelor	-0.0330	0.6172	0.3886	0.1920	-0.4130	0.6280	-0.3470	1.0000
Black	0.0199	-0.1879	0.2400	-0.0102	0.4855	-0.2086	0.3700	-0.0627
Hispanic	0.0617	0.0342	0.0568	0.0084	0.0761	0.0554	-0.0183	0.1333
Young	-0.0176	0.0382	0.3153	-0.0262	0.3329	-0.2222	0.1437	0.1729

	Unemployment	Bachelor	Black	Hispanic
Unemployment	1.0000			
Bachelor	-0.3470	1.0000		
Black	0.3700	-0.0627	1.0000	
Hispanic	-0.0183	0.1333	-0.0719	1.0000
Young	0.1437	0.1729	0.2942	0.1782

Table 5. Spatial lag model for the P2P expansion as a function of competition and crisis variables with volume of loans per capita as a dependent variable

We estimate cross-sectional models of the geographic expansion of the P2P lending during the period 2006-2013. Dependent variable is the amount of P2P lending per capita in a county. Variable definitions are provided in Table 2. Models are estimated with maximum likelihood approach while controlling for the spatial dependence with a spatial lag term (lambda). State dummies are not shown. Standard errors are in parentheses.
***, **, * denote significance at the 1, 5 and 10 percent level, respectively.

	P2P (volume)				
Crisis and market structure					
Branches	-0.013***	-0.0127***	-0.0139***	-0.0140***	-0.0140***
	(0.00382)	(0.00380)	(0.00379)	(0.00379)	(0.00378)
Payday	0.0925**	0.0644	0.0684	0.0683	0.0671
	(0.0447)	(0.0446)	(0.0446)	(0.0446)	(0.0447)
C3	-0.716*				
	(0.389)				
HHI		-1.777***	-1.802***	-1.804***	-1.792***
		(0.323)	(0.323)	(0.323)	(0.323)
Leverage	-9.082***	-8.688**			
	(3.426)	(3.412)			
Tier1				0.128	
				(0.658)	
Failed					-0.322
					(0.553)
Other variables					
Patents	-0.00639	-0.0139	-0.00946	-0.00960	-0.00928
	(0.0607)	(0.0601)	(0.0601)	(0.0601)	(0.0601)
Density	0.403***	0.327***	0.333***	0.333***	0.334***
	(0.0491)	(0.0488)	(0.0488)	(0.0488)	(0.0488)
Internet	-0.131	-0.123	-0.145	-0.147	-0.143
	(0.255)	(0.254)	(0.254)	(0.254)	(0.254)
Poverty	-9.145***	-8.618***	-8.773***	-8.779***	-8.810***
	(1.456)	(1.451)	(1.452)	(1.452)	(1.453)
Income	-0.908**	-1.070**	-1.107***	-1.107***	-1.127***
	(0.421)	(0.420)	(0.420)	(0.420)	(0.421)
Unemployment	0.246***	0.247***	0.254***	0.254***	0.254***
	(0.0283)	(0.0282)	(0.0281)	(0.0281)	(0.0281)
Bachelor	3.892***	4.573***	4.828***	4.832***	4.853***
	(1.065)	(1.067)	(1.065)	(1.064)	(1.065)
Black	-0.891*	-0.670	-0.688	-0.689	-0.677
	(0.466)	(0.464)	(0.464)	(0.464)	(0.465)
Hispanic	6.201***	6.373***	6.447***	6.441***	6.501***
	(1.037)	(1.028)	(1.029)	(1.029)	(1.033)
Young	8.357***	6.567**	6.564**	6.566**	6.474**
	(3.133)	(3.138)	(3.141)	(3.141)	(3.144)
Constant	16.74***	18.46***	18.02***	18.02***	18.26***
	(4.645)	(4.611)	(4.614)	(4.613)	(4.630)
Lambda	0.538***	0.524***	0.523***	0.523***	0.523***
	(0.0346)	(0.0344)	(0.0345)	(0.0345)	(0.0345)
Sigma2	7.930***	7.866***	7.883***	7.883***	7.882***
	(0.203)	(0.201)	(0.202)	(0.202)	(0.202)
Observations	3,060	3,060	3,060	3,060	3,060

Table 6. Spatial lag model for the P2P expansion as a function of competition and crisis variables with number of loans per capita as a dependent variable

We estimate cross-sectional models of the geographic expansion of the P2P lending during the period 2006-2013. Dependent variable is the number of P2P loans per capita in a county. Variable definitions are provided in Table 2. Models are estimated with maximum likelihood approach while controlling for the spatial dependence with a spatial lag term (lambda). State dummies are not shown. Standard errors are in parentheses.

***, **, * denote significance at the 1, 5 and 10 percent level, respectively.

	P2P (number)				
Crisis and market structure					
Branches	-0.00282***	-0.00273***	-0.00295***	-0.00294***	-0.00287***
	(0.000998)	(0.000997)	(0.000993)	(0.000994)	(0.000991)
Payday	-0.00882	-0.00967	-0.00889	-0.00897	-0.00851
	(0.0120)	(0.0120)	(0.0120)	(0.0120)	(0.0120)
C3	-0.366***				
	(0.100)				
HHI		-0.330***	-0.336***	-0.335***	-0.338***
		(0.0847)	(0.0848)	(0.0847)	(0.0847)
Leverage	-1.448	-1.433			
	(0.920)	(0.919)			
Tier1				0.0367	
				(0.177)	
Failed					0.125
					(0.149)
Other variables					
Patents	-0.0260	-0.0221	-0.0213	-0.0214	-0.0215
	(0.0162)	(0.0161)	(0.0161)	(0.0161)	(0.0161)
Density	0.0364***	0.0339***	0.0347***	0.0347***	0.0346***
	(0.0112)	(0.0114)	(0.0114)	(0.0114)	(0.0114)
Internet	-0.0648	-0.0692	-0.0723	-0.0722	-0.0723
	(0.0664)	(0.0664)	(0.0664)	(0.0664)	(0.0664)
Poverty	-2.704***	-2.691***	-2.718***	-2.716***	-2.698***
	(0.392)	(0.391)	(0.391)	(0.391)	(0.392)
Income	0.0594	0.0492	0.0422	0.0429	0.0507
	(0.111)	(0.111)	(0.111)	(0.111)	(0.112)
Unemployment	0.0427***	0.0427***	0.0439***	0.0438***	0.0435***
	(0.00754)	(0.00754)	(0.00752)	(0.00751)	(0.00752)
Bachelor	1.906***	2.032***	2.081***	2.078***	2.065***
	(0.276)	(0.276)	(0.275)	(0.275)	(0.275)
Black	0.219*	0.223*	0.220*	0.220*	0.216*
	(0.121)	(0.121)	(0.121)	(0.121)	(0.121)
Hispanic	0.944***	1.006***	1.008***	1.010***	1.000***
	(0.194)	(0.194)	(0.194)	(0.194)	(0.194)
Young	0.451	0.257	0.244	0.243	0.273
	(0.779)	(0.784)	(0.785)	(0.785)	(0.785)
Constant	0.407	0.332	0.254	0.259	0.176
	(1.221)	(1.218)	(1.218)	(1.218)	(1.222)
Lambda	0.945***	0.948***	0.949***	0.949***	0.947***
	(0.0404)	(0.0402)	(0.0403)	(0.0403)	(0.0403)
Sigma2	0.573***	0.572***	0.572***	0.572***	0.572***
	(0.0148)	(0.0147)	(0.0148)	(0.0148)	(0.0148)
Observations	3,060	3,060	3,060	3,060	3,060

Table 7. Spatial lag model for the expansion of Prosper and Lending Club

We estimate cross-sectional models of the geographic expansion of the P2P lending during the period 2006-2013. Variable definitions are provided in Table 2. Models are estimated with maximum likelihood approach while controlling for the spatial dependence with a spatial lag term (lambda). State dummies are not shown. Standard errors are in parentheses. ***, **, * denote significance at the 1, 5 and 10 percent level, respectively.

	P2P (volume)		P2P (number)	
	Prosper	**Lending Club**	**Prosper**	**LendingClub**
Branches	-0.00817*	-0.0164***	-0.00100	-0.00322***
	(0.00470)	(0.00405)	(0.000870)	(0.00106)
HHI	-4.569***	-0.851**	-0.0705	-0.237***
	(0.398)	(0.342)	(0.0738)	(0.0897)
Payday	0.307***	-0.112**	-0.00616	-0.0251**
	(0.0550)	(0.0475)	(0.0104)	(0.0127)
Leverage	-21.13***	-3.590	-1.421*	-0.317
	(4.212)	(3.639)	(0.803)	(0.975)
Patents	-0.00280	-0.194***	0.0231*	-0.0183
	(0.0744)	(0.0640)	(0.0140)	(0.0170)
Density	0.532***	0.429***	0.0265***	0.0112
	(0.0605)	(0.0523)	(0.00995)	(0.0121)
Internet	0.0745	-0.298	0.0211	-0.0876
	(0.313)	(0.270)	(0.0580)	(0.0704)
Poverty	-11.97***	-6.031***	-2.145***	-2.411***
	(1.805)	(1.545)	(0.342)	(0.413)
Income	-1.306**	0.287	-0.210**	0.0940
	(0.518)	(0.446)	(0.0969)	(0.118)
Unemployment	0.252***	0.256***	0.0121*	0.0322***
	(0.0351)	(0.0301)	(0.00657)	(0.00796)
Bachelor	5.738***	5.190***	1.667***	1.311***
	(1.317)	(1.139)	(0.241)	(0.293)
Black	-0.575	-1.434***	0.435***	0.303**
	(0.573)	(0.495)	(0.106)	(0.128)
Hispanic	1.951	6.257***	0.658***	0.856***
	(1.265)	(1.100)	(0.168)	(0.205)
Young	19.21***	0.0390	-1.048	0.123
	(3.878)	(3.345)	(0.685)	(0.831)
Constant	19.82***	1.668	2.809***	-0.365
	(5.681)	(4.898)	(1.060)	(1.286)
Lambda	0.324***	1.143***	0.672***	1.024***
	(0.0454)	(0.0294)	(0.0528)	(0.0436)
Sigma2	11.99***	8.947***	0.436***	0.643***
	(0.307)	(0.231)	(0.0112)	(0.0166)
Observations	3,060	3,060	3,0600	3,0600

Table 8. Spatial lag model for the expansion of P2P lending year by year

We estimate cross-sectional models of the geographic expansion of the P2P lending during the period 2007-2013 for each year. Variable definitions are provided in Table 2. Models are estimated with maximum likelihood approach while controlling for the spatial dependence with a spatial lag term (lambda). State dummies are not shown. Standard errors are in parentheses. ***, **, * denote significance at the 1, 5 and 10 percent level, respectively.

	P2P (volume)						
	2007	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**
Branches	-0.00486	0.00583	0.00358	-0.00212	-0.00929*	-0.0103**	-0.0156***
	(0.00451)	(0.00458)	(0.00393)	(0.00452)	(0.00488)	(0.00479)	(0.00422)
HHI	-1.427***	-1.842***	-0.554*	-2.006***	-2.698***	-3.155***	-1.949***
	(0.385)	(0.391)	(0.335)	(0.383)	(0.413)	(0.408)	(0.358)
Payday	0.0718	0.0945*	-0.0234	0.0680	0.186***	0.0895	0.0328
	(0.0532)	(0.0540)	(0.0466)	(0.0533)	(0.0576)	(0.0569)	(0.0501)
Leverage	-17.25***	-12.98***	-7.744**	-11.35***	-11.60***	-8.011*	-0.822
	(4.053)	(4.122)	(3.554)	(4.076)	(4.411)	(4.343)	(3.816)
Patents	-0.0807	-0.396***	-0.192**	-0.281***	-0.321***	-0.277***	-0.108
	(0.0877)	(0.0908)	(0.0782)	(0.0878)	(0.0923)	(0.0899)	(0.0814)
Density	0.542***	0.694***	0.638***	0.699***	0.715***	0.438***	0.421***
	(0.0546)	(0.0567)	(0.0506)	(0.0578)	(0.0621)	(0.0602)	(0.0531)
Internet	-0.433	0.0538	-0.250	-0.130	-0.232	0.0564	-0.634**
	(0.301)	(0.306)	(0.264)	(0.303)	(0.327)	(0.321)	(0.282)
Poverty	-3.931**	-9.236***	-1.872	-5.481***	-8.045***	-9.123***	-9.058***
	(1.751)	(1.753)	(1.482)	(1.696)	(1.814)	(1.766)	(1.573)
Income	0.0905	-0.947*	0.540	0.958*	-0.175	-0.841*	-0.611
	(0.538)	(0.503)	(0.467)	(0.507)	(0.490)	(0.458)	(0.395)
Unemployment	0.110**	0.136***	0.0435**	0.109***	0.174***	0.223***	0.241***
	(0.0446)	(0.0384)	(0.0215)	(0.0264)	(0.0314)	(0.0324)	(0.0296)
Bachelor	9.793***	11.33***	10.43***	8.668***	8.054***	6.983***	3.336***
	(1.299)	(1.270)	(1.112)	(1.242)	(1.309)	(1.279)	(1.124)
Black	-0.756	-1.007*	0.135	-1.363**	-1.491**	-0.655	-0.714
	(0.547)	(0.553)	(0.477)	(0.545)	(0.596)	(0.585)	(0.511)
Hispanic	7.116***	4.449***	6.791***	5.848***	4.248***	6.784***	6.995***
	(1.259)	(1.248)	(1.086)	(1.233)	(1.326)	(1.312)	(1.153)
Young	9.441**	11.58***	3.471	12.14***	10.60***	10.03**	3.272
	(3.762)	(3.780)	(3.263)	(3.736)	(4.045)	(3.979)	(3.469)
Lambda	0.730***	0.367***	0.558***	0.539***	0.576***	0.720***	0.886***
	(0.0486)	(0.0529)	(0.0510)	(0.0492)	(0.0471)	(0.0414)	(0.0340)
Sigma2	11.19***	11.47***	8.533***	11.20***	13.07***	12.66***	9.812***
	(0.288)	(0.294)	(0.219)	(0.287)	(0.335)	(0.325)	(0.252)
Constant	0.684	12.44**	-4.489	-8.020	5.577	12.98**	12.02***
	(5.823)	(5.487)	(5.071)	(5.541)	(5.426)	(5.098)	(4.379)
Observations	3,059	3,059	3,059	3,059	3,059	3,059	3,059

Table 9. Panel model for the expansion of P2P lending

We estimate a panel model of the geographic expansion of the P2P lending during the period 2007-2013 for each year. Variable definitions are provided in Table 2. Standard errors are in parentheses. ***, **, * denote significance at the 1, 5 and 10 percent level, respectively.

	P2P (volume)			
L.Branches	83.01	119.2	123.3	146.5
	(165.4)	(165.1)	(165.1)	(163.6)
L.Payday	-657.2	-723.7	-702.1	-592.5
	(1,183)	(1,183)	(1,184)	(1,175)
L.C3	22,033***			
	(6,507)			
L.HHI		10,290**	10,347**	9,682**
		(4,406)	(4,406)	(4,359)
L.Tier1			-2,734	
			(5,328)	
L.Leverage	-30,893**	-30,926**		
	(14,006)	(14,009)		
L.Unemployment	-312.2	-331.4	-330.1	-324.3
	(316.0)	(316.0)	(316.0)	(312.5)
L.Income	-35,870***	-36,514***	-36,279***	-35,161***
	(6,781)	(6,779)	(6,782)	(6,576)
L.Density	335.6***	344.0***	343.3***	345.8***
	(39.76)	(39.66)	(39.67)	(39.69)
2009.year	106.6	134.3	298.7	197.9
	(1,213)	(1,213)	(1,211)	(1,202)
2010.year	2,048	2,078	2,249	2,100
	(1,767)	(1,768)	(1,766)	(1,746)
2011.year	8,219***	8,425***	8,509***	8,331***
	(1,923)	(1,923)	(1,924)	(1,899)
2012.year	25,858***	26,150***	26,162***	26,016***
	(2,011)	(2,009)	(2,013)	(1,979)
2013.year	65,833***	66,132***	66,050***	65,381***
	(1,982)	(1,980)	(1,988)	(1,946)
Constant	335,369***	354,767***	349,703***	337,530***
	(71,029)	(70,620)	(70,640)	(68,466)
Observations	18,309	18,309	18,309	18,496
R-squared	0.249	0.249	0.248	0.247
Number of obs	3,060	3,060	3,060	3,087

Table 10. Marginal effects with volume of P2P lending

Following Drukker et al. (2013) and Pace and LeSage (2008), the table presents average direct impact, average indirect impact and average total impact.

	Average direct impact	**Average indirect impact**	**Average total impact**
Branches	-0.013	-0.004	-0.017
HHI	-1.795	-0.531	-2.326
Payday	0.065	0.019	0.084
Leverage	-8.778	-2.598	-11.376
Patents	-0.014	-0.004	-0.018
Density	0.330	0.098	0.428
Internet	-0.125	-0.037	-0.161
Poverty	-8.708	-2.577	-11.285
Income	-1.080	-0.320	-1.400
Unemployment	0.250	0.074	0.324
Education	4.620	1.368	5.988
Black	-0.676	-0.201	-0.877
Hispanic	6.439	1.905	8.344
Age	6.635	1.964	8.599

Table 11. Marginal effects with number of P2P loans

Following Drukker et al. (2013) and Pace and LeSage (2008), the table presents average direct impact, average indirect impact and average total impact.

	Average direct impact	**Average indirect impact**	**Average total impact**
Branches	-0,003	-0,003	-0,006
HHI	-0,380	-0,263	-0,643
Payday	-0,009	-0,006	-0,015
Leverage	-1,505	-1,041	-2,546
Patents	-0,027	-0,019	-0,046
Density	0,038	0,026	0,064
Internet	-0,067	-0,047	-0,114
Poverty	-2,809	-1,943	-4,753
Income	0,062	0,042	0,104
Unemplyment	0,044	0,031	0,075
Bachelor	1,980	1,370	3,349
Black	0,228	0,158	0,385
Hispanic	0,981	0,679	1,660
Age	0,469	0,324	0,793