# What drives the expansion of the peer-to-peer lending?

Olena Havrylchyk[1], Carlotta Mariotto[2], Talal Rahim[3], Marianne Verdier[4]

## Abstract

Peer-to-peer lending platforms are online intermediaries that match lenders with borrowers. We use data from the two leading P2P consumer lending platforms, Prosper and Lending Club, to explore main drivers of their expansion in the United States. We exploit the heterogeneity in local credit markets at the county level to analyze three hypotheses for the penetration of online lenders: 1) crisis-related; 2) competition-related; and 3) innovation-related. Our findings support the crisis-related and competition-related hypothesis, as lending platforms have expended more to counties with overleveraged banks and lower density of branch network. At the same time, lending platforms have difficulty penetrating countries with high bank concentration. We also document that spatial, socio-economic and demographic characteristics determine the expansion of online lenders.

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

Keywords: peer-to-peer lending, online lenders, market structure, brand loyalty, financial crisis, internet, information and communication technologies

[1] LEM, University of Lille; CEPII, EconomiX and Labex ReFi, contact: olena.havrylchyk@univ-lille1.fr
[2] ESCP Europe, LabeX ReFi and CERNA, Ecole des Mines de Paris, contact: carlotta.mariotto@mines-paristech.fr
[3] Boston University, contact: rahimt@bu.edu
[4] CRED, University Paris 2 Panthéon Assas, and CERNA, Ecole des Mines de Paris, contact : marianne.verdier@u-paris2.fr

**“Banking is necessary; banks are not”**

Bill Gates, 1990

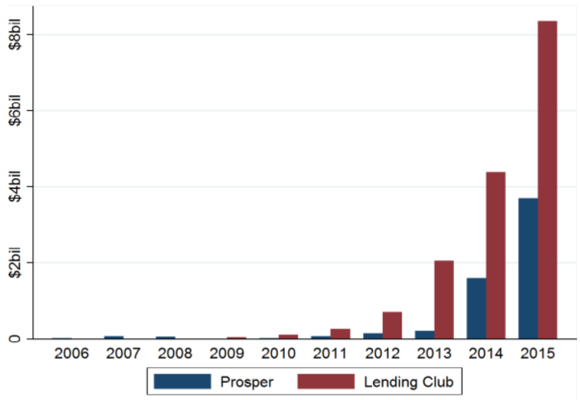
**“Is information technology going to disrupt finance? My first response is: please. My second response is: yes.”**

Martin Wolf, 2016

## 1. Introduction

First peer-to-peer (P2P) lending platforms, Zopa, Prosper and Lending Club, have been launched in 2005-2007 in the UK and the US. These online lenders[5] directly match savers with borrowers who need personal and business loans. Although, online lending amounts to a small share of total lending, it has been growing rapidly (Figure 1) and in 2015, the flow of US online consumer lending was equivalent to 12.5% of traditional consumer lending (Wardrop et al., 2016). Not surprisingly, the emergence of online lenders, which are a part of the wider FinTech movement, has provoked a debate about their ability to disrupt traditional banking (Phillipon, 2016; The Economist, 2015; Wolf, 2016; Citi, 2016). 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.

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




Source: Websites of the Lending Club and Prosper Marketplace

The objective of this paper is to provide the first exploration of the main drivers of the expansion of the P2P lending in the US. Is rapid development of online lenders due to structural factors in the brick-and-mortar banking, such as weak competition in the consumer lending market due to high switching costs or barriers to entry? Has it been spurred by the Great Recession, bank failures, banks’ deleveraging and credit crunch? Could the timing of the P2P lending be

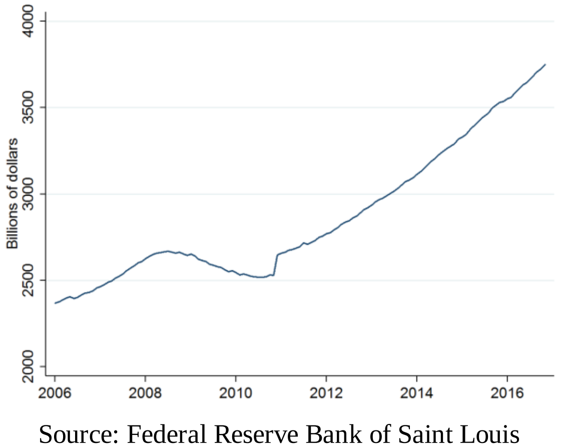
5 Peer-to-peer lending was born to match directly lenders and borrowers without the use of the intermediation of banks. However, as the market expanded, a large part of it has been funded not by individual lenders, but traditional banks, hedge funds and other financial institutions. Hence, the name peer-to-peer lending has been changing to marketplace lending. In this paper we use terms peer-to-peer lending platforms, marketplace lenders and online lenders interchangeably.

explained by the spread of Internet, sophistication of Internet users and trust in new technologies? What role do social networks play? What are the socio-economic and demographic characteristics of online borrowers? Ultimately, we would like to get closer to understanding whether online lenders could be potentially disrupt the traditional banking sector.

In light of these questions, we outline three main hypotheses for the expansion of online lenders. Our *first hypothesis* is that P2P lending development could be related to the nature of the banking competition. The banking sector is characterized by monopolistic competition due to high entry barriers, switching costs and strong brand loyalty (Claessens and Laeven, 2004; Shy, 2002; Kim et al., 2003). Philippon (2015) demonstrates that the cost of financial intermediation in the US have remained unchanged since the 19 century. This fact is astonishing in the context of rapid progress in the communication and information technologies that should have driven down the price of financial services for end users. Hence, the entry of new Fintech players could be needed to improve the provision of financial services and disrupt traditional players. Indeed, online lenders argue 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.[6] We test the impact of the market structure on the expansion of online lenders and refer to these explanations as *competition-based hypotheses*.[7]

The expansion of online lenders might have been spurred by the financial crisis and the Great Recession. On the credit supply side, as interest rates approached zero, new lenders entered the market, attracted by the higher return (and risk) available from exposure to P2P assets. On the credit demand side, a wider and more creditworthy pool of potential borrowers appeared as the banking sector was weak, regulation has tightened, banks have deleveraged and mistrust in the banks has spread (Atz and Bholat, 2016). As shown by figure 2 below, total consumer credit significantly decreased in the years 2008-2011. The credit rationing may have spurred the demand for alternative forms of financing.

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




Source: Federal Reserve Bank of Saint Louis

For example, Koetter and Blaseg (2015) show that bank instability in Germany has pushed

---

6 Operating expenses include the costs of originating the loan, processing payments, collection and bad debt expenses.

7 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).

businesses to use equity crowdfunding as a source of external finance. We refer to this explanation as *crisis-based hypothesis*.

It is also possible that the surge in P2P lending is not caused by problems in the banking sector. Online lenders claim to harness big data innovations to revolutionize credit risk assessment and efficiently match lenders with borrowers. Furthermore, the entry of online lenders reflects the readiness of the society to embrace internet to perform financial transactions. Indeed, Fintech is part of the larger revolution as new internet platforms (Amazon, Uber, BlaBlaCar and AirBnB) are on the way to disrupt other service markets, such as retail trade, transport and accommodation. Similar to previous financial innovation, online lenders could expand and cheapen access to financial services (Einav et al., 2013). We refer to this explanation as *innovation-based hypothesis*.

Sorting out these three 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 the diffusion of communication and information technologies (e.g., smartphones, broadband). Our identification strategy relies on the exploration of the geographic heterogeneity of the P2P lending expansion at the county level. The choice of the local dimension of a market is relevant for consumer and SME lending that are targeted by online lenders. The county unit is the standard definition of the local banking market in the literature (e.g., Prager and Hannan, 1998; Berger, Demsetz, and Strahan, 1999; Rhoades, 2000; and Black and Strahan, 2002).

Since the expansion of the P2P lending is similar to the diffusion of other technologies, it could be explained by spatial network effects due to human interactions (Comin et al., 2012). Notwithstanding the online nature of the P2P lending, geography might still play a crucial role in its diffusion. Indeed, we document an important spatial correlation, as P2P lending per capita is higher in counties close to California, New York and Florida. Hence, our econometric approach relies on incorporating a spatial lag variable in our model.[8]

This paper contributes to the nascent literature on the peer-to-peer lending. 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).[9] The only paper that explores how borrowers choose between traditional and alternative sources of finance is Butler et al. (2014), who show that borrowers who reside in areas with good access to bank finance request loans with lower interest rates.

This paper makes the first attempt to analyze the expansion patterns of online lenders. For the first time, we aggregate data for the two leading P2P consumer lending platforms in the US - Prosper and Lending Club – and study the geography of online lenders. We measure the expansion of the P2P lending by aggregating the number and the volume of loans provided by

---

[8] 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.

[9] 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).

these two online lenders. As early as 2007, 1183 counties had P2P borrowers, and their number has increased to 2609 in 2013. We then use this data to relate the amount of P2P lending to a wide range of county level determinants that could affect the speed of its penetration.

By focusing on the expansion of a new technology, our paper is related to the literature on the diffusion of innovation (Bass, 1969 and Rogers, 2003).[10] The literature on financial innovation is scarce and focuses on the new products and 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.[11] 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.

The paper is structured as follows. In section 2, we describe the institutional environment in which peer-to-peer lending platforms evolve. In section 3, we explain how we assemble our data set, provide data sources and variable definition. In section 4, we explain our identification strategy and provide empirical results. In section 5, we conclude.

## 2. Institutional environment of peer-to-peer lending platforms in the United States

Online lending marketplaces are platforms that connect individuals or businesses wishing to obtain a loan with individuals and institutions willing to commit to fund this loan. Marketplace lending encompasses P2P lending platforms, which offer lending-based crowdfunding for consumers and small businesses, and online lending platforms by large institutions (e.g., OnDeck Capital, Kabbage), which offer credit exclusively to businesses, rather than consumers.[12] 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 United-States respectively in 2006 and 2007, followed by other companies such as Upstart, Funding Circle, CircleBack Lending or Peerform. Between 2006 and 2015, the two most important platforms, Prosper and Lending Club, have facilitated approximately $8.7 billion loans.[13] Both platforms believe that their online marketplace model has key advantages relative to traditional bank lending both for borrowers and investors, among which convenience of online operations, automation, reduced cost and time to access credit.

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.[14]

---

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

[11] Frame and White (2009) mention three different types of innovations: products and services (e.g., subprime mortgages, new means of payment and online banking), production processes (such as Automated Clearing Houses, small business credit scoring, asset securitization, risk management), organizational forms (such as Internet only banks).

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

[13] The figures and information of this paragraph is based on the study of Prosper and Lending Club annual reports, which can be found on the companies' websites.

[14] 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.

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. In December 2014, Lending Club became the first publicly traded online peer-to-peer lending company in the United-States, after its Initial Public Offering on the New York Stock Exchange.

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 increases the size of network effects. 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 balances or unsecured installment loans funded by traditional banks.[15] 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 loan, 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, online lending marketplaces face 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.[16] 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

[15] 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.
[16] Notes can be viewed as debt-back securities.

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.

An important issue is the potential violation of states' usury laws. The interest rates charged to 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.[17] 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. Data

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.

Since loan book data provides information about 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.[18] Our analysis ends in 2013, because platforms have stopped providing city names afterwards. 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, we aggregate this data at the year-county level to construct two measures of P2P lending diffusion: number of P2P loans per capita and 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.

**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 |

[17] Of the fourty-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.

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

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 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 (Figure 3). As early as 2007, 1183 counties had P2P borrowers, and their number has increased to 1881 in 2010 and to 2609 in 2013.

For cross-sectional regressions, we aggregate yearly 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 penetration of the P2P lending, we rely on two types of variables. First, we compute the share of deposits in each county affected by bank failures 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 relies on the FDIC Summary of Deposits to identify the presence of branches in each county that we merge with information on capital at the bank consolidated level, taken from Call Reports. This measure is based on the assumption that banks' capital management is done at the consolidated level (Haas and van Lelyveld, 2010). We rely on two measures of capital (unweighted leverage ratio and risk-weighted tier 1 capital ratio) computed during the crisis period 2009-2010[19]. 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 competition and brand loyalty*

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

Ideally, we would like to explore banking competition, but this is notoriously difficult to measure, particularly at the county level. The FDIC Summary of Deposits allows us to compute concentration measures, such as HHI and C3 indices, as well as branch density per 10000 population. To eliminate any endogeneity due to reverse causality, we estimate these variables in 2007. Since some studies show that market structure could be unrelated to the banking competition (Claessens and Laeven, 2004), we prefer to refer to these measures as market structure or concentration measures.

Market structure measures could be correlates of bank quality and brand loyalty. In particular, branch density measures the outreach of the financial sector in terms of access to banks' physical outlets (Benfratello et al., 2008; Beck et al., 2007). Branch density is also a measure of the quality of the overall bank network and could play an important role in the bank's advertising strategy to develop brand loyalty (Dick, 2007). Indeed, branches are a form of advertising for banks. Dick (2007) provides plenty of anecdotal evidence on how banks hope to attract customers using their branches, usually with stylish merchandising and customer service. Banks become more visible to consumers through their branches; in fact, banks are known to put clocks outside their branches for this reason. Importantly, there is evidence that banks open branches mostly in response to their own market targets, as opposed to their existing customers' needs.

Banking sector is a highly concentrated market with high switching costs. If bank customers wanted to switch to P2P lending, they would need to incur learning costs about P2P platforms, transaction costs to set up their profile, describe their loan (a task that is performed by their credit officer in a bank), as well as to overcome brand loyalty. Since our study is done in the homogeneous institutional environment in the context of switching to one of the two very similar lending platforms, learning and transaction costs should be similar across counties. We control for educational attainment and age, which could be correlated with learning costs. The remaining geographic heterogeneity in banking concentration could be a subjective measure of brand loyalty.

In light of this discussion, the impact of the concentration measures on the expansion of the P2P lending could be interpreted differently. A positive correlation between market concentration and P2P lending platforms could signal that customers from highly concentrated markets try to switch to alternative, less costly providers. A negative correlation, on the contrary, could signal that high market concentration reflects high brand loyalty, which slows down the penetration of the P2P lending.

Finally, since lending marketplaces operate online, their entry decision at the county level is exogenous and it is not correlated to the density of bank branches.

*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 compute 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 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 the penetration of internet at the county level, we rely on the NTIA's State Broadband Initiative that allows us to compute the following measures: 1) percent of county population with access to any broadband technology (excluding satellite); 2) percent of county population with access to Mobile Wireless (Licensed) technology; 3) percent of county population with access to upload speed 50 mbps or higher. Each measure is computed as an average between 2010 and 2013, the only data available at the county level. All these variables should have an expected positive sign if our *innovation-based hypothesis* is confirmed.

*Socio-economic characteristics*

We control for the socio-economic characteristics, such as age, education attainment, population density, poverty level, race etc. 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. These characteristics could also be correlates with brand loyalty.[20]

As to poverty rate and race, we have no theoretical priors about the sign of their impact. Racial minorities might be less familiar with online lending opportunities, but their demand could be higher because race identification is no longer possible on P2P lending platforms.[21] Interestingly, 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 incentivise racial minorities to turn to the P2P platforms to avoid discrimination that is well documented 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.

*Spatial relations*

Our data contain explicit spatial relationships, as counties are likely to be subject to observable and unobservable common disturbances which will lead to spatial correlation. This could be explained by various channels of interdependence due to regional business cycles and economic shocks, technology diffusion, access to bank branches, policy coordination, regional disparities for which we do not control with our right-hand variables (see e.g. Garrett et al. 2005 for the importance of spatial correlation in state branching policy). Spatial correlation could also occur because of the boundary mismatch problems when the economic notion of a market does not correspond well with the county boundaries (Rey and Montouri, 1999). Spatial correlation is particularly important for the diffusion of technology due to a theory of human interactions (Comin et al., 2012). Borrowers from P2P lending platform require acquiring knowledge about

[20] Surveys have found that consumer credit use is greatest in early family life stages when the rate of return of additional goods that might be financed using credit is high.

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

their existence, as well as trust in their reliability, which often comes from interactions with other agents. The frequency and success of these interactions is likely to be shaped by geography. Hence, we expect that knowledge about P2P potential is likely to be more easily transmitted between agents in counties that are close than between counties that are far apart. Figure 3 also attest to this hypothesis. To account for spatial correlation, we introduce a spatial lag in our model.

Overall, we have sufficient cross-sectional data for 3,059 out of 3,144 counties and county equivalents. Table 2 provides exact definition of all variables and Table 3 provides summary statistics.

## 4. Methodology

### A. Model specification: a spatial autoregressive model

Our objective is to test

i) The three hypothesis on the adoption of P2P lending (See Section 3);
ii) Whether adopting P2P lending in a county has a positive impact on the adoption of P2P lending in neighboring counties.

We specify the following regression model, also known as a SARAR model in the literature (See Anselin, 1988):

$$y_i = \beta_0 + \lambda\, \mathrm{W} y_j + \beta_1 * competition_i + \gamma_1 * crisis_i + \delta_1 * innovation_i + \alpha * X_i + \mathrm{u}_i;$$

where

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

and

$$u_i = \rho \sum_{j=1}^{n} w_{ij}\, u_j + \varepsilon_i, \qquad \text{with } \varepsilon_i \sim \mathrm{N}(0, \sigma^2 \mathrm{I}).$$

*i* and *j* represent the $n^{th}$ counties; $y_i$ is the log of our observed dependent variable, that is either the volume of P2P lending per county per capita 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 (volume or number of P2P loans per capita), known as a spatial lag, where the weights are determined by an N × N spatial weights contiguity matrix W=$\sum_{j=1}^{n} w_{ij}$ where each element $w_{ij}$ expresses the degree of spatial proximity between county i and county j[22]; λ is the unobserved spatial autoregressive coefficient; $\beta_1$ is the unobserved coefficient of our observed independent variables regarding competition and market structure; $\gamma_1$ is the unobserved coefficient of our observed independent variables regarding the credit rationing; $\delta_1$ is the unobserved coefficient of our observed independent variables regarding the innovation and internet variables; α is the coefficient for our socio-economic and demographic variables (See table 2 for the detailed list of observed independent variables) ; ρ is the unobserved spatial autoregressive coefficient as, in our model,

[22] 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.

we allow the error term to be affected by the disturbances of neighbors; $\varepsilon_i$ 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. Ignoring spatial relation, in this case, could potentially lead to inconsistency in the standard errors.

Our main objects of interest are the coefficients $\beta, \gamma$ ,δ, α and λ. $\beta, \gamma$ , δ measure the marginal impact of market structure variables, crisis variables, innovation variables as well as socio-economic and demographic variables on the adoption of P2P lending in each county. When the dependent variable is the volume of P2P loans per capita, the magnitude of the coefficient $\beta, \gamma$ , δ, α predict of how many dollars the volume of P2P loans will increase or decrease for a one unit increase of the control variable. When the dependent variable is the number of loans, the magnitude of the coefficients $\beta, \gamma$ , δ, α predict how many additional or less loans there will be following a one unit increase of the control variable. Finally, λ measures how 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 correlation between the adoption of P2P lending between neighbouring counties,

To compute our cross-sectional spatial regressions, we use the Maximum-Likelihood Estimator method,[23]as the OLS estimation will be biased and inconsistent due to simultaneity bias (See Anselin, 2003 and LeSage and Pace, 2009 for a theoretical explanation on why MLE solves the simultaneity bias).[24]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.

Our findings are presented in Tables 4-7 and they all show that we always reject the null hypothesis that the spatial lag lambda is greater or equal to 0. Spatial lag is always positive and statistically significant, pointing to the existence of strong spatial effects. In other words, the higher the level of P2P loans in one county, the higher it is going to be in the contingent counties.

### B. OLS vs. SARAR

Since from the SARAR model the estimates for the coefficients ρ and λ are significantly different from zero, ordinary least-squares may lead to inconsistent estimations. Table 9 in the Appendix shows the estimates from the OLS regression model. If we compare these estimates to the output from our SARAR model, we realize that they are mostly biased up-words as in Lesage (2008).

## 5. Empirical results

The SARAR model estimates cannot be interpreted as partial derivatives like in the typical regressions (see Le Sage and Pace, 2009). Therefore the coefficients cannot be interpreted as marginal effects of the explanatory variable on the dependent variable in one region, because a change in the explanatory variable is likely to impact the dependent variable in all neighboring regions too. In subsection A we will discuss the short-run impacts of a change in the

[23] The maximum likelihood estimator method relies on the assumption that the error terms are normally distributed.

explanatory variables on the volume and number of P2P lending per capita in each county. In subsection B, we will compute the average total direct impact (ATDI), the average total indirect impacts (ATII) and the average total impact (ATI) which is the sum of the direct and indirect impacts.

### A. Empirical results: short run impacts of the explanatory variables on the dependent variable

Table 4 and table 5 present our empirical findings for the P2P expansion (in terms of volume and number of loans respectively) as a function of different county characteristic, with a particular focus on crisis and competition characteristics.

Among socio-demographic variables, higher population density, higher educational attainment, lower levels of poverty, lower levels of income and higher share of Hispanic and Black minorities have a positive and significant impact on the expansion of the P2P lending. An increase of population density by one standard deviation significantly increases the volume of the P2P lending and the number of loans. An increase of bachelor graduates by one standard deviation significantly increases the volume of the P2P lending and the number of loans. An increase of the share of Hispanic minorities by one standard deviation increases the volume of the P2P lending and the number of loans. As reported in table 8, this result is driven by Lending Club. Also, an increase of the share of Black minorities by one standard deviation increases the number of the P2P loans, but does not affect the volume. An increase in the percentage of people leaving under the poverty line decreases the volume of P2P lending and the number of P2P loans. Also, the income per capita affects negatively only the volume of loans: an increase in the income per capita decreases the volume of P2P loans. The variables measuring the age of the population are never significant for these specifications.

Our finding that the expansion of the P2P lending is faster in counties with higher share of Black and Hispanic minorities could be a sign of higher demand from these areas to escape discrimination in traditional credit markets. As online lenders have removed the possibility to post a photo, identifying the race of the borrower has become much more difficult. During our sample period, 2007-2013, investors had access to the information on the location of borrowers. Although this information could have been used by institutional investors as a proxy for race, it is unlikely that retail investors would do that. Recently, any information on the location of the borrower has been removed, which makes the identification of the race completely impossible. Hence, racial discrimination is not anymore possible in the online lending.

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 switching costs due to lower cost of learning. 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.

As to the crisis variables, our findings show that in both specifications of table 4 and 5, the leverage ratio is statistically significant and has a negative effect on P2P lending expansion both in terms of volume and loans. A decrease of the leverage ratio during the financial crisis increases the volume of lending, and increases the number of loans. The share of deposits affected by failed banks and the Tier 1 capital ratios during the crisis did not have an impact on the diffusion of P2P lending. This finding is consistent with the idea that leverage ratios appear to be better predictors of future banks' performance and problems (Blundell-Wignall and

Roulet, 2013; Haldane, 2011a, 2012) with respect to weighted leverage ratios, since weights may be inconsistent and subject to manipulations Mariathasan and Merrouche, 2014; Le Leslé and Avramova, 2012; Haldane 2012; FSA, 2010).

Most of P2P borrowers use lending platforms to consolidate and manage their credit card debt and a minority borrow for business purposes. To account for difficulties in the credit card market, we test the robustness of our results by constructing two additional crisis variables: percentage change in credit card debt balance per capita and percent of credit card debt balance with more than 90 days of delinquency during crisis years. The data comes from the New York Fed Consumer Credit Panel / Equifax that is available only for 2220 counties. None of these variables turns out to be statistically significant. Results are available upon request.

In addition, Table 4 and table 5 present the empirical findings for the P2P expansion as a function of market structure variables. Our findings demonstrate that low branches density in 2007 is a statistically significant driver of the P2P lending. We interpret this result as a suggestion that customers living in counties with low outreach of traditional banks and low quality of financial services are more likely to turn to P2P lending due to weaker brand loyalty. Counties that had one standard deviation less branches in 2007, experienced an increase in the average volume of P2P lending and an increase in the number of P2P loans.

Turning our attention to concentration measures, both our concentration measures C3 and HHI have a negative and statistically significant sign. In other words, P2P lending penetrates fewer counties with higher concentration of the largest three banks and with a higher overall traditional banking market concentration. This is consistent with the interpretation of the high market concentration as an outcome of high switching costs due to strong brand loyalty. An increase of the concentration of the three biggest banks by one standard deviation diminishes the average amount of the P2P lending and the number of loans, whereas an increase in the concentration of the whole traditional banking market in one county diminishes the average amount of P2P lending and the number of loans.

We additionally test the impact of the alternative consumer credit providers, such as payday loans. 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). We find that P2P lending is more diffused in counties with a higher number of payday loan establishments. In particular, an increase in the number of payday loans establishments increases the volume of P2P lending at a 10% level of significance. This might reflect a higher demand for alternative consumer credit.

Table 6 and table 7 present results with variables that capture the geographic heterogeneity of the innovation, measured by the quality of Internet connection and by the number of patents issued by each county. Since the variable which measures the number of patents is correlated to the level of education, we performed one specification excluding the level of education, and found that it is statistically significant and with a positive sign. Counties with density of patents that is one standard deviation above the average exhibit a higher volume of P2P lending and an increase in the number of loans. Among the variables describing the quality of Internet, only broadband and mobile are statistically significant and have a negative sign only when the dependent variable is the volume of loans. High Internet quality and speed do not impact the number of P2P borrowers.

To compare the expansion patterns of different online platforms, we estimate the model separately for Prosper Marketplace and Lending Club. The results, presented in Table 8, show that not all local characteristics play a similar role in the case of both online lenders. The market structure variables (HHI and Branches) played a similar role for the two platforms, whereas payday loan establishments have a strong and positive impact only on Prosper's volume of loans and a negative but small impact on the number of Lending Club borrowers. Moreover, the leverage ratio during the crisis played a role in the case of Prosper but is not significant for Lending Club. Interestingly, broadband access plays a positive role for the Prosper lending, and a negative one for Lending Club volume of loans. To understand this difference, one should remember that Proper platform had an earlier start than the Lending Club. A large part of the Prosper's lending in our sample has been done in 2006-2008 and it has experienced a sharp decline in 2008-2009 due to regulatory uncertainty about its legal status, followed by a slow expansion since 2010. The finding that broadband access plays a role for the Prosper lending is likely to reflect this earlier period when there was still an important geographic heterogeneity in access to Internet. This intuition is reinforced by the estimates of the SARAR model regressions performed each year separately, as shown in table 9. As a matter of fact, the negative and significant effect of broadband is present only starting from the year 2012, whereas it is positive and significant on the year 2008 and otherwise it is never significant.

The age structure only plays a role for Lending Club: a higher percentage of population aged between 20 and 34 increases the volume of P2P loans but decreases the number of loans. With respect to the minorities, counties with a higher share of Hispanic population have a higher number of P2P loans on both platforms but only a higher volume of Lending Club loans.

Finally, the spatial lag is always positive and significant in all the regressions, suggesting the presence of positive spatial relations among contingent counties. It is interesting to note from table 9, that, starting from 2008, this coefficient increased systematically during the years, going from 0.3777 in 2008 to 0.915 in 2013.

### B. Computing marginal effects

Following the method proposed by Drukker et al. 2013, we manually compute the average total direct and indirect impacts of the explanatory variables (crisis, competition, innovation and socio-economic and demographic variables) on the dependent variable (either volume or number of P2P loans per capita per county) using the reduced-form predictors coming from the SARAR regression. Doing so allows us to understand the magnitude of these effects. For example, as shown in table 11, an increase by one standard deviation of the number of branches in a given region decreases the average volume of P2P lending per capita of all regions by 0.0013% (ATDI). Similarly, an increase by one standard deviation of the number of branches in all neighboring regions, reduces by 0.0004 % the volume of P2P lending per capita in that one region (ATII). The signs of the coefficients are the same as the short-run impacts shown in table 4-8, and in general the direct impacts are stronger than the indirect ones, which leads to the fact that total impacts are composed mainly by direct impacts in our main sample.

## Concluding remarks and future extensions

This paper is a first attempt to explore the drivers of the expansion of online lenders. We have proposed three hypotheses related to (1) the competition in the brick-and-mortar banking sector and switching costs to online lenders, (2) the consequences of the financial crisis and (3) the innovation and internet expansion. We also account for spatial effects and socio-economic and demographic characteristics.

Our findings suggest that online lenders have made inroads into counties that have a poor branch network. This suggests that borrowers that either 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 due to lower brand loyalty. We also find that counties with a more concentrated banking structure have witnessed slower growth of online lenders, which is also consistent with the idea of higher brand loyalty. Higher education and higher propensity to innovate play a significant and positive role, possibly because these characteristics diminish the costs of learning about online lenders. Our results show that the leverage ratio during the crisis has affected the demand for online lending. Despite the online nature of the P2P lending, spatial effects play a crucial role, which could be interpreted as an important role of social interactions in building trust in online markets.

Our analysis could be extended in a number of ways. First, we would like to use the panel nature of the data to estimate Bass model of the innovation diffusion. Second, we would like to explore the balancing of demand and supply in the P2P lending. This is possible due to the information in our dataset about loan demand that has not been met because loans have been rejected by online lenders or have failed to attract potential lenders.

## References


Aghion, P., Bloom, N., Blundell, R., Griffith, R., Howitt, P., 2005. Competition and Innovation: An Inverted U-relationship. *Quarterly Journal of Economics,* 120(2): 701–728

Agrawal, A., Catalini, C., and Goldfarb, A. 2011. The Geography of Crowdfunding, NBER WP No. 1682.

Anselin, L., 1980. Estimation Methods for Spatial Autoregressive Structures. Regional Science Dissertation and Monograph Series 8. Field of Regional Science, Cornell University, Ithaca, N.Y.

Anselin, L., 2003. A Companion to Theoretical Econometrics. *Blackwell Publishing Ltd,* chapter 4, pp.310-330.

Atz, U. and D. Bholat, 2016. Peer-to-peer Lending and Financial Innovation in the United Kingdom. Bank of England Staff Working Paper No. 598.

Aubuchon, C. P., Wheelock, D. C., 2010. The Geographic Distribution and Characteristics of U.S. Bank Failures, 2007-2010: Do Bank Failures Still Reflect Local Economic Conditions?**.** *Federal Reserve Bank of St. Louis Review*. 92(5): 395-415.

Bass, F., 1969. A New Product Growth Model for Consumer Durables. *Management Science,* 15(5): 215–227.

Benfratello, L., Schiantarelli, F. and Sembenelli, A., 2008. Banks and Innovation: Microeconometric Evidence on Italian firms. *Journal of Financial Economics*, 90(2): 197-217.

Beck, T., Demirguc-Kunt, A., Martinez P., and Martinez,M. S., 2007. Reaching out: Access to and Use of Banking Services Across Countries, *Journal of Financial Economics*, 85(1): 234-266.

Berger, A., Demsetz, R.S., and Strahan, P.E., 1999. The consolidation of the Financial Services Industry: Causes, Consequences, and Implications for the Future, *Journal of Banking & Finance*, 23(2-4): 135-194.

Bhutta, N., 2013. Payday Loans and Consumer Financial Health, Finance and Economics Discussion Series, Federal Reserve Board, Washington, D.C.

Black, S.E., and Strahan P.E., 2002. Entrepreneurship and Bank Credit Availability. *Journal of Finance,* 57(6):2807-2833.

Blundell-Wignall, A. and C. Roulet (2013), "Business Models of Banks, Leverage and the Distance-to-default",OECD Journal: Financial Market Trends, Vol. 2012/2,OECD Publishing.

Butler, A. W., J. Cornaggia and U. G. Gurun, 2014. Do Local Capital Market Conditions Affect Consumers' Borrowing Decisions? Mimeo.

Citi, 2016. Banking and FinTech. Competition and Collaboration in the Uber Age, Citi Research

Claessens, Stijn & Laeven, Luc, 2004. What Drives Bank Competition? Some International Evidence, *Journal of Money, Credit and Banking, Blackwell Publishing*, 36(3): 563-83.

Cohen, W.M. and Levin, R.C., 2010. Fifty Years of Empirical Studies of Innovative Activity and Performance, Handbook of the Economics of Innovation, vol.1:129-213.

Comin, D. A., Mikhail D., Rossi-Hansberg, E. 2012. The Spatial Diffusion of Technology, NBER Working Papers 18534, National Bureau of Economic Research, Inc.

De Haas, R. and van Lelyveld, I., 2010. Internal Capital Markets and Lending by Multinational bank subsidiaries, *Journal of Financial Intermediation*, 19(1):1-25.

DeYoung, R., Lang, W. W., and Nolle, D. L., 2007. How the Internet Affects Output and Performance at Community Banks, *Journal of Banking & Finance,* 31:1033–60.

Demyanyk, Y. and Kolliner, D., 2014. Peer-to-peer Lending is Poised to Grow, working paper of the Federal Reserve Bank of Cleveland.

Dick, A., 2007. Market Size, Service Quality and Competition in Banking. *Journal of Money, Credit and Banking*, 39(1): 49-81.

Drukker D.M., Peng, H., Prucha,I.R. and Raciborski, R., 2013. Creating and managing Spatial Weighting matrices with the spmat command, *The Stata Journal*, 13(2): 242-286.

Drukker D.M., Prucha,I.R. and Raciborski, R., 2013. Maximum lilelihood and generalized spatial two-stage least-squares estimators for a spatial-autoregressive model with spatial autoregressive disturbances, *The Stata Journal*, 13(2): 221-241.

Duarte, J., S. Siegel, L. Young, 2012. Trust and Credit: The Role of Appearance in Peer-to-peer Lending. *Review of Financial Studies*, 25(8): 2455-2484.

Einav, L., Jenkins, M., and Levin, J., 2013. The Impact of Credit Scoring on Consumer Lending. *RAND Journal of Economics*, 44(2): 249–274.

Frame, S.W. and White, L., 2009. Technological Change, Financial Innovation, and Diffusion in Banking, The Oxford Handbook of Banking, Oxford University Press, Chapter 19.

Freedman, S. and Jin G.Z., 2008. Do Social Networks Solve Information Problems for Peer-to-Peer Lending? Evidence from Prosper.com, Net Institute Working Paper, 08-43.

Freedman, S.M. and Jin, G.Z.. 2014, The Signaling Value of Online Social Networks: Lessons from Peer-to-Peer Lending, NBER Working Papers19820, National Bureau of Economic Research, Inc.

Gao, Q. and M. Lin, 2012. Linguistic Features and Peer-to-Peer Loan Quality: A Machine Learning Approach. Working paper.

Garrett T. & Wagner G. & Wheelock,D.C., 2005. A Spatial Analysis of State Banking Regulation, Papers in Regional Science, 84(4), 575-595.

Geroski, Paul A, 1989. Entry, Innovation and Productivity Growth, *The Review of Economics and Statistics*, 71(4): 572-78.

Haldane,A. (2011a),"Capital Discipline",based on a speech given at the American Economic Association, Denver, 9 January 2011.

Haldane,A. (2012),"The dog and the Frisbee", speech given at the Federal Reserve Bank of Kansas City's 36th economic policy symposium, "The Changing Policy Landscape", Jackson Hole, Wyoming, 31August 2012.

Haldane, A.J., 2016. Is there an Industrial Revolution in Financial Services? Joint Bank of England/London Business School Conference.

Hasan, I., M. Koetter, & M. Wedow, 2009. Regional Growth and Finance in Europe: Is There a Quality Effect of Bank Efficiency? *Journal of Banking & Finance,* 33(8): 1446-1453.

Hannan, T. and Prager, R., 1998. The Relaxation of Entry Barriers in the Banking Industry: An Empirical Investigation, *Journal of Financial Services Research*, 14(3): 171-188.

Hernando, I. and Nieto, M. J. 2007. Is the Internet Delivery Channel Changing Banks' Performance? The Case of Spanish Banks, *Journal of Banking & Finance*, 31: 1083–99.

Herzenstein, M., S. Sonenshein and U. Dholakia, 2011. Tell Me a Good Story and I May Lend You My Money: The Role of Narratives in Peer-to-Peer Lending Decisions, *Journal of Marketing Research*, 48: 138-149.

Kim, M., Kliger, D. and Vale, B., 2003. Estimating switching costs: The case of banking. *The Journal of Financial Intermediation*, 12: 25–56.

LeSage, J.P., 2009. An introduction to Spatial Econometrics, *Revue d'Economie Industrielle, 123(3).*

LeSage, J.P. and Pace K.P., 2009. Introduction to Spatial Econometrics. *STATISTICS: Textbooks and Monographs D. B. Owen Founding Editor.*

LeSage, J.P. and Pace K.P., 2010. The biggest myth in spatial econometrics. *Econometrics, MDPI, Open Access Journal*, vol. 2(4), pages 217.

Mariathasan and Merrouche, 2014. The manipulation of Basel risk-weights. Journal of Financial Intermediation 3, 300-321.

Morse, A., 2015. Peer-To-Peer Crowdfunding: Information And The Potential For Disruption In Consumer Lending, NBER Working Paper 20899.

Mitra, T., and Gilbert, E., 2014. The Language that Gets People to Give: Phrases that Predict Success on Kickstarter, CSCW Georgia Tech.

Pagern D. and H. Shepherd, 2008. The Sociology of Discrimination: Racial Discrimination in Employment, Housing, Credit, and Consumer Markets, *Annual Review of Sociolgy,* 34: 181–209.

Pope, D., & Sydnor, J. 2011. What's in a Picture? Evidenc of Discrimination from Prosper.com., *Journal of Human Resources*, 46(1): 53-92.

Philippon, T., 2015. Has the US Finance Industry Become Less Efficient? On the Theory and Measurement of Financial Intermediation, *American Economic Review,* 105 (4): 1408-38.

Rey, S. J. and. Montouri, B.D., 1999. U.S. Regional Income Convergence: A Spatial Econometric Perspective, *Regional Studies*, 33(2): 143-156.

Rhoades, S.A., 2000. Bank Mergers and Banking Structure in the US, Staff study, Board of governors of the Federal Reserve System.

Rogers, E. M., 2003. The Diffusion of Innovations. Fifth Edition ed: The Free Press, New York.

Ravina, E., 2012. Love & Loans: The Effect of Beauty and Personal Characteristics in Credit Markets. *Working Paper.*

Rysman, M. ,2009. The Economics of Two-Sided Markets. *Journal of Economic Perspectives, 23*, 125-144.

Shy, O., 2002. A Quick-and-Easy Method for Estimating Switching Costs, *International Journal of Industrial Organization*, 20(1): 71-87.

The Economist, 2015. From the People, for the People. But Will Financial Democracy Work in a Downturn?, May 9th 2015.

Wolf, M., 2016. Good News — Fintech Could Disrupt Finance, The Financial Times, March 8, 2016.

**Figure 3:** Depth of the P2P development at the county level during 2007-2013.

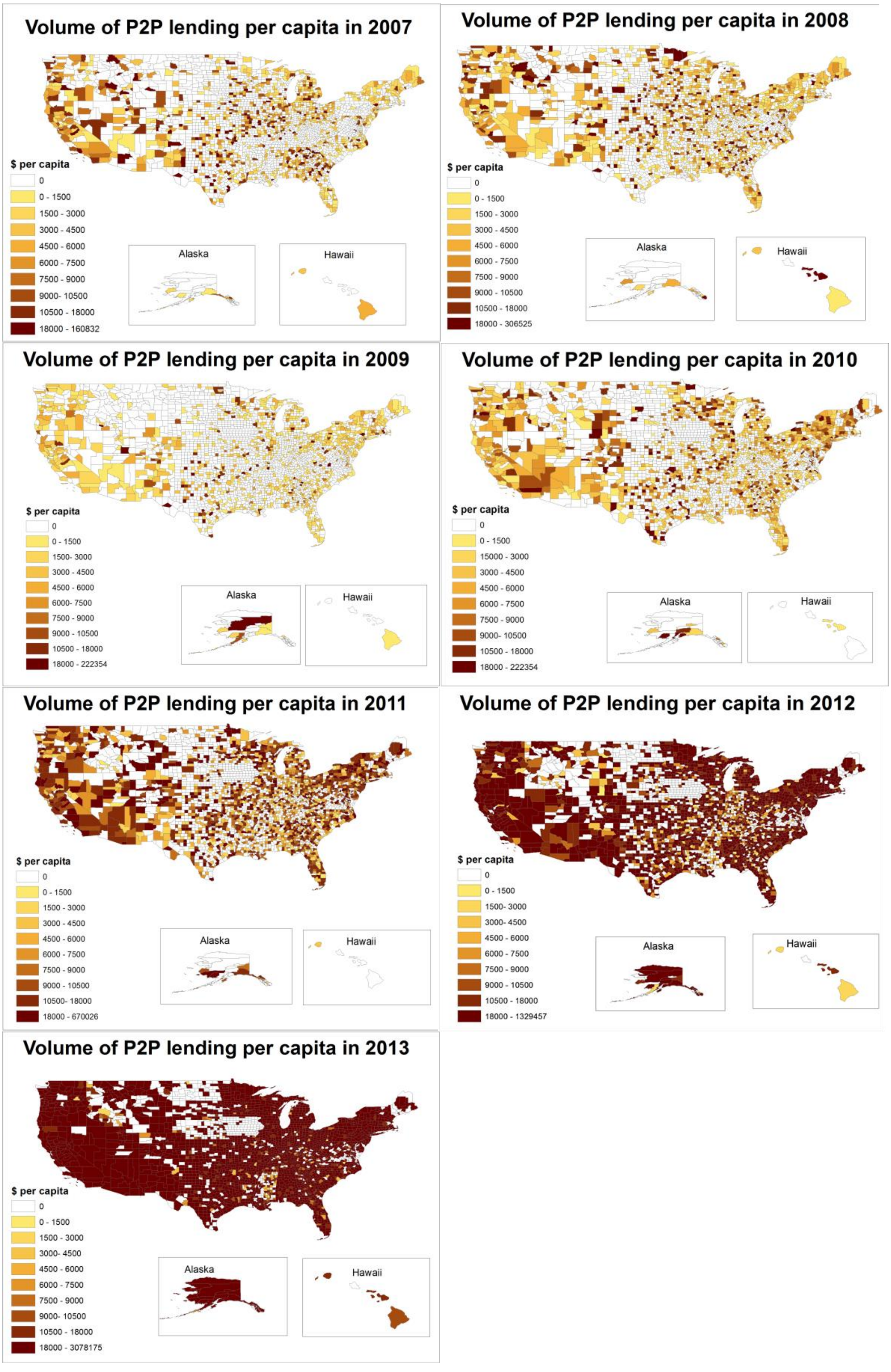


**Table 2. Variable definitions and data sources**

| Variable | Definition and data source |
|---|---|
| | |
| **Dependant variables** | |
| Number of P2P loans per capita | The sum of credit lines from Prosper and Lending Club aggregated for the period 2006-2013 at the county level per 10 000 population.<br>Sources: Prosper and Lending Club |
| P2P volume per capita | The sum of lending from Prosper and Lending Club aggregated for the period 2006-2013 at the county level per 10 000 population<br>Sources: Prosper and Lending Club |
| | |
| **Market structure variables** | |
| HHI | Herfindahl-Hirschmann index, computed in terms of deposits<br>Source: FDIC Summary of Deposits |
| C3 | The share of deposits of the three largest deposit taking institutions in a county<br>Source: FDIC Summary of Deposits |
| Branches per capita | Number of branches in a county divided per 10 000 population<br>Source: FDIC Summary of Deposits |
| Pay Day loans | Number establishment divided by 10 000 population. Non-depository consumer lending (NAICS: 522291)<br>Other activities related to credit intermediation (NAICS 522390)<br>Source: County Business Patterns |
| | |
| **Crisis variables** | |
| Crisis 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.<br>Source: FDIC Call Reports, Summary of Deposits |
| Crisis 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.<br>Source: FDIC Call Reports, Summary of Deposits |
| Failed banks | % of deposits affected by bank failures in a county during the whole period.<br>Source: FDIC Failed Bank List |
| Credit growth | % change in Credit Card Debt Balance per Capita during crisis years 2009-2010<br>Source: New York Fed Consumer Credit Panel / Equifax |
| Delinquencies | % of Credit Card Debt Balance 90+ Days Delinquent during crisis years 2009-2010<br>Source: New York Fed Consumer Credit Panel / Equifax |
| | |
| **Innovation and internet variables** | |
| Patents | Number of patents per 10 000 population<br>Source: U.S. Patent And Trademark Office |
| Broadband | % of county population with access to any broadband technology (excluding satellite)<br>Source: NTIA’s State Broadband Initiative |
| Mobile | % of county population with access to Mobile Wireless (Licensed) technology<br>Source: NTIA’s State Broadband Initiative |
| Speed | % of county population with access to upload speed 50 mbps or higher<br>Source: NTIA’s State Broadband Initiative |

| Socio-economic and demographic variables | |
|---|---|
| Age 20 to 34 | The share of the population between 20-34 years<br>Source: American Community Survey 5-year average (2009-2013) |
| Population density | Population number divided by area in sq. m. in a county<br>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<br>Source: American Community Survey 5-year average (2009-2013) |
| Poverty | % of county population below poverty line<br>Source: American Community Survey 5-year average (2009-2013) |
| Black | % of Afro-Americans in the county population<br>Source: American Community Survey 5-year average (2009-2013) |
| Hispanic | % of Hispanic population in the county population<br>Source: American Community Survey 5-year average (2009-2013) |
| Asian | % of Asian population in the county population<br>Source: American Community Survey 5-year average (2009-2013) |

## Table 3. Summary statistics

| Variable | Obs | Mean | Std.Dev. | Min | Max |
|---|---|---|---|---|---|
| Prosper volume | 3059 | 13930 | 28786 | 0 | 777512 |
| Lending Club volume | 3059 | 81080 | 147689 | 0 | 4517468 |
| Volume of P2P loans | 3059 | 95010 | 171766 | 0 | 5294980 |
| Number of P2P loans | 3059 | 5.96 | 11.58 | 0.00 | 451.34 |
| **Crisis variables** | | | | | |
| Failed | 3059 | 0.02 | 0.08 | 0.00 | 1.00 |
| Crisis Tier1 | 3059 | 0.14 | 0.08 | 0.06 | 3.99 |
| Crisis leverage | 3059 | 0.09 | 0.02 | 0.04 | 0.33 |
| **Competition variables** | | | | | |
| C3 | 3059 | 0.77 | 0.19 | 0.28 | 1.00 |
| HHI | 3059 | 0.31 | 0.21 | 0.05 | 1.00 |
| Branches | 3059 | 15.68 | 17.18 | 0.61 | 216.74 |
| Payday | 3059 | 1.01 | 1.25 | 0.00 | 8.67 |
| **Innovation variables** | | | | | |
| Mobile | 3059 | 0.95 | 0.11 | 0.00 | 1.00 |
| Broadband | 3059 | 0.98 | 0.05 | 0.01 | 1.00 |
| Speed50000k | 3059 | 0.42 | 0.35 | 0.00 | 1.00 |
| Speed10000k | 3059 | 0.23 | 0.35 | 0.00 | 1.00 |
| Patents | 3059 | 8.60 | 19.32 | 0.00 | 372.86 |
| **Other variables** | | | | | |
| Density | 3059 | 77 | 473 | 0 | 18354 |
| Age 20 to 34 | 3059 | 0.19 | 0.02 | 0.09 | 0.32 |
| Bachelor | 3059 | 0.17 | 0.08 | 0.04 | 0.61 |
| Income | 3059 | 34733.9 | 8860.966 | 14885.43 | 158212.1 |
| Poverty | 3059 | 0.17 | 0.06 | 0.03 | 0.50 |
| Asian | 3059 | 0.01 | 0.02 | 0.00 | 0.58 |
| Hispanic | 3059 | 0.05 | 0.08 | 0.00 | 0.49 |
| Black | 3059 | 0.08 | 0.15 | 0.00 | 0.88 |

**Table 4. 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. Dependant variable is the amount of P2P lending per capital 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.

| | Volume of P2P loans per capita in log | | | | | |
|---|---|---|---|---|---|---|
| **Competition variables** | | | | | | |
| Branches | -0.0138*** | -0.0135*** | -0.0149*** | -0.0150*** | -0.0150*** | -0.0139*** |
| | (0.00384) | (0.00382) | (0.00381) | (0.00381) | (0.00380) | (0.00384) |
| C3 | -0.800** | | | | | |
| | (0.390) | | | | | |
| HHI | | -1.997*** | -2.029*** | -2.035*** | -2.038*** | |
| | | (0.330) | (0.331) | (0.331) | (0.331) | |
| Payday | 0.119** | 0.0848* | 0.0898* | 0.0900* | 0.0900* | 0.134*** |
| | (0.0480) | (0.0480) | (0.0480) | (0.0480) | (0.0481) | (0.0475) |
| **Crisis variables** | | | | | | |
| Crisis leverage | -11.31*** | -10.75*** | | | | -11.55*** |
| | (3.442) | (3.426) | | | | (3.442) |
| Capital_crisis | | | -0.441 | | | |
| | | | (1.030) | | | |
| Tier1_crisis | | | | -0.0844 | | |
| | | | | (0.663) | | |
| Failed banks | | | | | 0.0181 | |
| | | | | | (0.558) | |
| **Other variables** | | | | | | |
| Density_log | 0.546*** | 0.466*** | 0.480*** | 0.480*** | 0.480*** | 0.592*** |
| | (0.0471) | (0.0461) | (0.0460) | (0.0460) | (0.0460) | (0.0414) |
| Broadband | -3.626*** | -4.395*** | -4.532*** | -4.534*** | -4.536*** | -3.495*** |
| | (0.918) | (0.924) | (0.924) | (0.924) | (0.925) | (0.916) |
| Income_log | -1.755*** | -1.914*** | -1.984*** | -1.989*** | -1.989*** | -1.691*** |
| | (0.412) | (0.411) | (0.411) | (0.411) | (0.412) | (0.411) |
| Poverty | -7.070*** | -6.524*** | -6.649*** | -6.662*** | -6.664*** | -7.387*** |
| | (1.425) | (1.417) | (1.419) | (1.419) | (1.419) | (1.417) |
| Bachelor | 2.672*** | 3.291*** | 3.581*** | 3.598*** | 3.599*** | 2.830*** |
| | (1.001) | (0.996) | (0.993) | (0.993) | (0.993) | (0.998) |
| Black | -0.240 | 0.0493 | 0.0430 | 0.0434 | 0.0427 | -0.399 |
| | (0.461) | (0.458) | (0.458) | (0.459) | (0.459) | (0.454) |
| Hispanic | 6.362*** | 6.583*** | 6.691*** | 6.684*** | 6.677*** | 6.539*** |
| | (1.045) | (1.037) | (1.038) | (1.038) | (1.042) | (1.042) |
| Age 20 to 34 | 4.058 | 2.225 | 2.053 | 2.061 | 2.067 | 4.474 |
| | (3.133) | (3.133) | (3.137) | (3.137) | (3.142) | (3.128) |
| Constant | 31.93*** | 34.36*** | 34.37*** | 34.38*** | 34.37*** | 30.52*** |
| | (4.554) | (4.525) | (4.532) | (4.532) | (4.551) | (4.504) |
| Lambda | 0.571*** | 0.557*** | 0.558*** | 0.557*** | 0.557*** | 0.581*** |
| | (0.0347) | (0.0344) | (0.0345) | (0.0345) | (0.0345) | (0.0343) |
| Sigma2 | 8.078*** | 7.998*** | 8.023*** | 8.024*** | 8.024*** | 8.085*** |
| | (0.207) | (0.205) | (0.205) | (0.206) | (0.206) | (0.207) |
| Number of counties | 3,059 | 3,059 | 3,059 | 3,059 | 3,059 | 3,059 |
| State dummies | Yes | Yes | Yes | Yes | Yes | Yes |

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

We estimate cross-sectional models of the geographic expansion of the P2P lending during the period 2006-2013. Dependant variable is the amount of P2P lending per capital 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.

| | Number of P2P loans per capita in log | | | | | |
|---|---|---|---|---|---|---|
| **Competition variables** | | | | | | |
| Branches | -0.00301*** | -0.00295*** | -0.00321*** | -0.00319*** | -0.00314*** | -0.00278*** |
| | (0.000997) | (0.000995) | (0.000992) | (0.000992) | (0.000989) | (0.000996) |
| C3 | -0.346*** | | | | | |
| | (0.1000) | | | | | |
| HHI | | -0.329*** | -0.337*** | -0.336*** | -0.341*** | |
| | | (0.0865) | (0.0866) | (0.0866) | (0.0866) | |
| Payday | -0.0105 | -0.0123 | -0.0113 | -0.0113 | -0.0107 | -0.00307 |
| | (0.0128) | (0.0128) | (0.0128) | (0.0128) | (0.0129) | (0.0126) |
| **Crisis variables** | | | | | | |
| Crisis leverage | -1.813** | -1.789* | | | | -1.944** |
| | (0.921) | (0.920) | | | | (0.921) |
| Capital_crisis | | | 0.0483 | | | |
| | | | (0.276) | | | |
| Tier1_crisis | | | | -0.00377 | | |
| | | | | (0.178) | | |
| Failed banks | | | | | 0.155 | |
| | | | | | (0.150) | |
| **Other Variables** | | | | | | |
| Density | 0.0557*** | 0.0542*** | 0.0563*** | 0.0563*** | 0.0559*** | 0.0717*** |
| | (0.0110) | (0.0110) | (0.0109) | (0.0109) | (0.0109) | (0.00996) |
| Broadband | -0.192 | -0.324 | -0.352 | -0.352 | -0.370 | -0.0818 |
| | (0.320) | (0.325) | (0.325) | (0.325) | (0.325) | (0.319) |
| Income_log | -0.0936 | -0.101 | -0.114 | -0.114 | -0.103 | -0.0835 |
| | (0.108) | (0.108) | (0.108) | (0.108) | (0.108) | (0.108) |
| Poverty | -2.146*** | -2.157*** | -2.181*** | -2.180*** | -2.167*** | -2.317*** |
| | (0.384) | (0.383) | (0.383) | (0.383) | (0.383) | (0.381) |
| Bachelor | 1.486*** | 1.620*** | 1.674*** | 1.672*** | 1.661*** | 1.595*** |
| | (0.257) | (0.255) | (0.254) | (0.253) | (0.254) | (0.255) |
| Age 20 to 34 | -0.174 | -0.348 | -0.389 | -0.389 | -0.343 | 0.0615 |
| | (0.778) | (0.782) | (0.782) | (0.782) | (0.784) | (0.776) |
| Black | 0.346*** | 0.355*** | 0.355*** | 0.355*** | 0.351*** | 0.291** |
| | (0.119) | (0.120) | (0.120) | (0.120) | (0.120) | (0.119) |
| Hispanic | 0.982*** | 1.044*** | 1.051*** | 1.052*** | 1.038*** | 1.020*** |
| | (0.195) | (0.195) | (0.195) | (0.195) | (0.196) | (0.195) |
| Constant | 2.596** | 2.644** | 2.650** | 2.651** | 2.548** | 2.102* |
| | (1.197) | (1.196) | (1.197) | (1.197) | (1.201) | (1.190) |
| Lambda | 0.960*** | 0.964*** | 0.965*** | 0.966*** | 0.964*** | 0.973*** |
| | (0.0402) | (0.0401) | (0.0401) | (0.0401) | (0.0401) | (0.0400) |
| Sigma2 | 0.577*** | 0.576*** | 0.577*** | 0.577*** | 0.577*** | 0.579*** |
| | (0.0149) | (0.0149) | (0.0149) | (0.0149) | (0.0149) | (0.0149) |
| Number of counties | 3,059 | 3,059 | 3,059 | 3,059 | 3,059 | 3,059 |
| State dummies | Yes | Yes | Yes | Yes | Yes | Yes |

**Table 6. Spatial lag model for the P2P expansion as a function of innovation variables with volume of loans per capita as dependent variable**

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.

| | Volume of P2P loans per capita in log | | | | | |
|---|---|---|---|---|---|---|
| **Innovation variables** | | | | | | |
| Patents_log | 0.118** | | | | | |
| | (0.0566) | | | | | |
| Broadband | | -4.395*** | | | | |
| | | (0.924) | | | | |
| Optical fiber | | | -0.348 | | | |
| | | | (0.255) | | | |
| Mobile | | | | -1.278*** | | |
| | | | | (0.348) | | |
| Speed10000k | | | | | -0.0316 | |
| | | | | | (0.168) | |
| Speed50000k | | | | | | 0.0367 |
| | | | | | | (0.169) |
| **Other variables** | | | | | | |
| Branches | -0.0121*** | -0.0135*** | -0.0126*** | -0.0135*** | -0.0131*** | -0.0132*** |
| | (0.00382) | (0.00382) | (0.00385) | (0.00382) | (0.00385) | (0.00384) |
| HHI | -1.630*** | -1.997*** | -1.738*** | -1.978*** | -1.744*** | -1.744*** |
| | (0.327) | (0.330) | (0.327) | (0.333) | (0.327) | (0.327) |
| Payday | 0.0668 | 0.0848* | 0.0685 | 0.0837* | 0.0702 | 0.0689 |
| | (0.0482) | (0.0480) | (0.0480) | (0.0481) | (0.0481) | (0.0481) |
| Crisis levergae | -12.19*** | -10.75*** | -11.34*** | -11.70*** | -11.55*** | -11.49*** |
| | (3.431) | (3.426) | (3.437) | (3.428) | (3.436) | (3.441) |
| Density | 0.449*** | 0.466*** | 0.446*** | 0.465*** | 0.449*** | 0.444*** |
| | (0.0476) | (0.0461) | (0.0461) | (0.0462) | (0.0468) | (0.0488) |
| Income_log | -1.460*** | -1.914*** | -1.899*** | -1.955*** | -1.962*** | -1.964*** |
| | (0.371) | (0.411) | (0.415) | (0.411) | (0.412) | (0.412) |
| Poverty | -5.722*** | -6.524*** | -5.865*** | -6.481*** | -5.882*** | -5.852*** |
| | (1.431) | (1.417) | (1.415) | (1.422) | (1.417) | (1.417) |
| Bachelor | | 3.291*** | 3.454*** | 3.313*** | 3.439*** | 3.392*** |
| | | (0.996) | (0.999) | (0.997) | (1.007) | (1.004) |
| Age 20 to 34 | 4.916* | 2.225 | 2.075 | 2.552 | 1.944 | 1.927 |
| | (2.981) | (3.133) | (3.145) | (3.142) | (3.145) | (3.148) |
| Black | -0.0367 | 0.0493 | -0.107 | 0.0653 | -0.115 | -0.135 |
| | (0.463) | (0.458) | (0.458) | (0.460) | (0.462) | (0.460) |
| Hispanic | 6.690*** | 6.583*** | 6.419*** | 6.668*** | 6.451*** | 6.424*** |
| | (1.040) | (1.037) | (1.040) | (1.040) | (1.045) | (1.041) |
| Constant | 25.08*** | 34.36*** | 29.82*** | 31.71*** | 30.50*** | 30.51*** |
| | (4.048) | (4.525) | (4.494) | (4.471) | (4.468) | (4.468) |
| Lambda | 0.550*** | 0.557*** | 0.549*** | 0.548*** | 0.551*** | 0.550*** |
| | (0.0346) | (0.0344) | (0.0346) | (0.0345) | (0.0345) | (0.0345) |
| Sigma2 | 8.079*** | 7.998*** | 8.055*** | 8.025*** | 8.059*** | 8.059*** |
| | (0.207) | (0.205) | (0.206) | (0.206) | (0.206) | (0.206) |
| Number of counties | 3,059 | 3,059 | 3,059 | 3,059 | 3,059 | 3,059 |

| | | | | | | |
|---|---|---|---|---|---|---|
| State dummies | Yes | Yes | Yes | Yes | Yes | Yes |

**Table 7. Spatial lag model for the P2P expansion as a function of innovation variables with number of loans per capita as dependent variable**

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.

| | **Number of P2P loans per capita** | | | | | |
|---|---|---|---|---|---|---|
| **Innovation variables** | | | | | | |
| Patents_log | 0.0252* | | | | | |
| | (0.0149) | | | | | |
| Broadband | | -0.324 | | | | |
| | | (0.325) | | | | |
| Optical fiber | | | -0.109 | | | |
| | | | (0.0663) | | | |
| Mobile | | | | -0.0313 | | |
| | | | | (0.148) | | |
| Speed10000k | | | | | -0.0412 | |
| | | | | | (0.0515) | |
| Speed50000k | | | | | | 0.0239 |
| | | | | | | (0.0517) |
| **Other variables** | | | | | | |
| Branches | -0.00229** | -0.00295*** | -0.00277*** | -0.00295*** | -0.00286*** | -0.00298*** |
| | (0.000996) | (0.000995) | (0.00100) | (0.000995) | (0.00100) | (0.000999) |
| HHI | -0.280*** | -0.329*** | -0.310*** | -0.316*** | -0.315*** | -0.307*** |
| | (0.0856) | (0.0865) | (0.0848) | (0.0871) | (0.0850) | (0.0854) |
| Payday | -0.0161 | -0.0123 | -0.0137 | -0.0129 | -0.0136 | -0.0133 |
| | (0.0129) | (0.0128) | (0.0128) | (0.0129) | (0.0128) | (0.0128) |
| Crisis leverage | -2.348** | -1.789* | -1.782* | -1.828** | -1.872** | -1.786* |
| | (0.922) | (0.920) | (0.920) | (0.919) | (0.921) | (0.924) |
| Density | 0.0620*** | 0.0542*** | 0.0533*** | 0.0537*** | 0.0551*** | 0.0516*** |
| | (0.0113) | (0.0110) | (0.0109) | (0.0110) | (0.0111) | (0.0117) |
| Income_log | 0.178* | -0.101 | -0.0844 | -0.105 | -0.104 | -0.106 |
| | (0.0984) | (0.108) | (0.109) | (0.108) | (0.108) | (0.108) |
| Poverty | -2.119*** | -2.157*** | -2.098*** | -2.119*** | -2.132*** | -2.091*** |
| | (0.385) | (0.383) | (0.379) | (0.384) | (0.380) | (0.380) |
| Bachelor | | 1.620*** | 1.651*** | 1.629*** | 1.664*** | 1.615*** |
| | | (0.255) | (0.255) | (0.255) | (0.257) | (0.257) |
| Age 20 to 34 | 0.685 | -0.348 | -0.355 | -0.381 | -0.419 | -0.405 |
| | (0.766) | (0.782) | (0.781) | (0.784) | (0.781) | (0.781) |
| Black | 0.363*** | 0.355*** | 0.335*** | 0.344*** | 0.353*** | 0.334*** |
| | (0.120) | (0.120) | (0.119) | (0.120) | (0.120) | (0.119) |
| Hispanic | 1.116*** | 1.044*** | 1.017*** | 1.032*** | 1.044*** | 1.027*** |
| | (0.195) | (0.195) | (0.194) | (0.196) | (0.195) | (0.194) |
| Constant | -0.531 | 2.644** | 2.145* | 2.391** | 2.374** | 2.360** |
| | (1.072) | (1.196) | (1.172) | (1.169) | (1.164) | (1.164) |
| Lambda | 0.977*** | 0.964*** | 0.963*** | 0.963*** | 0.964*** | 0.962*** |
| | (0.0401) | (0.0401) | (0.0401) | (0.0401) | (0.0401) | (0.0401) |
| Sigma2 | 0.583*** | 0.576*** | 0.576*** | 0.577*** | 0.577*** | 0.577*** |
| | (0.0150) | (0.0149) | (0.0149) | (0.0149) | (0.0149) | (0.0149) |
| Number of counties | 3,059 | 3,059 | 3,059 | 3,059 | 3,059 | 3,059 |

| State dummies | Yes | Yes | Yes | Yes | Yes | Yes |
|---|---|---|---|---|---|---|

**Table 8. 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.

| | **Volume of P2P loans per capita** | | **Number of P2P loans per capita** | |
|---|---|---|---|---|
| | Lending Club | Prosper | Lending Club | Prosper |
| Branches | -0.0177*** | -0.00816* | -0.00325*** | -0.00118 |
| | (0.00406) | (0.00471) | (0.00105) | (0.000865) |
| HHI | -1.157*** | -4.339*** | -0.284*** | -0.0352 |
| | (0.349) | (0.407) | (0.0915) | (0.0751) |
| Payday | -0.0796 | 0.273*** | -0.0281** | -0.0124 |
| | (0.0510) | (0.0591) | (0.0136) | (0.0112) |
| Crisis leverage | -5.110 | -24.37*** | -0.657 | -1.546* |
| | (3.643) | (4.228) | (0.974) | (0.800) |
| Density | 0.540*** | 0.637*** | 0.0190 | 0.0443*** |
| | (0.0494) | (0.0574) | (0.0116) | (0.00952) |
| Broadband | -6.414*** | 3.009*** | -0.546 | 0.382 |
| | (0.981) | (1.139) | (0.344) | (0.283) |
| Income_log | -0.601 | -2.197*** | -0.0349 | -0.230** |
| | (0.435) | (0.507) | (0.114) | (0.0934) |
| Poverty | -3.414** | -8.524*** | -2.068*** | -1.978*** |
| | (1.504) | (1.756) | (0.404) | (0.333) |
| Bachelor | 2.473** | 4.979*** | 0.995*** | 1.709*** |
| | (1.058) | (1.227) | (0.269) | (0.222) |
| Age 20 to 34 | -3.879 | 14.23*** | -0.227 | -1.290* |
| | (3.332) | (3.864) | (0.828) | (0.680) |
| Black | -0.447 | -0.0792 | 0.440*** | 0.408*** |
| | (0.487) | (0.566) | (0.127) | (0.104) |
| Hispanic | 6.677*** | 2.032 | 0.912*** | 0.627*** |
| | (1.106) | (1.275) | (0.207) | (0.169) |
| Constant | 19.80*** | 28.79*** | 1.825 | 2.829*** |
| | (4.797) | (5.587) | (1.259) | (1.034) |
| Lambda | 1.169*** | 0.378*** | 1.033*** | 0.679*** |
| | (0.0293) | (0.0446) | (0.0436) | (0.0525) |
| Sigma2 | 9.045*** | 12.16*** | 0.646*** | 0.436*** |
| | (0.233) | (0.311) | (0.0167) | (0.0112) |
| Number of counties | 3,059 | 3,059 | 3,059 | 3,059 |
| State dummies | Yes | Yes | Yes | Yes |

### Table 9. 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.

| **Volume of P2P lending** | **2007** | **2008** | **2009** | **2010** | **2011** | **2012** | **2013** |
|---|---|---|---|---|---|---|---|
| Branches | -0.00557 | 0.00490 | 0.00236 | -0.00380 | -0.0109** | -0.0111** | -0.0166*** |
| | (0.00448) | (0.00457) | (0.00391) | (0.00451) | (0.00489) | (0.00480) | (0.00422) |
| HHI | -1.426*** | -1.981*** | -0.718** | -2.186*** | -2.923*** | -3.413*** | -2.180*** |
| | (0.388) | (0.396) | (0.340) | (0.390) | (0.421) | (0.415) | (0.365) |
| Payday | 0.0639 | 0.0706 | -0.00717 | 0.0668 | 0.148** | 0.109* | 0.0899* |
| | (0.0532) | (0.0559) | (0.0491) | (0.0571) | (0.0620) | (0.0568) | (0.0512) |
| Crisis leverage | -18.14*** | -15.27*** | -8.714** | -13.22*** | -14.52*** | -11.41*** | -2.877 |
| | (4.052) | (4.129) | (3.546) | (4.075) | (4.421) | (4.339) | (3.826) |
| density_log | 0.561*** | 0.728*** | 0.678*** | 0.767*** | 0.787*** | 0.531*** | 0.530*** |
| | (0.0541) | (0.0560) | (0.0481) | (0.0558) | (0.0611) | (0.0591) | (0.0523) |
| Broadband | 1.281 | 1.997* | -1.088 | -0.882 | -0.730 | -3.385*** | -5.488*** |
| | (1.093) | (1.110) | (0.955) | (1.096) | (1.187) | (1.169) | (1.030) |
| Income_log | -0.123 | -1.301*** | 0.300 | 0.388 | -1.075** | -1.762*** | -1.447*** |
| | (0.534) | (0.496) | (0.459) | (0.496) | (0.471) | (0.442) | (0.384) |
| Poverty | -2.520 | -7.419*** | -1.526 | -3.929** | -5.620*** | -6.741*** | -6.658*** |
| | (1.699) | (1.724) | (1.475) | (1.678) | (1.795) | (1.741) | (1.542) |
| Bachelor | 9.016*** | 9.365*** | 9.182*** | 6.777*** | 6.128*** | 5.310*** | 1.803* |
| | (1.245) | (1.218) | (1.046) | (1.176) | (1.248) | (1.228) | (1.063) |
| Black | -0.743 | -0.726 | 0.275 | -0.940* | -0.581 | 0.347 | 0.00288 |
| | (0.548) | (0.553) | (0.476) | (0.542) | (0.586) | (0.574) | (0.505) |
| Hispanic | 6.900*** | 4.552*** | 6.814*** | 6.204*** | 5.107*** | 7.809*** | 7.375*** |
| | (1.253) | (1.249) | (1.082) | (1.236) | (1.331) | (1.314) | (1.157) |
| Age 20 to 34 | 8.764** | 10.72*** | 2.962 | 10.15*** | 7.376* | 5.554 | -0.575 |
| | (3.757) | (3.780) | (3.252) | (3.708) | (4.008) | (3.950) | (3.466) |
| Constant | 2.268 | 15.47*** | -0.129 | 0.468 | 18.02*** | 28.71*** | 28.68*** |
| | (5.853) | (5.460) | (5.056) | (5.458) | (5.228) | (4.941) | (4.266) |
| Lambda | 0.742*** | 0.377*** | 0.568*** | 0.565*** | 0.616*** | 0.754*** | 0.915*** |
| | (0.0481) | (0.0521) | (0.0502) | (0.0481) | (0.0465) | (0.0411) | (0.0339) |
| Sigma2 | 11.21*** | 11.57*** | 8.556*** | 11.29*** | 13.24*** | 12.82*** | 9.934*** |
| | (0.288) | (0.296) | (0.220) | (0.290) | (0.340) | (0.329) | (0.255) |
| Observations | 3,059 | 3,059 | 3,059 | 3,059 | 3,059 | 3,059 | 3,059 |

## Table 10. OLS regressions

| VARIABLES | Volume | Number |
|---|---|---|
| Branches | -0.0110*** | -0.00211* |
| | (0.00400) | (0.00110) |
| HHI | -2.632*** | -0.465*** |
| | (0.344) | (0.0955) |
| Payday | 0.113** | -0.0160 |
| | (0.0503) | (0.0142) |
| Crisis leverage | -10.80*** | -2.304** |
| | (3.594) | (1.017) |
| Density | 0.499*** | 0.0700*** |
| | (0.0483) | (0.0121) |
| Broadband | -3.843*** | -0.0923 |
| | (0.968) | (0.359) |
| income_log | -3.083*** | -0.445*** |
| | (0.424) | (0.118) |
| Poverty | -8.178*** | -3.124*** |
| | (1.483) | (0.421) |
| Bachelor | 3.899*** | 2.142*** |
| | (1.044) | (0.281) |
| Black | 0.228 | 0.512*** |
| | (0.480) | (0.132) |
| Hispanic | 7.831*** | 1.703*** |
| | (1.084) | (0.214) |
| Age 20 to 34 | 2.981 | -0.420 |
| | (3.286) | (0.865) |
| Constant | 48.71*** | 6.739*** |
| | (4.655) | (1.309) |
| Observations | 3,059 | 3,059 |
| R-squared | 0.192 | 0.150 |

## Table 11. Marginal effects

| **Volume of P2P loans** | **ATDI** | **ATII** | **ATI** |
|---|---|---|---|
| Branches | -0,0013 | -0,0004 | -0,0018 |
| HHI | -0,1963 | -0,0628 | -0,2591 |
| Broadband | -0,4321 | -0,1382 | -0,5703 |
| Poverty | -0,6414 | -0,2052 | -0,8466 |
| Hispanic | 0,6472 | 0,2070 | 0,8542 |
| Income_log | -0,1882 | -0,0602 | -0,2484 |
| Payday | 0,0083 | 0,0027 | 0,0110 |
| Education | 0,3235 | 0,1035 | 0,4270 |
| Black | 0,0048 | 0,0016 | 0,0064 |
| Age | 0,2187 | 0,0700 | 0,2887 |
| Crisis leverage | -1,0565 | -0,3379 | -1,3944 |
| Density | 0,0458 | 0,0147 | 0,0605 |

| **Number of P2P loans** | **ATDI** | **ATII** | **ATI** |
|---|---|---|---|
| Branches | -0,0022 | -0,0016 | -0,0038 |
| HHI | -1,4631 | -0,4680 | -1,9312 |
| Broadband | -3,2202 | -1,0300 | -4,2502 |
| Poverty | -4,7799 | -1,5290 | -6,3089 |
| Hispanic | 4,8232 | 1,5428 | 6,3660 |
| Income_log | -1,4023 | -0,4486 | -1,8509 |
| Payday | 0,0621 | 0,0199 | 0,0820 |
| Education | 2,4111 | 0,7712 | 3,1823 |
| Black | 0,0361 | 0,0116 | 0,0477 |
| Age | 1,6300 | 0,5214 | 2,1514 |
| Crisis leverage | -7,8735 | -2,5185 | -10,3921 |
| Density | 0,3417 | 0,1093 | 0,4509 |

| **Lending Club_volume** | **ATDI** | **ATII** | **ATI** |
|---|---|---|---|
| Branches | -0,0020 | -0,0021 | -0,0041 |
| HHI | -0,1318 | -0,1352 | -0,2670 |
| Broadband | -0,7305 | -0,7494 | -1,4799 |
| Poverty | -0,3888 | -0,3988 | -0,7876 |
| Hispanic | 0,7605 | 0,7801 | 1,5405 |
| Income_log | -0,0684 | -0,0702 | -0,1386 |
| Payday | -0,0091 | -0,0093 | -0,0184 |
| Education | 0,2817 | 0,2890 | 0,5707 |
| Black | -0,0509 | -0,0522 | -0,1031 |
| Age | -0,4418 | -0,4532 | -0,8950 |
| Crisis leverage | -0,5820 | -0,5970 | -1,1790 |
| Density | 0,0615 | 0,0631 | 0,1246 |

| **Prosper_volume** | **ATDI** | **ATII** | **ATI** |
|---|---|---|---|
| Branches | -0,0011 | -0,0002 | -0,0013 |
| HHI | -0,5643 | -0,1117 | -0,6760 |
| Broadband | 0,3914 | 0,0775 | 0,4688 |
| Poverty | -1,1087 | -0,2195 | -1,3282 |
| Hispanic | 0,2643 | 0,0523 | 0,3166 |
| Income_log | -0,2857 | -0,0566 | -0,3423 |
| Payday | 0,0355 | 0,0070 | 0,0426 |
| Education | 0,6477 | 0,1282 | 0,7759 |
| Black | -0,0103 | -0,0020 | -0,0123 |
| Age | 1,8512 | 0,3665 | 2,2176 |
| Crisis leverage | -3,1695 | -0,6275 | -3,7970 |
| Density | 0,0829 | 0,0164 | 0,0993 |

| **Lending Club_number** | **ATDI** | **ATII** | **ATI** |
|---|---|---|---|
| Branches | -0,0035 | -0,0028 | -0,0063 |
| HHI | -0,3026 | -0,2445 | -0,5471 |
| Broadband | -0,5816 | -0,4700 | -1,0516 |
| Poverty | -2,2045 | -1,7814 | -3,9859 |
| Hispanic | 0,9721 | 0,7855 | 1,7576 |
| Income_log | -0,0372 | -0,0300 | -0,0672 |
| Payday | -0,0299 | -0,0242 | -0,0541 |
| Education | 1,0607 | 0,8571 | 1,9178 |
| Black | 0,4693 | 0,3793 | 0,8486 |
| Age | -0,2423 | -0,1958 | -0,4382 |
| Crisis leverage | -0,7002 | -0,5658 | -1,2660 |
| Density | 0,0203 | 0,0164 | 0,0367 |

| **Prosper_number** | **ATDI** | **ATII** | **ATI** |
|---|---|---|---|
| Branches | -0,0026 | -0,0011 | -0,0036 |
| HHI | -0,0767 | -0,0320 | -0,1088 |
| Broadband | 0,8330 | 0,3479 | 1,1809 |
| Poverty | -4,3074 | -1,7989 | -6,1064 |
| Hispanic | 1,3654 | 0,5702 | 1,9356 |
| Income_log | -0,5017 | -0,2095 | -0,7113 |
| Payday | -0,0270 | -0,0113 | -0,0383 |
| Education | 3,7217 | 1,5543 | 5,2760 |
| Black | 0,8891 | 0,3713 | 1,2604 |
| Age | -2,8091 | -1,1732 | -3,9822 |
| Crisis leverage | -3,3679 | -1,4066 | -4,7745 |
| Density | 0,0966 | 0,0403 | 0,1369 |