Lighthouse in the Dark: Search in Marketplace Lending

Wednesday 16th February, 2022

Abstract

This paper sheds light on the search friction in the Fintech credit market and finds that informational public goods can help reduce the search costs of borrowers and improve marketplace lending outcomes. From 2012, the Chinese government gradually introduced private-lending registration service centers (PLcenters) in many cities to disseminate market information and financial knowledge. Exploiting the introduction of PLcenters as a natural experiment, I apply a staggered difference-in-differences (DID) analysis using a novel data set from a leading marketplace lending platform. To address the endogeneity, I use a measure of China's political cycle as an instrumental variable. I find PLcenters effectively boost marketplace lending. Remarkably, PLcenters help borrowers secure lower interest rates from the platform and reduce the dispersion of interest rates. Less sophisticated borrowers mainly drive the effects. The findings imply PLcenters reduce search costs of borrowers, pointing to a potentially important role of informational public goods in reducing search frictions in the Fintech credit market.

Keywords: Search Frictions, Fintech Credit, Informational Public Goods
JEL Codes: G14, G23, G28, O16, D83

I. Introduction

The recent rapid growth of Fintech credit allows direct lending transactions between borrowers and lenders, thereby improves access to credit for underserved segments.[1] Though Fintech improves financial inclusion, the individual borrowers who newly the market may not have enough financial knowledge and thus face high search costs, resulting in price dispersion and deviations of prices from market efficiency. Similar evidences are found in the online shopping market and consumer credit market (e.g., see the evidence in Lynch Jr and Ariely, 2000; Berlin and Mester, 2004; Stango and Zinman, 2016). For instance, the individual borrowers, do not know the complete market information and have to search for the best choices at a cost, either pecuniary or non-pecuniary. Individuals with high search costs due to lack of financial knowledge or IT skills will not enter the market, or even if they enter, they borrow at too high interest rates. Indeed,

Yet, how to reduce the search costs of Fintech credit borrowers remains unclear. Furthermore, what is the best manner to provide information to individuals? Possible ways could be price disclosure (e.g. Duffie et al., 2017), consumer education (e.g. Chang and Hanna, 1992), and financial literacy (e.g. Panos and Wilson, 2020). Furthermore, who can provide the information services, private firms or public institutions?

This paper starts from these thoughts and puts forward a "rational economic planner" solution to reduce the dead-weight cost caused by search frictions: public information service centers as public goods.[2] Using a data set from a leading Chinese marketplace lending platform, Renrendai, with great detail on borrower and loan characteristics, I provide novel evidence suggesting public information service centers can work effectively in reducing the search cost, and thus lowering the interest rate dispersion. The experiment I look at is the staggered introduction of private-lending registration service centers (PLcenters) by the Chinese government in different cities since 2012.[3]

PLcenters gather, process, and disseminate the private-lending information and financial knowledge. Take Wenzhou city's PLcenters as an example. Second, PLcenters publish local prevailing interest rates of private-lending regularly, hold financial seminars, and provide private-loan contract templates. Second, PLcenters gather all private lending related agen-

[1] According to the Financial Stability Board's (FSB) definition, Fintech credit, one type of non-banks, is all credit activity facilitated by electronic platforms that directly connect borrowers and lenders. One example is marketplace lending, including peer-to-peer (e.g., LendingClub, Renrendai) and peer-to-business (e.g., Funding Circle) lending. China is the largest Fintech credit market.

[2] "A 'rational economic planner' could economize on information costs by eliminating the price dispersion; for with no price dispersion, there is no need for costly search..."(Salop and Stiglitz, 1977).

[3] "民间借贷登记服务中心" in Chinese. In some cities, PLcenters are called "Folk Financing Service Centre" (e.g., Guangzhou), "民间金融街综合服务中心" in Chinese.

cies, such as marketplace lending companies, notary offices, and law firms, in one place by providing them with almost free office spaces. Overall, we can consider PLcenters as public information service centers that offer free information services with public goods' characteristics: market information disclosure and financial education.

Specifically, this paper tries to answer the following questions: Can PLcenters help borrowers lower their financing costs? And what are the impacts of PLcenters on marketplace lending outcomes? Through a staggered difference-in-differences (DID) analysis, I find PLcenters boost marketplace lending and help borrowers secure lower interest rates. More remarkably, the dispersion of interest rates goes down with PLcenters mediating search frictions.

To guide the empirical investigation, I use a conceptual framework of search cost following Salop and Stiglitz (1977). An identical commodity, money, exists in the market.[4] The borrowers seek money for their consumption or investment and buy it with an interest rate. Due to knowledge heterogeneity, borrowers differ in the search costs of becoming perfectly informed. Some high-search-cost borrowers decide to stay uninformed and could borrow at the high-interest rate, whereas low-search-cost borrowers would search and find the low interest rate. The coexistence of high and low interest rates caused by search frictions generates interest-rate dispersion. PLcenters enter the framework by lowering the search cost of borrowers. The model predicts a higher total lending amount, lower interest rates, and less interest-rate dispersion in the wake of lower search costs.

To test the predictions, I exploit the staggered introduction of PLcenters as a natural experiment and use a staggered DID setting, based on a data set from Renrendai during the period of October 2010 to June 2015. The data set comprises all listings of private loan applications, both failed and successful. With the staggering adoption, I can isolate the contribution of the introduction of PLcenters on outcomes of online marketplace lending from changes in the conditions of the marketplace lending industry and macroeconomic trends.

One challenge for this staggered DID setting is that PLcenters might be not randomly assigned across Chinese cities. Unobserved regional demographic or economic characteristics correlated with the setup of PLcenters may drive the results. To address this problem, I use a measure of China's political cycle, namely the presence of abnormally high political attention on private-lending issues in the new-mayor period, to instrument the introduction of PLcenters, in the spirit of the literature on political cycle instrumental variables (see Levitt, 1997; Bian et al., 2017). The new-mayor period is when the city has a mayor in his/her

[4] To have the identical money in the empirical analysis, I control for loan characteristics (e.g., maturity, amount, loan use) and borrower characteristics (e.g., age, gender, marriage status) in the regression of interest rate on treatment.

first year of tenure. Abnormal political attention on private-lending issues is proxied by an abnormally large number of private-lending news of neighboring cities, that is other cities in the same province, similar to the construction of Instrumental Variable (IV) in Ponticelli and Alencar (2016). When the neighboring cities have more private-lending news posted online than the past half a year's average, the city's provincial government places abnormal attention on private-lending issues. The provincial government's evaluation is an essential factor for a city mayor's promotion in China. With the politician's motivation of achieving an excellent political record in related topics for promotion, a city with a new mayor is more likely to open PLcenters.

One crucial assumption for this identification strategy to work is that the assignment of a new mayor is not related to the local economic conditions. Thus, the following online marketplace lending outcomes are not driven by political-cycle-related factors. With empirical evidence, I argue this instrument variable is valid for the introduction of PLcenters, in the sense that it strongly predicts the opening of the city PLcenters, and it is uncorrelated with online marketplace lending outcomes before the treatment.

The findings are consistent with the search explanation. First, PLcenters boost marketplace lending. With lower search costs due to PLcenters, Renrendai's total requested lending amount increases by \$1,711,000, and the matched lending amount increases by \$456,000. Moreover, both the number of monthly loan applications and of active borrowers on Renrendai increase by 171. Second, borrowers whose working cities have PLcenters borrow at lower interest rates on average. The annual interest rate of private loans matched through Renrendai is 1.6% lower. Third, PLcenters reduce the dispersion of interest rates, and the effect is mainly driven by the less financially sophisticated group of borrowers. If we push it to the extreme, identical money should have the same price (i.e., interest rate) in the market. Deviation from the "the law of one price" is a sign of market inefficiency. A less varied interest rate implies the market moves closer to efficiency, and PLcenters mediate the search friction. Furthermore, I find fewer extremely low-interest-rate proposals from marketplace lending borrowers after they have access to PLcenters.

To the best of my knowledge, this paper is among the first to look at search frictions in Fintech credit market and suggest informational public goods can help reduce search costs of borrowers. The findings of this paper have implications both for theory and policy. First, it shows that search costs play nontrivial role in Fintech credit market where there are plenty of under-served individual borrowers. Second, it points to a potentially important role of the government in the Fintech credit market: playing a lighthouse role by providing a public information service. PLcenters help put all market participants in sight by lowering search costs and thus boosting and improving the lending outcomes. Moreover, beyond the scope of this paper, the private provision of informational public goods is also a possible direction.

Related Literature

This study contributes to several streams of literature. The first stream is the growing literature of non-banks and Fintech (e.g., Strausz, 2017; Franks et al., 2016; De Roure et al., 2019; Tang, 2019; Berg et al., 2020), especially the ones related to information efficiency. Franks et al. (2016) use the P2B auction data from a marketplace lending platform and find a sizable deviation from the market efficiency. Grennan and Michaely (2020) show Fintech data contains valuable information, so-called "crowd wisdom. " Moreover, unlike bank lending, the Fintech credit market has a lot of retail borrowers and lenders interacting with each other directly. Liskovich and Shaton (2017) suggest financial innovation enables less experienced households to participate in the credit market. Many studies focus on the decisions made by directly participating and less experienced borrowers and lenders. Zhang and Liu (2012) report novel evidence of rational herding behavior in the P2P lending market. Hertzberg et al. (2018)'s experiment result suggests online-lending borrowers' choice of maturity contains private information, including their future repayment performance. Berg et al. (2020) look at the sophistication of marketplace lenders and find the more sophisticated ones perform better in screening loans. This paper connects to the literature by looking at marketplace lending borrowers' search frictions and how the reduction of search frictions affects the interest rate and other market outcomes. I use the data from a leading online P2P lending platform in China, "Renrendai," as in Wu and Zhang (2020), Braggion et al. (2020a), Hasan et al. (2020), Braggion et al. (2020b), and Liao et al. (2017) and many other papers.

Furthermore, this work highlights the similarity between marketplace lending, especially P2P lending, and the retail consumer market: asymmetric information, search frictions, and retail buyers. The second stream of related literature is search friction and price dispersion (see Stigler, 1961; Salop, 1977; Salop and Stiglitz, 1977; Varian, 1980; Burdett and Judd, 1983; Pereira, 2005; Ellison and Ellison, 2009), especially its application in the financial market (e.g., Vayanos and Weill, 2008; Beaubrun-Diant and Tripier, 2015; Stango and Zinman, 2016; Brand et al., 2019; Ambokar and Samaee, 2019). The existence of search frictions can explain why price dispersion exists in a market with an identical commodity. Xu (2016) finds persistent interest-rate dispersion in the crowdfunding market, due to search frictions. Bhutta et al. (2020) document wide mortgage-rate dispersion and show the financial sophistication of borrowers matters for the rates obtained. Stango and Zinman (2016) reports self-reported borrower search is an important factor of the dispersion of credit-card borrowing costs. This paper contributes to the literature by applying the search-cost model (Salop, 1977; Salop and Stiglitz, 1977; Varian, 1980) in the context of the Fintech credit market. The results of this paper that show PLcenters reduce the price dispersion by lowering the search cost are consistent with the findings and explanations in the search-friction and price-dispersion literature. The findings point to a potentially important role of public goods (Coase, 1974) in informal financial markets such as the Fintech credit market where the majority are less financially sophisticated: providing public information services as public goods to mediate search friction.

The third stream of literature is the economic function of public goods (Maskus and Reichman, 2004; Straub, 2005). Coase (1974) mentions that the word "lighthouse" appears in economics "because the light is supposed to throw on the question of economic functions of government." Usually, the government has to maintain the lighthouse because it is unprofitable, providing essential public services. Global public goods, including policies and infrastructures that have international externality effects, are examples of public goods that have an economic impact (Maskus and Reichman, 2004). However, few papers have studied the role of public goods in the credit market. This paper tries to fill the gap by providing market information and financial knowledge as public goods. The public information service provided by PLcenters has the property of public goods: non-rivalrous and non-excludability. When a citizen learns from PLcenters how to write a private-loan contract, the contract template is still there for others to learn (non-rivalrous). No one in the city can be excluded from access to the PLcenter's information service (non-excludability), and it is free of charge. Though the informational public goods discussed in the paper are provided by the government, space for privately providing public goods is possible (West Jr, 2000; Menezes et al., 2001).

The rest of this paper is organized as follows. Section 2 talks about the institutional background. Section 3 describes the data and pre-test. Section 4 displays the conceptual framework of consumer search and generates predictions. Section 5 lays out the DID analysis. And the last section concludes.

II. Institutional Background

A. Private-lending in China

The private-lending market is indispensable for China's rapid economic growth because it is the main financing source of the private sector in China (e.g., Gregory and Tenev, 2001; Tsai, 2002; Allen et al., 2005). China's private sector generates more than half of its GDP, provides around 80% of jobs, and contributes to more than two-thirds of technological innovation (Guluzade, 2019). However, Chinese private firms have limited access to banking credit.[5] Only 1.3% of loans extended by state banks went to private firms (Li and Hsu, 2009). Meanwhile, many business owners and ordinary households who have spare money are looking for good investment opportunities. Thus, the informal lending market has been thriving in China. According to a survey by the People's Bank of China, the size of the Chinese private-lending market is estimated at 2.4 trillion yuan (around $357 billion) at the end of the first quarter of 2010, equivalent to 35% of China's GDP in 2010 or around 6% of China's total lending.[6]. Lenders in the private-lending market include friends, relatives, pawnshops, and loan sharks. In 2011, the annual interest rates of private-lending ranged from 36% to more than 150%, while China's then benchmark lending rates were around 6%, and the inflation rate was 5.5%.

However, private businesses were unlikely to afford such sky-high interest rates for a long time, given the economic slowdown in the wake of the 2008 global financial crisis. In late 2011, Wenzhou was the first Chinese city to face a severe private-credit crunch. Many large-scale local private-lending networks collapsing, around 100 bosses reporting running away from their private debts, and 20% of its private businesses ceasing operation (Lu, 2018). Shortly after the outbreak of the private-lending crisis in Wenzhou, a nationwide private-credit crisis started.

B. Private-lending registration service center (PLcenter)

The Chinese government noticed this private-credit crash and its non-negligible damages to the real economy. In late March 2012, the Chinese central government set up a pilot financial reform in Wenzhou to boost and stabilize the private-lending market. As part of the pilot scheme, Wenzhou private-lending registration service center (PLcenters) was inaugurated on April 26, 2012.

PLcenter acts as a public information service center for private-lending. Take Wenzhou PLcenters as an example. Local citizens can gain market information and financial knowledge and complete private-lending procedures in one location by visiting PLcenters. PLcenters provide free information services, such as publishing Wenzhou private-lending index (e.g., prevailing interest rates in the local private-lending market), preparing private-loan contract templates, and disseminating financial knowledge through seminars. Additionally, PLcenters offer almost-free office spaces to financial intermediaries and consultants such as P2P

[5] Banks mainly extend credit to collective and state enterprises.

[6] See also Farrell et al. (2006). These statistics omitted observations of illegal lending activities, which are difficult to obtain data.

companies, small-loan companies, notary offices, and legal consultancy offices.[7] Comparing products of different lenders and consulting professionals is much more convenient for citizens.

<insert Table 1 here>

Following Wenzhou, 54 other Chinese cities had built PLcenters as of June 2015. The first group of cities includes Guangzhou, Shaoxing, and Ningbo, where the private economy is developed. Table 2 shows the opening dates of PLcenters in Chinese cities. I manually collect the dates from the news and government announcements.[8]

<insert Table 2 here>

C. Renrendai P2P marketplace lending platform

The recent advances in digital technology brought new private-lending modes. For instance, online P2P marketplace lending, one type of Fintech credit, enables borrowers and lenders to interact directly with each other over the internet. The history of online P2P lending can be traced back to the launch of the UK-based company Zopa in 2005. China is the largest P2P lending market globally and has experienced the fastest growth of Fintech credit.

Renrendai, founded in 2010, is one of the leading online P2P lending platforms in China. On August 8, 2015, Renrendai's trading volume exceeded 10 billion yuan (around $1.47 billion), and the number of users had increased to approximately 2.5 million. Renrendai is open to users ranging in age from 22 to 60, and the amount of funds requested ranges from 3,000 to 500,000 yuan. Renrendai requires loan applicants to provide a credit report from the central bank, a work certificate, income certificate, and a resident identity card. Loan applicants can voluntarily provide other selective materials such as property ownership certificate and marriage certificate to Renrendai for verification. The verification status of personal information is indicated on the online P2P loan-application page.

Figure 1 shows how the demand side and supply side of Renrendai's online users interact with each other.

<insert Figure 1 here>

[7] CreditEase, Renrendai, Sudaibang, Eloan, Fpimc and Zhedaitong had offices in Wenzhou PLcenters.

[8] See, an example, of news about the opening of PLcenters in Guangzhou city in 2012: http://www.gz.gov.cn/guangzhouinternational/home/citynews/photonews/content/post_3104878.html.

Before a borrower can request a loan, a listing that specifies the contract terms, such as amount, interest rate, and maturity, should be created. For example, as shown in Figure 1, the borrower requested 10,000 yuan at an annualized interest rate of 13.2% with a maturity of 24 months for traveling. While creating the listing, the borrower can also provide personal information such as gender, education background, and debt status. The Renrendai platform then assigns borrowers a credit rating, ranging from AA (low risk), A, B, C, D, F, to HR (high risk), based on the materials provided. Renrendai will upgrade the borrower's credit rating if s/he has a good matching and repayment record on the platform and will downgrade it if the matching and repayment record is bad. The majority of borrowers in the market are lower-educated, as depicted in Figure 2. Around 80% of borrowers do not have a bachelor's degree.

<insert Figure 2 here>

Investors (i.e., lenders) observe the loan-request listing on the website and decide whether to take it or leave it. They offer bids (i.e., lend money) to the interested loan applications if they agree to the posted contract terms. The bidding is on a first-come, first-served basis. In Figure 1, the first lender with the nickname, "f*y", offered 1,000 yuan for this listing. When the fourth lender, "o*1", invested 2,000 yuan, this listing is 100% funded, and the loan proceeds are credited into the borrower's bank account. The listing will be visible online for a maximum of seven days. After seven days, if it's not fully funded, the listing closes and becomes a failed request. Lenders can diversify the risk by offering bids to different borrowers. Moreover, automatic bidding facilities are available to lenders.

Note that other than borrowers directly applying online (denoted as "credit" type), borrowers apply through Renrendai's offline branches (denoted as "field" type). "Field“ type borrowers visit the offline branches in person with their materials, and the officers complete the procedure of listing online on behalf of the borrowers.[9] "Field" type has an A rating, and the offline office usually fixes the interest rate.[10]

D. China's political cycle: A new broom sweeps clean

Unlike the bottom-to-top political systems in most European countries and America, China has a top-to-bottom political system (see Nordhaus, 1975; Rogoff, 1990; Yao and Geng,

[9]This paper rules out the "institution" type and "auto" type, which accounts for 4% of all listings on the Renrendai platform because they are essentially from other companies such as Zhong An Credit (中安信业), An Sheng (安盛), and Fu Ji (富基). However, including them does not change the results.

[10]This paper broadly considers the interest rate of offline-sourced P2P loan requests as set by the borrower. The "borrower“ and "lender" discussed in the analysis are assumed to absorb the platform's role in the demand and supply sides, respectively.

2016). Several studies suggest meritocracy is an important factor for the political selection in China (Maskin et al., 2000; Bo, 1996; Li and Zhou, 2005; Chen et al., 2005; Jia et al., 2015). The province government's evaluation is crucial for the assignment of a city mayor. Local leaders are more likely to be promoted if they have a good political record. Though the head of the local government is supposed to be elected every five years, the average tenure of a city mayor is less than three years, according to the Chinese mayor database.

With the expectation of short tenure and performance pressure, mayors are eager to have a good record as early as possible. Otherwise, the credit for policy implementation may go to their successors. Thus, mayors are more active in addressing social and economic problems in their newly assigned year. The new-mayor story of China's political cycle is similar to the typical electoral-cycle story in the political-economy literature (see Levitt, 2002, 1997).

An old Chinese saying conveys a similar message: a new broom sweeps clean (新官上任三把火). In the context of politics, the saying means newly selected leaders are more motivated and eager to pursue achievements than those who have served for a long time (Luo and Duan, 2016). For the purpose of this paper, I use a measure of the new mayor's abnormal high attention to private-lending as an instrument for the introduction of PLcenters in a city. When private-lending issues in the province receive abnormal high attention, a newly appointed city mayor is more likely to set up PLcenters to gain political achievement in their first year.

III. Data and Description

This section describes the data and test results. I also show the existence of search frictions in marketplace lending.

A. *Online P2P lending data from Renrendai*

This paper's online P2P loan data consists of 437,534 retail listings (san biao in Chinese pinyin), both successful and failed listings, from the Renrendai platform in October 2010 to June 2015, with detailed information about loan and borrower characteristics.

In July 2015, China's State Council issued the "Guiding Opinions on Advancing the Healthy Development of Internet Finance," officially giving the China Banking Regulatory Commission (CBRC) the responsibility to regulate P2P platforms. To rule out the effect caused by regulation and better estimate the effects of PLcenters, this paper only looks at the period before July 2015.

During the sample period, 118,694 out of 437,534 loan applications were successfully funded through Renrendai.com. On average, borrowers request P2P loans in the amount of \$9,050, an 18-month maturity, and an annual interest rate of 13.56%. Thus, the loan market is primarily for small-sized loans. According to Tang (2019) in the small loan market Fintech lenders are complements to banks, and borrowers are less experienced in borrowing. The average borrower is 35 years old with a credit score of 59 at the lowest credit level, HR. The successful loan applications, on average, offer an annual interest rate of 12.54% with an amount of \$8,482 and a maturity of 26-months. The average borrower who successfully receives funds is 39 years old with a credit score of 164 (at the AA credit level).

To estimate the effects of PLcenters on outcomes of online P2P lending, I aggregate the original listing-level data by year-month and borrower's working city.[11], resulting in 15,642 observations.

B. Private-lending news

The data of private lending news for each Chinese city are collected from news.baidu.com, which is often called "China's Google," by searching for the keywords "private lending" and "city name" in the title. News can be in neutral, negative, or positive tones. Many collected news reported "private lending lawsuits," "bankrupt private firms," "runaway bosses," and "private lending workshops."

C. City-level data

The city-level data is from the China Stock Market & Accounting Research Database (CSMAR), including the economic and demographic variables such as GDP, government expenditure, and the number of books per 100 citizens. To construct the political-cycle measure, I use the data from the Chinese mayor database, which is also available in CSMAR.

I manually collected the opening dates of PLcenters in Chinese cities from the news and government announcements.

D. Pre-treatment Balance Test

China's first PLcenter was opened in April 2012. Using data before 2012 (i.e., the assignment of treatment), Table 3 reports the results of the pre-treatment balance tests for borrower characteristics between the treatment group and the control group.

On Renrendai, P2P borrowers working in the cities that had PLcenters after 2012 are slightly older and richer than the ones from cities without PLcenters. But the difference is not

[11] Note that borrower's working certificate is verified by the platform.

statistically significant at the 5% level. In both groups, most borrowers are lower educated, male, and not working in the finance or law industry. Two groups do not differ significantly from each other in terms of other borrower characteristics including marital status, income level, credit rating, and whether they had taken out previous loans. [12]

<insert Table 3 here>

E. Search cost in online P2P market

On Renrendai, borrowers post loan requests online, and lenders invest in the interested loan requests. Because the borrower and lender directly interact with each other, the online P2P market works very similarly to the retail consumer market. Borrowers buy money to finance their investment or consumption with attractive prices (interest rates), whereas the lenders have spare money and offer a distribution of acceptable prices (interest rates).

As discussed in Salop (1977), the information a borrower requires in order to obtain the best (i.e., lowest and successfully matched) interest rate must be produced at a cost. This cost includes the loss of leisure and the time used to gather information. For example, borrowers pay for a subscription to the analyst's reports and spend time reading Fintech credit market reports. Moreover, the borrower's search ability varies due to knowledge heterogeneity. Usually, highly-educated are more efficient information searchers and, on average, obtain better buys (borrow with lower interest rate). Search frictions in the market can lead to market separation and price dispersion. The higher the search cost, the more dispersed the price.

Thus, in the literature, researchers often use price dispersion as a proxy for the consumer's search cost. Search cost is correlated with the consumer's education, age, income, and financial experience. The data of Renrendai's P2P lending shows the interest rates set by borrowers with less education and borrowers who do not work in the finance or law industry are more dispersed, consistent with the literature. In this paper, I use the standard deviation as a measure of dispersion. As we can see in Table 4, education and interest-rate dispersion are negatively correlated. Borrowers with at least a bachelor's degree face lower search costs. Also consistent with the intuition, gathering information is less costly for borrowers working in finance or the law industry. Table 4 reports the results of maturity dispersion and amount dispersion as well.

<insert Table 4 here>

[12] In the empirical analysis, I control for borrower characteristics such as income, age, industry, and credit rating.

IV. Conceptual Framework and Predictions

Before turning to empirical analysis, this section shows a simple borrower search framework with asymmetric information and search cost, following Salop and Stiglitz (1977), can generate predictions of the public information service's impact on marketplace lending.

A. Setup of search cost framework

Consider an economy with a large number, L, of risk-neutral borrowers who want to borrow money for their investment or consumption. Each borrower has an identical inelastic demand curve for one and only one unit of money. The maximum interest rate a borrower will pay (the reservation interest rate) is denoted by r^u. In other words, each L borrowers want to buy a unit of money with an interest rate not higher than r^u.

In the economy, n private lenders have spare money and each lender charges an interest rate from a vector of acceptable interest rates $\underline{r} = \{r_1, r_2, \cdots, r_n\}$. They appear in different time slots online. As in Salop and Stiglitz (1977), all lenders have an identical opportunity cost of lending the money, and each unit of money is considered as an identical commodity.

Assume the borrower knows the acceptable interest rates by lenders $\underline{r}$, but does not know which private lender charges which interest rate.[13] The borrower can pay a search cost, either pecuniary or non-pecuniary, to gather the complete information and find the lowest interest rate in the lending market. Assume three types of borrowers exist, each with different search costs. $\alpha_1 L$ of the L borrowers are knowledgeable borrowers with a low search cost c_1, $\alpha_2 L$ are high-search-cost borrowers with a high search cost of c_2 where $c_2 > c_1 > 0$, and the rest are naive borrowers whose search cost is infinitely $c_3 \to +\infty$. For example, financially sophisticated borrowers can collect interest rates of P2P loans from different platforms and do statistic analysis to find the best interest rate. By contrast, less financially sophisticated may take a long time to learn how to get and use the information, and they usually do random buys. And the naive ones do not even know how to use the computer.

Assume every private lender has an identical U-shaped average cost (AC) curve. The cost of the lender includes the time spent trying to understand the market and the money spent to buy the computer. For example, to start lending money, a private lender has to spend considerable time, a fixed cost T, searching for the platform. With the increase in the amount of lending, the average price of lending (interest) goes down first by splitting the fixed cost into each unit of lending and then rebounds. The rebound is reasonable because if the private lender has much money, doing some high-return business instead of lending

[13] In the context of marketplace lending, borrowers do not know which investor will appear online when applying.

out the money and bearing the default risk might be more profitable for him/her. Assume private lenders know the distribution of borrowers' search costs, and L is large enough that private lenders face no uncertainty.

Furthermore, assume the borrower chooses an optimal search strategy to minimize the total expected expenditure, $r^i + c^i$. If he/she searches, the interest rate is r^{min}, the lowest interest rate in the market, but bearing a search cost $c^i > 0$. Otherwise, he/she randomly borrows, and the total expected expenditure is $\bar{r} = (1/n)\sum_{j=1}^{n} r_j$. The borrower i will search if the expected benefit of searching is higher than the cost, that is, $c^i < \bar{r} - r^{min}$. And the borrower will enter the market if and only if his/her total cost does not exceed the reservation interest rate, r^u, that is, if and only if

$$r^u \geq \min\left[r^{min} + c^i, \bar{r}\right].$$

The third type will not enter the market, because for any interest r, $r + c_3 > r^u$. And consistent with the intuition, knowledgeable borrowers are more likely to search and enter the market than naive borrowers. Remember, the majority of the market participants in marketplace lending are high-search-cost individuals who have limited financial knowledge and search skills. Thus, the search friction in the market is not trivial.

Assume the private lender selects an interest rate to maximize its profit given the interest rates of other private lenders and the search strategy of borrowers. Finally, assume the entry of private lenders occurs as long as profits are positive.

B. *Equilibrium, search cost, and interest-rate dispersion*

Given the setup, an equilibrium in this market is defined by an interest-rate vector $\underline{r}^\star = \{r_1^\star, r_2^\star, \cdots, r_n^\star\}$, a number $n^\star$ of private lenders in the market, and a percentage $\alpha^\star$ of borrowers, $\alpha^\star = \alpha_1^\star/(\alpha_1^\star + \alpha_2^\star)$, that gather information meeting the following conditions:

(i) Profit Maximization. Every private lender $j \in [1, 2, \cdots, n^\star]$ solves the optimization problem below:

$$\max_{r} \pi(r_j \mid \underline{r}^{\star-j}) = r_j D(r_j \mid \underline{r}^{\star-j}) - D(r_j \mid \underline{r}^{\star-j}) AC\left[D(r_j \mid \underline{r}^{\star-j})\right].$$

(ii) Zero Profits. Every private lender $j \in [1, 2, \cdots, n^\star]$ has zero profit: $\pi(r_j^\star \mid \underline{r}^{\star-j}) = 0$.

(iii) Search Equilibrium. At equilibrium, borrowers gather information optimally and will search only if the expected benefit is greater than the search cost:

$$\alpha^\star = \begin{cases} 1 \text{ for } c_1 < c_2 < \bar{r} - r^{min} \\ \alpha \text{ for } c_1 < \bar{r} - r^{min} \le c_2 \\ 0 \text{ for } \bar{r} - r^{min} \le c_1 < c_2 \end{cases}$$

As Salop and Stiglitz (1977) prove, two types of equilibria exist in the economy: a single price equilibrium (SPE) with a single price of r^u and a two price equilibrium (TPE). Because the evidence shows price dispersion in the online P2P lending (see Table 4), this paper focuses only on the TPE case.

B.1. Two price equilibrium (TPE)

As pictured in Figure 3, in a TPE there are $n^\star$ lenders entered the market and their profits are zero. $\beta n^\star$ lenders are lower-priced, r_l, lending a larger quantity of money, q_l, than the high-priced, r_h, private lenders. The $\alpha_1 L$ knowledgeable borrowers decide to search and hence borrow from a r_l private lender. And the $\alpha_2 L$ high information cost borrowers, the c_2 type, choose to stay uninformed and borrow randomly. This equilibrium property contains the possible interest rate dispersion.

<insert Figure 3 here>

The TPE is summarized as follows: [14]

$$A\left((1-\alpha^\star)\frac{L^\star}{n^\star}\right) = \min\left(r^u, r^\star + \frac{c_2}{(1-\beta)}\right) \quad (1)$$

$$A\left((1-\alpha^\star + \frac{\alpha^\star}{\beta})\frac{L}{n^\star}\right) = r^\star \quad (2)$$

where $L^\star = (\alpha_1 + \alpha_2)L$. Denote the competitive quantity as $A(q^\star) = r^\star$. From equation (2), we have

$$q^\star = (1-\alpha^\star + \frac{\alpha^\star}{\beta})\frac{L^\star}{n^\star}, \quad (3)$$

where $\alpha^\star$ is the proportion of informed borrowers, and β is the proportion of low-priced lenders.

The equilibrium has a proportion, $\gamma_l = \alpha^\star + (1-\alpha^\star)\beta$, of borrowers borrow at low interest rate $r_l = r^\star$, while $1-\gamma_l = (1-\alpha^\star)(1-\beta)$ borrow at high interest rate $r_h = min(r^u, r^\star + c_2/(1-\beta))$.

[14]Please check the proof of lemma 3 and lemma 4 in Salop and Stiglitz (1977).

The average market interest rate is $r_m = \gamma_l r_l + (1-\gamma_l) r_h$. And the quantities borrowers borrow are $q_m = (\gamma_l q_l + (1-\gamma_l) q_h) L^\star$.

C. A "rational economic planner"

Salop and Stiglitz (1977) states that in an economy with an identical commodity, "A 'rational economic planner.' could economize on information costs by eliminating the price dispersion; for with no price dispersion, there is no need for costly search." We introduce a rational economic planner into the framework.

Now consider a public information service center established by the government. The public information includes the dissemination of private-lending information and financial knowledge. Assume the centers eliminate search costs. Visiting the center can help the borrower lower the search cost to zero. For example, in the context of this paper, a local borrower can find the best interest rate with the help of PLcenters.

This public information service is free of charge, and it has the characteristics of public goods. A private lender is not able to function as a public information service center due to the free-rider problem. Note that very few people in real life are willing to pay for basic financial knowledge. Imagine now a private lender is providing free training courses to lower consumers' search costs. Because conducting a course is costly, the average cost of this private lender increases. Thus, this private lender can never provide the lowest price, because other lenders do not bear the cost of training. However, after training, borrowers can find the lowest interest rate and switch to other private lenders.

D. Predictions

To guide the empirical investigation, I discuss the relationships between the introduction of the public information service center and variables of interest and obtain the main predictions.

We start from TPE, as stated above, where there is no public information center. Now a city c introduces PLcenters eliminating search costs, and in that city, the proportion of informed borrowers changes to $\alpha'_c = 1$ from $\alpha_c = \alpha$, while other cities remain the same (see Figure 4).

As the marketplace lending is nationwide, and there are infinitely large borrowers L in the market. A city's change does not affect the TPE of the whole market. In the whole market, the proportion of low-interest -ate lenders stays the same as before, β. For the same reason, the high interest rate of the whole market is $r_h = r^\star + c_2/(1-\beta)$,where c_2 is the cost of all cities' high-search-cost borrowers, and $r_l = r^\star$.

However, things change for the city c. The proportion of low-interest-rate borrowers in city c, $r'_{lc} = \alpha_c(1-\beta)+\beta$, increases because α'_c increases from α to 1. In other words, city c's borrowers are all informed and secure the low-interest-rate. Due to the change, we get the following predictions.

Prediction 1. PLcenters will boost the total lending amount in the city c.

p*roof*. Before the treatment, the naive borrowers cannot enter the market since $\forall r, r+c_3 > r^u$ with $c_3 \to +\infty$. After the treatment, c_3 becomes zero and the third type, naive borrowers, can borrow at the low interest rate. Trading volume changes from $(\alpha_1+\alpha_2)L$ to L.

With this prediction, we expect to see a more massive total lending amount in the market. Other than trading volume, the second comparative static provides a prediction of the interest-rate change.

Prediction 2. With PLcenters, on average borrowers will get a lower interest rate in marketplace lending.

p*roof*. Before the treatment, two interest rates, r_h and r_l, exist. But after the treatment, only one interest rate, r_l, exists. The average interest rate goes down, because all borrowers become informed with the help of PLcenters.

It is better for the market because of less dead-weight loss caused by search frictions. The lower-interest-rate effect is especially significant for the high-information-gathering-cost borrowers.

Prediction 2.1. Less financial sophisticated groups are more affected by PLcenters.

Moreover, we can also expect to see a lower interest rate dispersion if city c's borrowers only borrow at low-interest-rate with access to PLcenters, as stated in prediction 3 below,

Prediction 3. The introduction of PLcenters should be followed by a lower interest rate dispersion.

If the market is efficient and no search friction exists, the identical commodity should have the same price. If the law of one price holds, there should be no interest rate dispersion for the same type of contract (identical borrower and lender characteristics and identical risks). The introduction of the public information service lowers the search friction, and the lending market moves closer to the efficient law-of-one-price world.

V. Empirical Analysis

The conceptual framework of borrower search suggests that, following the introduction of PLcenters, marketplace lending should experience higher lending amount, lower interest rate, and a reduction in interest-rate dispersion. This section starts by showing the basic specification of regressions and an identification strategy.

A. *Basic specification*

The basic regression specification is a staggered DID model, written in two-way fixed-effects form:

$$Y_{ct} = \beta_0 + \beta_1 Treated_{ct} + \beta_2 Post_{ct} + \beta_3 Treat_c + \beta_4 X^c_{c,t} + \beta_5 X^b_{c,t} + \beta_6 X^l_{c,t} + \alpha_c + \nu_t + \epsilon_{ct}, \quad (4)$$

where $Treated_{ct} = Treat_c \times Post_{ct}$ equals 1 if the borrower's working city c opened PLcenters in year-month t. $X^c_{c,t}$ is the city control variables such as government spending and the number of books per 100 citizens. $X^b_{c,t}$ represents the borrower and loan characteristics, to better fit the "identical commodity" setting as in the conceptual framework. $X^l_{c,t}$ is the lender characteristics, including average lending amount, the average number of lenders, and the proportion of manual bids (denoted as normal), to better fit the identical private-lender setting in the conceptual framework. α_c and ν_t represent city and year-month fixed effects. Y is the outcome of interest, which includes loan characteristics (e.g., interest rate, interest-rate dispersion) and other marketplace lending outcome variables (e.g., total lending amount).

The coefficient of interest is β_1, as mentioned before. I also average borrower and other loan characteristics, lender controls, and city controls to capture the compositional change of borrowers, loan-type changes, lender-side changes, and time-varying city variables. City fixed effects α_c in equation (4) control for factors changing each month that are common to all Chinese cities for a given month. Time fixed effects ν_t in equation (4) control for factors that are common to all the time but specific to each city.

Nonetheless, key challenges remain if we use the basic specification (4) to estimate the effects of PLcenters. The opening of PLcenters may be correlated with other unobserved variables that could affect the online marketplace lending outcomes as well. Some people may suspect local governments decide to open PLcenters due to the bad performance of the local private economy, which could also affect the online marketplace lending. Thus, I use an instrumental variable, the timing of abnormal private-lending attention in the Chinese local political cycle, for instrument the main independent dummy $Treated_{ct}$ following Levitt (1997), Bian et al. (2017), and Ponticelli and Alencar (2016), and apply two-stage-least-squares (2SLS) to estimate equations.

B. *Identification*

To address the potential endogeneity, I use a measure of the new mayor's career concern about private-lending issues, denoted as $NewmayorPL_{ct}$, to instrument for the introduction of PLcenters, $Treated_{ct}$.

The first stage of 2SLS regressions is denoted as equation (5):

$$Treated_{ct} = \gamma_0 + \gamma_1 NewmayorPL_{ct} + \gamma_2 X^c_{ct} + \gamma_3 X^b_{c,t} + \gamma_4 X^l_{c,t} + \alpha_c + \nu_t + \epsilon_{ct}, \tag{5}$$

where the dependent variable, $Treated_{ct} = Treat_c \times Post_t$, equals 1 if the borrower's working city c has PLcenters open at time t. The IV is $NewmayorPL_{ct}$, which is the number of times the city c has a new mayor with career concerns about private-lending, before time t.

A new mayor is defined as a mayor who is in the first year of his/her tenure. His/her career concern about private-lending is proxied by the abnormal attention on private-lending of the same province's other cities. As explained before, new mayors try to achieve good credits as early as possible (in the first year in our context) with an expectation of short tenure. A city mayor's next step in his/her political career is to be promoted to the provincial level. If the provincial government pays close attention to private-lending issues, the city mayor becomes motivated to gain achievement in private-lending (opening PLcenters in our context). The opinion of the provincial government matters most for the promotion of a city mayor. To rule out the possible direct effect of the IV on marketplace lending outcomes, I use the same province's other cities' abnormal private-lending attention to measure the provincial government's private-lending attention, in the spirit of the IV construction in Ponticelli and Alencar (2016). The abnormal private-lending attention of other cities in the province should not affect the marketplace lending outcomes in city c, but it raises city c's mayor's career concern about private-lending.

More precisely, $NewmayorPL_{ct} = \sum_{\tau}^{t} \left(D(Newmayor)_{c\tau} \times D(PLAttention)_{c\tau} \right)$, where $D(Newmayor)_{c\tau}$ equals 1 if at time τ a new mayor is in city c and $D(PLAttention)_{c\tau}$ equals 1 if city c's province pays abnormally high attention to private-lending. The province's abnormal attention to private-lending is captured by the number of prate-lending news of other cities in the same province. If the number of news online is higher than the last six months' average number, the province pays abnormal attention to private-lending in that month.

The new-mayor period in China is similar to the electoral cycle, which has been used to instrument for many policy implementations (see Levitt, 1997; Bian et al., 2017).

To address the concern that the new mayor may conduct policies other than opening PLcenters that affect the result of marketplace lending, I add a set of city controls X^c_{ct} including government expenditure to control for the possible effect of other policies.

Table 5 reports the results of first-stage regressions for all original listings and only successful applications. Both the Cragg-Donald Wald F statistic and Kleibergen-Paap rk Wald F statistic are largely greater than 10.

<insert Table 5 here>

This measure of a new mayor's career concern about private-lending is a valid instrument for the establishment of PLcenters, in the sense that it strongly predicts the introduction of PLcenters (as shown in Table 5) and only affect the marketplace lending results through PLcenters, conditional on a set of city controls.

Exclusion Restriction and Exogeneity

To address the concern about the endogeneity of the IV, I run the basic specification based on the data before April 2012 in the absence of a PLcenter, but replace the primary independent variable with the IV. If the new mayor's career concern about private-lending issues, $NewmayorPLP$, affects marketplace lending through channels other than PLcenters, we expect to see a significant effect of $NewmayorPLP$ on marketplace lending interest rates based on this restricted sample. However, the Table reports no significance, which implies a politician's career concern about private-lending affects the P2P lending through PLcenter after controlling for city variables.

<insert Table 6 here>

Another concern is that the assignment of a new mayor may be correlated with the economic condition in the city, which may alter the result in P2P lending. For example, perhaps a city's economic performance is bad; thus, a new mayor is assigned to solve the problem. The evidence in Table 7 also shows that whether there is a new mayor or not does not depend on the city's economic condition. City c's GDP in the last year does not predict the assignment of the new mayor at time t.

<insert Table 7 here>

C. Effects of PLcenters on marketplace lending outcomes

In this section, I study the effects of PLcenters on marketplace lending outcomes and check whether the estimates are consistent with the predictions from the conceptual framework.

Result 1. PLcenters boost marketplace lending

First, Table 8 indicates PLcenters push up online P2P lending, as predicted by the search-cost model in the last section. The variables of interest are the total lending amount of applications and the total lending amount of matched loans. I also check how the number of active borrowers and the number of loan applications on Renrendai relate to the introduction of PLcenters.

<insert Table 8 here>

Table 8 in columns (1) and (5) shows the effect of PLcenters on the total amount of lending is positive and significant. PLcenters push up the total amount of credit extended through Renrendai by $455,500 per month and the total requested lending amount by $1,711,800 per month. For actual loans, both numbers of loans and borrowers increase by around 56 per month, as shown in columns (6) and (7). The number of applications increases by 170 per month and the number of applicants increase by 141 per month. The significant positive effect is in line with Prediction 1.

Also, PLcenters increase the success rate. The success rate is defined as the proportion of listings successfully funded among all Renrendai loan-request listings from city c in year-month t. Column (4) of Table 8 reports that PLcenters increase the success rate by 4.5%.

Result 2. PLcenters Lower the interest rate

In Table 9, column (4) indicates the interest rate of private-loans on Renrendai decreases by 1.6% ceteris paribus if borrowers have access to PLcenters, as predicted by Prediction 2. When high-information-cost borrowers' search costs are smaller, more private lenders will choose a low interest rate. The average interest rate of applications also decreases by 0.98% (column 1). Moreover, the maturity goes up slightly by around two months according to the results listed in columns (2) and (5).

It is a more efficient outcome, because a competitive market with an identical good should have only one price, namely, the lowest one. Due to the search friction caused by the limited knowledge and lack of search skills of borrowers, the interest rate is higher than the competitive interest rate (lowest). With a private-lending center helping borrowers understand the market better, the interest rate will naturally go down.

The too-high interest rate has long been a problem in private-lending. Private-lending is the primary financing source for most private firms. Interest-rate decreases can help the private firms lower the cost of capital and enable the firm to make investment and management decisions closer to the optimal ones. The public information service as a public good not only benefits the lower educated individual borrowers but also may stimulate the economy.

<insert Table 9 here>

Result 3. PLcenters reduce the dispersion of contract terms

As foreseen by Prediction 3, this section finds interest-rate dispersion goes down after having PLcenters in borrowers' working cities, and the less experienced group mainly drives the effect.

In this paper, I use the standard deviation (s.d.) as a measure of the dispersion of contract terms (Borenstein and Rose, 1994). As reported in columns (1) to (4) of Table 10, the analysis based on all listings and the successful applications in the sample period consistently finds a significant negative coefficient of the treatment indicator. It shows the introduction of PLcenters reduces the variation of interest rates in marketplace lending. Borrowers with access to PLcenters' public information services tend to propose less dispersed interest rates when they apply for loans. More importantly, the successful sample sees a significant decrease in the dispersion of interest rates. With other variables constant, PLcenters reduce the standard deviation of interest rate by -0.71.

When local people have access to PLcenters, they can ask for a legal consultant service or ask for information from officers in the centers, who better understand the usual contract settings and who the good lenders are. They will also find the small loan companies and P2P lending platforms inside PLcenters, which makes their searching much more convenient. PLcenters help fill the knowledge gap between experienced people and inexperienced people.

With the search-cost framework in mind, I conjecture PLcenters mainly affect the inexperienced borrowers. If PLcenters indeed lower search costs, the reduction in the dispersion of interest rates should be more significant in a group with less informed people. To test this guess, I check how the lower-dispersion effect is associated with the financial experience of borrowers. I split the borrowers into two groups based on their working industry. Columns (2) and (5) report the results of the group of borrowers who work in finance or law industry, the more financially sophisticated group, and the remaining columns (3) and (6) are the result of the less sophisticated group. The negativity and significance of the coefficient of interest only appear in the group of less experienced borrowers.

<insert Table 10 here>

The distribution of interest rates before and after the introduction of PLcenters shown in Figure 5 suggests that less extremely low interest rates after PLcenters are built. This can be explained in the search framework. The borrowers with high search costs have higher expected expenditure ($r^i + c^i$). If the search cost is very high and close to the reservation interest rate of r^u, their proposal for the interest rate will be deficient. However, with PLcenters, this super high-search-cost problem is mediated.

<insert Figure 5 here>

VI. Robustness and Additional Results

To strengthen the conclusion that PLcenters have significant effects on marketplace lending, this section checks the robustness. Moreover, this section discusses additional results.

A. *Two period OLS regression*

To address the concern about the serial correlation in the error term, this section follows Bertrand et al. (2004) to collapse the data into two periods for each city, before and after the introduction of PLcenters. The results of OLS estimates are shown in Table 11 and Table 12. Consistent with the previous main results, PLcenters raise the lending amount and help more borrowers entering the market, lower the interest rate, and reduce interest-rate dispersion. Moreover, I split the sample into two groups: the borrowers who work and do not work in finance or law. As shown in columns (3)-(6) of Table 11 and last two columns of Tables 12 and 13, the group with less financial knowledge, the one that does not work in finance or law, mainly drives the results.

Table 13 further looks at the new borrowers. Results show the increase in the number of borrowers in the online market is mainly due to the entrance of first-time borrowers. Again, the results are driven by the less financially sophisticated group, as shown in columns (3) and (4).

B. *Distributional effects on credit score*

Chetverikov et al. (2016) present a quantile regression model with endogenous group-level treatment to estimate the distributional effects. Following their method, this paper estimates the coefficients of the treatment dummy in group-by-group quantile regressions by 2SLS. The model of the quantile regression is as follows:

$$Q_{y_{ig}|z_{ig},x_g,\epsilon_g}(u) = z'_{ig}\gamma(u) + x'_g\beta(u) + \epsilon_g, u \in \mathcal{U},$$

where $y_{ig}(u)$ is the u-th quantile of y in group g, and x_g is the group level treatment dummy. In the context of this paper, the group is $city \times time$ (ct), x_g is $Treated_{ct}$, and z_{ig} is individual listing-level observable covariates. $\mathcal{U}$ is a set of quantile indices of interest, which comprises of the 5th, 10th, 15th,..., 90th, 95th percentiles.

This section does not include z_{ig}. The estimation is conducted in two steps.

Step 1. In each $city \times time$ group, I compute the quantile (5th, 10th, 15th,..., 90th, 95th percentiles) of dependent variable y within the group. y includes loan characteristics (e.g., amount, interest rate and maturity) and user characteristics (e.g., credit score etc.).

Step 2. I conduct a 2SLS regression of coefficients on the treatment dummy, instrumenting with the IV $NewmayorPLP$ as mentioned before.

As a comparison, I also estimate the corresponding average effects.

Figure 6 suggests the lower tail of borrowers in terms of credit scores is significantly more affected by the introduction of PLcenters. It indicates PLcenters help the lower tail of borrowers understand the market better. It improves the "effective" quality of the borrowers in the online market.

VII. Conclusion

The scale of flows and the direct participation of individuals in the Fintech credit market is raising concerns(FSB, 2018). This paper focuses on the search frictions in marketplace lending and explores how the introduction of information as the lighthouse, public goods, affects the market. I put marketplace lending in a context of the search-cost model (Salop and Stiglitz, 1977) and empirically test the derived predictions by using P2P lending data from Renrendai to examine the effects of PLcenters introduced in China.

Results show PLcenters boost marketplace lending in terms of lending volume. The interest rate in the market significantly decreases, and more remarkably, PLcenters reduce the interest-rate dispersion. The effect is mainly driven by the group of borrowers who do not work in finance or law (less experienced). The findings are in line with the explanation in the search-cost framework, where borrowers' search costs, interest-rate level, and interest-rate dispersion are highly correlated.

This work contributes to the literature by empirically testing the role of informational public goods in the Fintech credit market. It has an important policy implication for mediating search frictions, financial literacy, and market efficiency. Technological advancement is breaking down the barriers and providing financial tools for individuals who would not have access otherwise. Provision of informational public goods to help individuals understand the market better is important. The findings in this paper provide another reason why we need financial literacy in college regardless of the major, which is often discussed in the United States.

REFERENCES

Allen, Franklin, Jun Qian, and Meijun Qian, 2005, Law, finance, and economic growth in china, *Journal of financial economics* 77, 57–116.

Ambokar, Sumedh, and Kian Samaee, 2019, Inaction, search costs, and market power in the us mortgage market .

Beaubrun-Diant, Kevin E, and Fabien Tripier, 2015, Search frictions, credit market liquidity and net interest margin cyclicality, *Economica* 82, 79–102.

Berg, Tobias, Valentin Burg, Ana Gombović, and Manju Puri, 2020, On the rise of fintechs: Credit scoring using digital footprints, *The Review of Financial Studies* 33, 2845–2897.

Berlin, Mitchell, and Loretta J Mester, 2004, Credit card rates and consumer search, *Review of Financial Economics* 13, 179–198.

Bertrand, Marianne, Esther Duflo, and Sendhil Mullainathan, 2004, How much should we trust differences-in-differences estimates?, *The Quarterly journal of economics* 119, 249–275.

Bhutta, Neil, Andreas Fuster, and Aurel Hizmo, 2020, Paying too much? price dispersion in the us mortgage market .

Bian, Bo, Rainer Haselmann, Thomas Kick, and Vikrant Vig, 2017, The political economy of decentralization: Evidence from bank bailouts, *Unpublished manuscript* .

Bo, Zhiyue, 1996, Economic performance and political mobility: Chinese provincial leaders, *Journal of Contemporary China* 5, 135–154.

Borenstein, Severin, and Nancy L Rose, 1994, Competition and price dispersion in the us airline industry, *Journal of Political Economy* 102, 653–683.

Braggion, Fabio, Alberto Manconi, Nicola Pavanini, and Haikun Zhu, 2020a, The value of "new" and "old" intermediation in online debt crowdfunding .

Braggion, Fabio, Alberto Manconi, and Haikun Zhu, 2020b, Can technology undermine macroprudential regulation? evidence from online marketplace credit in china .

Brand, Thomas, Marlène Isoré, and Fabien Tripier, 2019, Uncertainty shocks and firm creation: Search and monitoring in the credit market, *Journal of Economic Dynamics and Control* 99, 19–53.

Burdett, Kenneth, and Kenneth L Judd, 1983, Equilibrium price dispersion, *Econometrica: Journal of the Econometric Society* 955–969.

Chang, YU-CHUN REGINA, and Sherman Hanna, 1992, Consumer credit search behaviour, *Journal of Consumer Studies & Home Economics* 16, 207–227.

Chen, Ye, Hongbin Li, and Li-An Zhou, 2005, Relative performance evaluation and the turnover of provincial leaders in china, *Economics Letters* 88, 421–425.

Chetverikov, Denis, Bradley Larsen, and Christopher Palmer, 2016, Iv quantile regression for group-level treatments, with an application to the distributional effects of trade, *Econometrica* 84, 809–833.

Coase, Ronald H, 1974, The lighthouse in economics, *The journal of law and economics* 17, 357–376.

De Roure, Calebe, Loriana Pelizzon, and Anjan V Thakor, 2019, P2p lenders versus banks: Cream skimming or bottom fishing? .

Duffie, Darrell, Piotr Dworczak, and Haoxiang Zhu, 2017, Benchmarks in search markets, *The Journal of Finance* 72, 1983–2044.

Ellison, Glenn, and Sara Fisher Ellison, 2009, Search, obfuscation, and price elasticities on the internet, *Econometrica* 77, 427–452.

Farrell, Diana, Susan Lund, Jaeson Rosenfeld, Fabrice Morin, Niyati Gupta, and Ezra Greenberg, 2006, Putting china’s capital to work: The value of financial system reform, *McKinsey Global Institute Report* .

Franks, Julian R, Nicolas Andre Benigno Serrano-Velarde, and Oren Sussman, 2016, Marketplace lending, information aggregation, and liquidity, *Information Aggregation, and Liquidity (November 15, 2016)* .

FSB, Financial Stability Board, 2018, Global monitoring report on non-bank financial intermediation .

Gregory, Neil, and Stoyan Tenev, 2001, The financing of private enterprise in china, *Finance and Development* 38, 14–17.

Grennan, Jillian, and Roni Michaely, 2020, Fintechs and the market for financial analysis, *Journal of Financial and Quantitative Analysis* Forthcoming.

Guluzade, Amir, 2019, Explained, the role of china’ s stateowned companies, in *World Economic Forum*, volume 7.

Hasan, Iftekhar, Qing He, and Haitian Lu, 2020, The impact of social capital on economic attitudes and outcomes, *Journal of International Money and Finance* 102162.

Hertzberg, Andrew, Andres Liberman, and Daniel Paravisini, 2018, Screening on loan terms: evidence from maturity choice in consumer credit, *The Review of Financial Studies* 31, 3532–3567.

Jia, Ruixue, Masayuki Kudamatsu, and David Seim, 2015, Political selection in china: The complementary roles of connections and performance, *Journal of the European Economic Association* 13, 631–668.

Levitt, Steven D, 1997, Using electoral cycles in police hiring to estimate the effect of policeon crime, Technical report, American Economic Review.

Levitt, Steven D, 2002, Using electoral cycles in police hiring to estimate the effects of police on crime: Reply, *American Economic Review* 92, 1244–1250.

Li, Hongbin, and Li-An Zhou, 2005, Political turnover and economic performance: the incentive role of personnel control in china, *Journal of public economics* 89, 1743–1762.

Li, Jianjun, and Sara Hsu, 2009, *Informal finance in China: American and Chinese perspectives* (OUP Us).

Liao, Li, Zhengwei Wang, Jia Xiang, and Jun Yang, 2017, Thinking fast, not slow: Evidence from peer-to-peer lending, *Kelley School of Business Research Paper* .

Liskovich, Inessa, and Maya Shaton, 2017, Borrowers in search of feedback: Evidence from consumer credit markets .

Lu, Lerong, 2018, *Private Lending in China: Practice, Law, and Regulation of Shadow Banking and Alternative Finance* (Routledge).

Luo, Yexiao, and Longlong Duan, 2016, Individual characteristics, administration preferences and corruption: Evidence from chinese local government officials’ work experience, *Sociology Mind* 6, 53.

Lynch Jr, John G, and Dan Ariely, 2000, Wine online: Search costs affect competition on price, quality, and distribution, *Marketing science* 19, 83–103.

Maskin, Eric, Yingyi Qian, and Chenggang Xu, 2000, Incentives, information, and organizational form, *The review of economic studies* 67, 359–378.

Maskus, Keith E, and Jerome H Reichman, 2004, The globalization of private knowledge goods and the privatization of global public goods, *Journal of International Economic Law* 7, 279–320.

Menezes, Flavio M, Paulo K Monteiro, and Akram Temimi, 2001, Private provision of discrete public goods with incomplete information, *Journal of Mathematical Economics* 35, 493–514.

Nordhaus, William D, 1975, The political business cycle, *The review of economic studies* 42, 169–190.

Panos, Georgios A, and John OS Wilson, 2020, Financial literacy and responsible finance in the fintech era: capabilities and challenges.

Pereira, Pedro, 2005, Do lower search costs reduce prices and price dispersion?, *Information Economics and Policy* 17, 61–72.

Ponticelli, Jacopo, and Leonardo S Alencar, 2016, Court enforcement, bank loans, and firm investment: evidence from a bankruptcy reform in brazil, *The Quarterly Journal of Economics* 131, 1365–1413.

Rogoff, Kenneth, 1990, Equilibrium political budget cycles, *The American Economic Review* 21–36.

Salop, Steven, 1977, The noisy monopolist: Imperfect information, price dispersion and price discrimination, *The Review of Economic Studies* 44, 393–406.

Salop, Steven, and Joseph Stiglitz, 1977, Bargains and ripoffs: A model of monopolistically competitive price dispersion, *The Review of Economic Studies* 44, 493–510.

Stango, Victor, and Jonathan Zinman, 2016, Borrowing high versus borrowing higher: price dispersion and shopping behavior in the us credit card market, *The Review of Financial Studies* 29, 979–1006.

Stigler, George J, 1961, The economics of information, *Journal of political economy* 69, 213–225.

Straub, Stéphane, 2005, Informal sector: the credit market channel, *Journal of Development Economics* 78, 299–321.

Strausz, Roland, 2017, A theory of crowdfunding: A mechanism design approach with demand uncertainty and moral hazard, *American Economic Review* 107, 1430–76.

Tang, Huan, 2019, Peer-to-peer lenders versus banks: substitutes or complements?, *The Review of Financial Studies* 32, 1900–1938.

Tsai, Kellee S, 2002, *Back-alley banking: Private entrepreneurs in China* (Cornell University Press).

Varian, Hal R, 1980, A model of sales, *The American economic review* 70, 651–659.

Vayanos, Dimitri, and Pierre-Olivier Weill, 2008, A search-based theory of the on-the-run phenomenon, *The Journal of Finance* 63, 1361–1398.

West Jr, Lawrence A, 2000, Private markets for public goods: Pricing strategies of online database vendors, *Journal of Management Information Systems* 17, 59–85.

Wu, Yu, and Tong Zhang, 2020, Can credit ratings predict defaults in peer-to-peer online lending? evidence from a chinese platform, *Finance Research Letters* 101724.

Xu, Menghan, 2016, Search frictions in crowdfunding markets .

Yao, and Geng, 2016, 官员任期与政绩挤压: 中国政府人事的“试用期任职”, 学海 49–55.

Zhang, Juanjuan, and Peng Liu, 2012, Rational herding in microloan markets, *Management science* 58, 892–912.

Appendix A. Tables and Graphs

Tables

Table 1. Wenzhou Private Lending Index, overall 20.14% on March 18 2013

Maturity (month)	1	3	6	12	12+
Interest rate	21.93	19.63	18.43	13.66	14.44

Table 2. Opening Dates of Private Lending Registration Service Centers

City Name	Open Date	City Name	Open Date
Wenzhou	2012-04-26	Hangzhou	2014-06-18
Guangzhou	2012-06-28	Weinan	2014-06-26
Zhenjiang	2012-07-18	Nanchang	2014-06-30
Eerduosi	2012-11-18	Xian	2014-07-29
Dongying	2012-11-29	Jilin	2014-08-06
Shaoxing	2013-01-26	Weihai	2014-08-30
Changsha	2013-04-23	Jian	2014-09-19
Zibo	2013-05-08	Shangrao	2014-09-22
Jinzhong	2013-05-22	Fuzhou	2014-10-16
Anyang	2013-05-28	Kaifeng	2014-10-21
Yueyang	2013-06-14	Xiangtan	2014-12-05
Foshan	2013-09-01	Binzhou	2014-12-18
Ningbo	2013-10-16	Yantai	2015-01-01
Chengdu	2013-10-24	Bijie	2015-01-08
Dongguan	2013-10-30	Zhoushan	2015-01-09
Zhuzhou	2013-11-13	Zhuhai	2015-01-18
Quanzhou	2013-12-04	Qianxin	2015-02-01
Changzhi	2013-12-31	Mudanjiang	2015-03-01
Guiyang	2014-02-23	Siping	2015-03-08
Taizhou	2014-03-17	Tongliao	2015-03-18
Huzhou	2014-03-19	Lishui	2015-03-18
Xining	2014-04-03	Yiyang	2015-04-16
Jinan	2014-04-20	Hulunbeier	2015-05-01
Taian	2014-04-25	Putian	2015-05-04
Jinhua	2014-05-11	Enshi	2015-05-09
Daqing	2014-05-12	Xinganmeng	2015-05-22
Wuhan	2014-05-28	Bayzhou	2015-06-03
Weifang	2014-06-16		

Table 3. Pre-treatment Balance Test

This table shows the pre-treatment balance test of covariates between treatment group and control group. The original sample comprises all listings .*, **, and *** indicate statistically different from zero at the 10%, 5%, and 1% level of significance, respectively.

	Control			Treatment			
	n	mean	sd	n	mean	sd	Diff
Degree(1=Bachelor)	10178	0.21	0.41	5868	0.18	0.39	-0.023
Marriage(1=Married)	10178	0.45	0.50	5868	0.42	0.49	-0.033
Incomeindex	10167	3.31	1.08	5862	3.42	1.13	0.108*
Gender(1=F)	10178	0.13	0.34	5868	0.14	0.35	0.008
Age	10178	34.20	5.88	5868	33.84	5.69	-0.363*
CreditRating	10178	2.02	0.26	5868	2.02	0.27	0.002
Degree(1=Bachelor)	10178	0.21	0.41	5868	0.18	0.39	-0.023
Industry(1=Fin/Law)	10178	0.05	0.22	5868	0.04	0.20	-0.007
HaveLoan	10178	0.14	0.35	5868	0.12	0.32	-0.020

Table 4. Search Cost in P2P Lending Market

This table shows the OLS regression coefficients of contract term dispersion on borrower characteristics. First, aggregate the data in borrower and year level and get the dispersion for each borrow. Second, regress dispersion on borrower characteristics such as degree and income, controlling for year fixed effects. *, **, and *** indicate statistically different from zero at the 10%, 5%, and 1% level of significance, respectively.

	full	sucess
	(1) sdr	(2) sdr
Marriage(1=Married)	-0.00461	0.224***
	(-0.38)	(3.36)
Incomeindex	-0.0249***	-0.0136
	(-5.04)	(-0.66)
Gender(1=F)	-0.0910***	-0.0417
	(-5.45)	(-0.47)
Age	-0.0125***	-0.0220***
	(-13.43)	(-4.61)
CreditRating	0.0180*	0.0587**
	(1.80)	(2.04)
Degree(1=Bachelor)	-0.0335**	-0.0160
	(-2.48)	(-0.25)
Industry(1=Fin/Law)	-0.0144	0.181
	(-0.49)	(1.27)
LoanType(1=Consump.)	0.0126	0.0773*
	(1.50)	(1.87)
HaveLoan	0.0000203	0.0475
	(0.00)	(0.76)
Maturity	-0.0442***	-0.0185***
	(-63.67)	(-3.05)
R	0.136***	0.142***
	(58.10)	(11.20)
Year-Month FE	Yes	Yes
Observations	63866	2130

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5. First Stage Regression

This table reports the first stage estimates from 2SLS regressions. The sample period is from 2010 October to 2015 June. The full sample comprises all listing. The success sample comprises successful applications.

$$Treated_{ct} = \gamma_0 + \gamma_1 NewmayorPLP_{ct} + \gamma_2 X_{ct}^c + \alpha_c + \nu_t + \epsilon_{ct}$$

where $Treated_{ct} = Treat_c \times Post_t$ equals to 1 if city c has PLcentres in month t. $Treat_{ct}$ is instrumented by $NewmayorPLP_{ct} = \sum_{\tau}^{t} \left(D(Newmayor)_{c\tau} \times D(PLAttention)_{c\tau} \right)$, where $D(Newmayor)_{c\tau}$ is one if city c's mayor is in the first year of his/her tenure and $D(PLAttention)_{c\tau}$ equals to one if city c's province's other cities get abnormal attention on private lending. The abnormal attention is captured by larger number of private lending news than the last six months' average number. Borrower characteristic controls are aggregated at (city month) level by taking the mean. City controls include city c's government expenditure and book per 100 citizens last year. All regressions include city fixed effects α_c and year-month fixed effects ν_t. T statistics are reported in parentheses. *, **, and *** indicate statistically different from zero at the 10%, 5%, and 1% level of significance, respectively.

	full	success
	(1) Treated	(2) Treated
NewmayorPL	0.0497***	0.0553***
	(26.20)	(16.49)
Married	0.0108	-0.00653
	(1.54)	(-0.78)
Incomeindex	-0.00102	-0.00147
	(-0.35)	(-0.50)
Female	-0.00158	-0.0192*
	(-0.17)	(-1.76)
Age	-0.00103*	-0.000487
	(-1.94)	(-0.89)
CreditRating	0.00902**	0.00634*
	(2.43)	(1.73)
Bachelor	0.00336	-0.00982
	(0.42)	(-1.26)
Finlaw	0.00000338	-0.0406**
	(0.00)	(-2.29)
Consump.	-0.00296	-0.00434
	(-1.01)	(-1.06)
Haveloan	-0.00420	0.00200
	(-0.48)	(0.26)
Constant	0.0540**	0.135***
	(2.54)	(3.94)
BorrowerControls	Yes	Yes
LenderControls	Yes	Yes
CityControls	Yes	Yes
City FE	Yes	Yes
Year-Month FE	Yes	Yes
R^2	0.475	0.598
Observations	13057	6296

Table 6. Placebo Test, time period without PLcentres

This table reports coefficients estimates from the regressions relating the dummy of new mayor to interest rate based on all listings and successful samples. The sample period is from 2010 October to 2012 March.

$$InterestRate_{c,t} = \beta_0 + \beta_1 NewmayorPLP_{c,t} + \beta_2 X^c_{c,t} + \beta_3 X^b_{c,t} + \beta_4 X^l_{c,t} + \alpha_c + \nu_t + \epsilon_{c,t}$$

where $IV = NewmayorPLP_{c,t}$ is the instrument variable. $GDP_{c,t-12}$ is city c's last year GDP. *pop* is the population and *area* is the area. All regressions include city fixed effects α_c and year-month fixed effects ν_t. T statistics are reported in parentheses. *, **, and *** indicate statistically different from zero at the 10%, 5%, and 1% level of significance, respectively.

	full	success
	(1) R	(2) R
IV	-0.0308	0.0264
	(-0.24)	(0.13)
Govexpend	0.000780	0.000450
	(0.43)	(0.22)
Bookper100	0.000600	0.000812
	(0.67)	(0.96)
Maturity	-0.0635***	0.0516**
	(-5.29)	(2.35)
Avg.A	0.0194	0.0213
	(1.08)	(0.50)
Constant	8.786***	15.66***
	(7.13)	(3.93)
BorrowerControls	Yes	Yes
LenderControls	Yes	Yes
City FE	Yes	Yes
Year-Month FE	Yes	Yes
Observations	3154	870
R^2	0.444	0.466

Table 7. Economic Condition and New Mayor

This table reports coefficients estimates from the regression relating the dummy of new mayor to last year's GDP. The sample period is from 2010 October to 2015 June. The full sample comprises all listings. The success sample comprises successful applications.

$$D(Newmayor)_{c,t} = \beta_0 + \beta_1 GDP_{c,t-12} + \beta_2 X^c_{c,t} + \alpha_c + \nu_t + \epsilon_{c,t}$$

where $D(Newmayor)_{ct}$ is a dummy equals to 1 if city c's mayor is in the first year of his/her tenure. $GDP_{c,t-12}$ is city c's last year GDP. *pop* is the population and *area* is the area. All regressions include city fixed effects α_c and year-month fixed effects ν_t. T statistics are reported in parentheses. *, **, and *** indicate statistically different from zero at the 10%, 5%, and 1% level of significance, respectively.

	full
	(1) D(Newmayor)
L12.GDP	0.00000590 (0.33)
population	0.000234 (0.45)
area	-0.00000748** (-2.45)
Constant	0.353 (1.47)
City FE	Yes
Year-Month FE	Yes
Observations	9900
R^2	0.191

Table 8. The Effect of Private Lending Centers on Total Lending Amount

This table reports coefficients estimates from DID regressions relating the trading volume to the introduction of PLcentres in the borrower's working city. The sample period is from 2010 October to 2015 June. The full sample comprises all listings (column 1-4). The success sample comprises successful applications (column 5-7).

$$Y_{ct} = \beta_0 + \beta_1 Treated_{ct} + \beta_2 Post_{ct} + \beta_3 Treat_c + \beta_4 X^c_{c,t} + \beta_5 X^b_{c,t} + \beta_6 X^l_{c,t} + \alpha_c + \nu_t + \epsilon_{ct}$$

where $Treated_{ct} = Treat_c \times Post_{ct}$ equals to 1 if borrower's working city c's has Pcenters in month t. $X^b_{c,t}$ are borrower characteristics including marriage status, income level, gender, age, credit rating, education, working industry, loan use, and have car/house loan or not. $X^l_{c,t}$ controls average number of lenders and lender's average lending amount on each request, and proportion of manual bids. City controls include last year's government expenditure and book per 100 citizen. All regressions include city fixed effects α_c and year-month fixed effects ν_t. Borrower characteristic controls are aggregated at (city month) level by taking the mean. T statistics are reported in parentheses. *, **, and *** indicate statistically different from zero at the 10%, 5%, and 1% level of significance, respectively.

	full				success		
	(1) Tot.A	(2) N(L)	(3) N(A)	(4) SuccR	(5) Tot.A	(6) N(L)	(7) N(A)
Treated	1711.8***	170.2***	141.1***	0.0572***	455.5***	56.20***	55.82***
	(15.73)	(15.95)	(15.36)	(2.62)	(5.56)	(6.43)	(6.38)
Married	-19.25	-0.354	-0.190	0.0235***	13.36	1.738	1.664
	(-0.96)	(-0.18)	(-0.11)	(5.85)	(1.18)	(1.43)	(1.37)
Incomeindex	21.87***	-1.817**	-1.965***	0.000536	-5.158	-0.719*	-0.734*
	(2.63)	(-2.23)	(-2.80)	(0.32)	(-1.30)	(-1.70)	(-1.74)
Female	31.74	2.151	1.983	-0.00687	17.63	1.505	1.416
	(1.20)	(0.83)	(0.89)	(-1.30)	(1.19)	(0.95)	(0.89)
Age	5.943***	0.268*	0.247*	0.00140***	2.003***	0.170**	0.170**
	(3.92)	(1.81)	(1.93)	(4.62)	(2.72)	(2.16)	(2.16)
CreditRating	235.3***	24.37***	23.63***	0.0209***	31.64***	2.459***	2.420***
	(22.10)	(23.35)	(26.30)	(9.81)	(6.33)	(4.61)	(4.53)
Bachelor	-50.05**	-4.734**	-4.334**	0.0245***	-19.41*	-1.630	-1.774
	(-2.22)	(-2.14)	(-2.28)	(5.41)	(-1.84)	(-1.45)	(-1.58)
Finlaw	-26.91	-3.142	-2.749	0.0105	5.890	0.750	0.836
	(-0.57)	(-0.68)	(-0.69)	(1.11)	(0.24)	(0.29)	(0.32)
Consump.	35.61***	4.375***	4.095***	0.00807***	24.38***	3.150***	3.104***
	(4.25)	(5.33)	(5.79)	(4.81)	(4.42)	(5.35)	(5.27)
Haveloan	102.1***	7.018***	6.286***	0.0406***	32.88***	0.783	0.829
	(4.10)	(2.87)	(2.99)	(8.12)	(3.19)	(0.71)	(0.75)
BorrowerControls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
LenderControls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CityControls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.076	0.114	0.167	0.627	0.476	0.474	0.476
Observations	13057	13057	13057	13057	6296	6296	6296

Table 9. The Effect of Private Lending Centers on Contract Terms

This table reports coefficients estimates from DID regressions relating the contract terms to the introduction of PLcentres in the borrower's working city. The sample period is from 2010 October to 2015 June. The full sample comprises all listings (column 1-3). The success sample comprises successful applications (column 4-6).

$$Y_{ct} = \beta_0 + \beta_1 Treated_{ct} + \beta_2 Post_{ct} + \beta_3 Treat_c + \beta_4 X^c_{c,t} + \beta_5 X^b_{c,t} + \beta_6 X^l_{c,t} + \alpha_c + \nu_t + \epsilon_{ct}$$

where $Treated_{ct} = Treat_c \times Post_{ct}$ equals to 1 if borrower's working city c's has Pcenters in month t. $X^b_{c,t}$ are borrower characteristics including marriage status, income level, gender, age, credit rating, education, working industry, loan use, and have car/house loan or not. $X^l_{c,t}$ controls average number of lenders and lender's average lending amount on each request, and proportion of manual bids. City controls include last year's government expenditure and book per 100 citizen. All regressions include city fixed effects α_c and year-month fixed effects ν_t. Borrower characteristic controls are aggregated at (city month) level by taking the mean. T statistics are reported in parentheses. *, **, and *** indicate statistically different from zero at the 10%, 5%, and 1% level of significance, respectively.

	full			success		
	(1) R	(2) Maturity	(3) Avg.A	(4) R	(5) Maturity	(6) Avg.A
Treated	-0.833*	2.100**	0.490	-1.520***	1.975	0.0154
	(-1.91)	(2.54)	(0.36)	(-2.79)	(1.29)	(0.02)
Married	-0.293***	0.116	0.118	-0.327***	0.268	0.00548
	(-3.67)	(0.77)	(0.47)	(-4.34)	(1.26)	(0.05)
Incomeindex	-0.0101	-0.822***	3.995***	-0.120***	-0.311***	0.664***
	(-0.29)	(-12.42)	(38.11)	(-4.41)	(-4.10)	(16.74)
Female	-0.320***	1.213***	-0.351	-0.335***	0.622**	0.519***
	(-3.03)	(6.05)	(-1.05)	(-3.39)	(2.24)	(3.50)
Age	-0.00542	0.0243**	0.209***	0.00378	0.0286**	0.0924***
	(-0.89)	(2.11)	(10.95)	(0.76)	(2.05)	(12.54)
CreditRating	0.325***	1.185***	-0.297**	-0.154***	0.183*	0.104**
	(6.70)	(14.66)	(-2.19)	(-4.49)	(1.95)	(2.08)
Bachelor	-0.398***	-0.414**	1.451***	-0.410***	0.0302	0.158
	(-4.41)	(-2.42)	(5.10)	(-5.87)	(0.15)	(1.50)
Finlaw	0.0821	-0.246	0.707	-0.510***	1.100**	-0.109
	(0.44)	(-0.69)	(1.20)	(-3.18)	(2.43)	(-0.45)
Consump.	0.0854**	0.194***	-0.332***	-0.0102	0.501***	-0.0348
	(2.54)	(3.05)	(-3.14)	(-0.28)	(4.85)	(-0.63)
Haveloan	-0.399***	1.097***	1.169***	-0.237***	0.415**	-0.0651
	(-4.00)	(5.79)	(3.71)	(-3.44)	(2.16)	(-0.63)
Maturity	0.0180***		0.343***	0.104***		0.0451***
	(3.79)		(23.67)	(23.34)		(6.52)
Avg.A	0.0113***	0.123***		0.0450***	0.158***	
	(4.02)	(23.59)		(5.15)	(6.54)	
minR	-0.387***			-0.205***		
	(-3.99)			(-4.77)		
maxR	0.175***			0.0985***		
	(6.87)			(6.81)		
R		0.0445***	0.122***		0.806***	0.0898***
		(2.63)	(4.37)		(22.62)	(4.53)
BorrowerControls	Yes	Yes	Yes	Yes	Yes	Yes
LenderControls	Yes	Yes	Yes	Yes	Yes	Yes
CityControls	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.066	0.177	0.179	0.094	0.406	0.706
Observations	13057	13057	13057	6296	6296	6296

Table 10. The Effect of Private Lending Centers on Interest Rate Dispersion

This table reports coefficients estimates from DID regressions relating the interest rate dispersion to the introduction of PLcentres in the borrower's working city. The sample period is from 2010 October to 2015 June. The full sample comprises all listings. The success sample comprises successful applications.

$$Y_{ct} = \beta_0 + \beta_1 Treated_{ct} + \beta_2 Post_{ct} + \beta_3 Treat_c + \beta_4 X^c_{c,t} + \beta_5 X^b_{c,t} + \beta_6 X^l_{c,t} + \alpha_c + \nu_t + \epsilon_{ct}$$

where $Treated_{ct} = Treat_c \times Post_{ct}$ equals to 1 if borrower's working city c's has Pcenters in month t. $X^b_{c,t}$ are borrower characteristics including marriage status, income level, gender, age, credit rating, education, working industry, loan use, and have car/house loan or not. $X^l_{c,t}$ controls average number of lenders and lender's average lending amount on each request, and proportion of manual bids. City controls include last year's government expenditure and book per 100 citizen. All regressions include city fixed effects α_c and year-month fixed effects ν_t. Borrower characteristic controls are aggregated at (city month) level by taking the mean. T statistics are reported in parentheses. *, **, and *** indicate statistically different from zero at the 10%, 5%, and 1% level of significance, respectively.

	full	full,/finlaw	full,finlaw	success	success,/finlaw	success,finlaw
	(1) sd(R)	(2) sd(R)	(3) sd(R)	(4) sd(R)	(5) sd(R)	(6) sd(R)
Treated	-0.974***	-0.975***	-1.118	-0.711*	-0.786*	0.255
	(-3.27)	(-3.27)	(-1.34)	(-1.72)	(-1.71)	(0.13)
Married	-0.0129	-0.0381	0.0850	0.164*	0.120	0.00196
	(-0.21)	(-0.61)	(0.73)	(1.93)	(1.37)	(0.01)
Incomeindex	-0.0184	-0.0265	0.0892	-0.0704**	-0.0696**	0.0861
	(-0.69)	(-0.99)	(1.50)	(-2.44)	(-2.37)	(1.58)
Female	0.0323	-0.0605	-0.137	-0.168	-0.141	-0.167
	(0.39)	(-0.72)	(-0.98)	(-1.58)	(-1.30)	(-1.14)
Age	-0.0119***	-0.0140***	-0.00418	-0.00428	-0.00400	-0.00747
	(-2.63)	(-3.07)	(-0.48)	(-0.76)	(-0.69)	(-1.45)
CreditRating	0.127***	0.128***	0.0497	0.0259	0.0379	-0.266*
	(3.39)	(3.38)	(0.40)	(0.71)	(1.02)	(-1.85)
Bachelor	-0.0543	-0.0439	-0.0585	-0.118	-0.107	-0.0589
	(-0.78)	(-0.62)	(-0.55)	(-1.50)	(-1.30)	(-0.54)
Finlaw	-0.230			-0.165		
	(-1.57)			(-0.93)		
Consump.	-0.0576**	-0.0343	0.113**	0.0155	0.0332	-0.00648
	(-2.06)	(-1.22)	(2.06)	(0.39)	(0.80)	(-0.11)
Haveloan	0.171**	0.117	-0.130	0.0704	0.0779	0.0285
	(2.23)	(1.51)	(-1.00)	(0.94)	(1.01)	(0.30)
Maturity	-0.0690***	-0.0704***	-0.0578***	-0.0271***	-0.0255***	-0.0644***
	(-18.79)	(-19.11)	(-9.81)	(-5.60)	(-5.16)	(-7.19)
Avg.A	-0.00346	-0.00318	-0.00435	-0.00187	-0.00217	0.00953
	(-1.61)	(-1.48)	(-0.96)	(-0.19)	(-0.21)	(1.08)
minR	-0.0298	-0.0259	0.146	-0.258***	-0.265***	0.253**
	(-0.43)	(-0.37)	(0.95)	(-5.41)	(-5.46)	(2.14)
maxR	0.0697***	0.0706***	0.0111	0.113***	0.116***	-0.0410
	(3.85)	(3.91)	(0.30)	(8.10)	(8.24)	(-1.09)
BorrowerControls	Yes	Yes	Yes	Yes	Yes	Yes
LenderControls	Yes	Yes	Yes	Yes	Yes	Yes
CityControls	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.040	0.043	0.045	0.079	0.076	0.441
Observations	11971	11885	2261	3829	3711	411

Table 11. Two Period Regression, Interest Rate and Dispersion

This table reports the simple correlation between the introduction of PLcenters and the variables of interest. we collapse the data in two periods and run the basic form of the regression below,

$$Y_{ct} = \gamma_0 + \gamma_1 Treated_{ct} + \gamma_2 Post_{ct} + \gamma_3 Treat_c + \alpha_c + \nu_t + \epsilon_{ct}$$

where $Treated_{ct} = Treat_c \times Post_t$ equals to 1 if city c has PLcenters at time t. All regressions include city fixed effects α_c and time fixed effects ν_t. Borrower characteristic controls are aggregated at (city time) level by taking the mean. Lender controls include average number of lenders, lender's average lending amount on each request in city c at t. City controls include city c's government expenditure and book per 100 citizens last year. The full sample comprises all listings. The success sample comprises successful applications. T statistics are reported in parentheses. *, **, and *** indicate statistically different from zero at the 10%, 5%, and 1% level of significance, respectively.

	success		success,/finlaw		success,finlaw	
	(1) sdr	(2) R	(3) sdr	(4) R	(5) sdr	(6) R
Treated	-0.534*	-1.128***	-0.521*	-1.038***	-1.125	-1.982**
	(-1.95)	(-3.94)	(-1.76)	(-3.10)	(-1.35)	(-2.52)
Married	-0.305	1.320*	-0.732	-0.0836		
	(-0.42)	(1.74)	(-0.93)	(-0.10)		
Incomeindex	0.373	0.206	0.466*	0.371		
	(1.52)	(0.80)	(1.72)	(1.21)		
Female	-1.619	-1.681	-1.175	-2.501**		
	(-1.64)	(-1.63)	(-1.04)	(-2.10)		
Age	0.0255	0.134**	-0.0128	0.0778		
	(0.46)	(2.32)	(-0.22)	(1.19)		
CreditRating	0.609***	0.687***	0.558**	1.006***		
	(2.77)	(2.98)	(2.13)	(3.66)		
Bachelor	-0.172	-0.440	0.309	-1.158		
	(-0.28)	(-0.69)	(0.49)	(-1.62)		
Consump.	0.454	0.0760	0.450	1.158***		
	(1.64)	(0.26)	(1.08)	(3.27)		
Haveloan	0.737	-0.590	0.272	0.357		
	(1.27)	(-0.97)	(0.45)	(0.53)		
Maturity	0.0224	0.145***	0.00292	0.138**	-0.0695	0.171**
	(0.55)	(3.40)	(0.06)	(2.50)	(-0.68)	(2.46)
mbamount	0.0324	-0.0903	0.0648	0.0633	0.122	-0.0371
	(0.31)	(-0.81)	(0.53)	(0.47)	(0.52)	(-0.19)
Constant	-4.807	2.217	-2.758	0.270	-0.966	10.43**
	(-1.54)	(0.68)	(-0.81)	(0.07)	(-0.21)	(2.78)
BorrowerControls	Yes	Yes	Yes	Yes	No	No
LenderControls	Yes	Yes	Yes	Yes	Yes	Yes
CityControls	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	100	100	98	100	28	48
R^2	0.881	0.904	0.850	0.897	0.754	0.694

Table 12. Two Period Regression, Lending Amount

This table reports the simple correlation between the introduction of PLcenters and the variables of interest. we collapse the data in two periods and run the basic form of the regression below,

$$Y_{ct} = \gamma_0 + \gamma_1 Treated_{ct} + \gamma_2 Post_{ct} + \gamma_3 Treat_c + \alpha_c + \nu_t + \epsilon_{ct}$$

where $Treated_{ct} = Treat_c \times Post_t$ equals to 1 if city c has PLcenters at time t. All regressions include city fixed effects α_c and time fixed effects ν_t. City controls include city c's government expenditure and book per 100 citizens last year. The full sample comprises all listings. The success sample comprises successful applications. T statistics are reported in parentheses. *, **, and *** indicate statistically different from zero at the 10%, 5%, and 1% level of significance, respectively.

	full	success	success,/finlaw	success,finlaw
	(1) tbamount	(2) tbamount	(3) tbamount	(4) tbamount
Treated	9051.9***	3776.3**	3589.1**	77.92
	(2.89)	(2.55)	(2.49)	(0.84)
Constant	-14563.1	251.4	94.23	-50.62
	(-1.57)	(0.06)	(0.02)	(-0.16)
CityControls	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Observations	102	100	100	48
R^2	0.712	0.718	0.718	0.737
	full	success	success,/finlaw	success,finlaw
	(1) lbn	(2) lbn	(3) lbn	(4) lbn
Treated	900.7**	348.9**	333.1**	4.122
	(2.63)	(2.15)	(2.09)	(0.56)
Constant	-1570.4	-129.1	-136.5	-12.11
	(-1.55)	(-0.27)	(-0.30)	(-0.48)
CityControls	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Observations	102	100	100	48
R^2	0.749	0.718	0.717	0.755
	full	success	success,/finlaw	success,finlaw
	(1) lun	(2) lun	(3) lun	(4) lun
Treated	609.8**	359.5**	343.4**	3.928
	(2.50)	(2.23)	(2.18)	(0.55)
Constant	-926.1	-141.3	-149.3	-16.38
	(-1.28)	(-0.30)	(-0.33)	(-0.67)
City FE	Yes	Yes	Yes	Yes
CityControls	Yes	Yes	Yes	Yes
Observations	102	100	100	48
R^2	0.757	0.716	0.715	0.769

Table 13. Two Period Regression, New Borrower

This table reports the simple correlation between the introduction of PLcenters and the variables of interest. we collapse the data in two periods and run the basic form of the regression below,

$$Y_{ct} = \gamma_0 + \gamma_1 Treated_{ct} + \gamma_2 Post_{ct} + \gamma_3 Treat_c + \alpha_c + \nu_t + \epsilon_{ct}$$

where $Treated_{ct} = Treat_c \times Post_t$ equals to 1 if city c has PLcenters at time t. All regressions include city fixed effects α_c and time fixed effects ν_t. City controls include city c's government expenditure and book per 100 citizens last year. The full sample comprises all listings. The success sample comprises successful applications. T statistics are reported in parentheses. *, **, and *** indicate statistically different from zero at the 10%, 5%, and 1% level of significance, respectively.

	full	success	success,/finlaw	success,finlaw
	(1)	(2)	(3)	(4)
	lnn	lnn	lnn	lnn
Treated	609.6**	359.9**	343.8**	3.628
	(2.50)	(2.24)	(2.18)	(0.50)
Constant	-942.3	-144.0	-152.3	-16.91
	(-1.31)	(-0.31)	(-0.33)	(-0.69)
CityControls	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Observations	102	100	100	48
R^2	0.752	0.714	0.713	0.769

Graphs

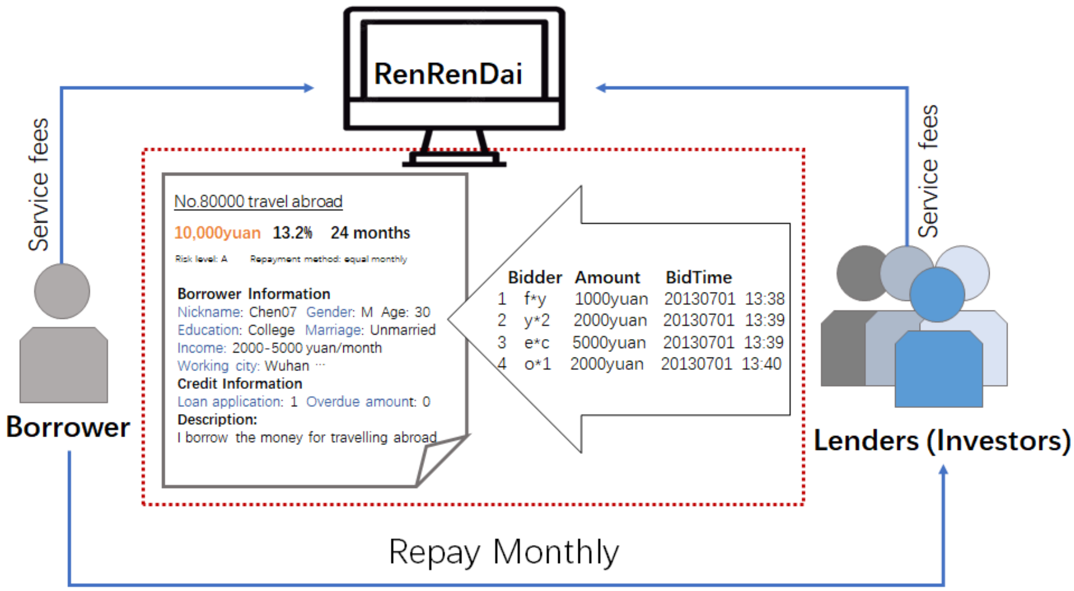


Figure 1. Renrendai loan bids.

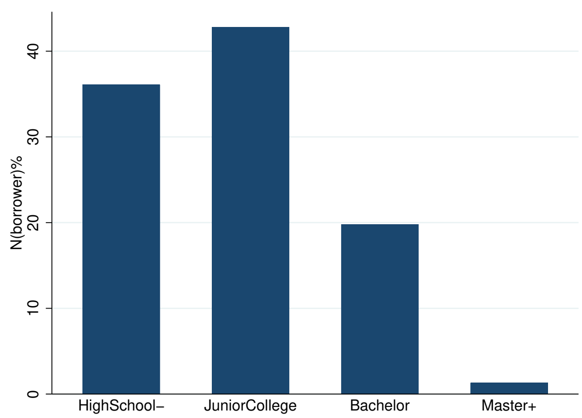


Figure 2. Renrendai Borrowers' Education.

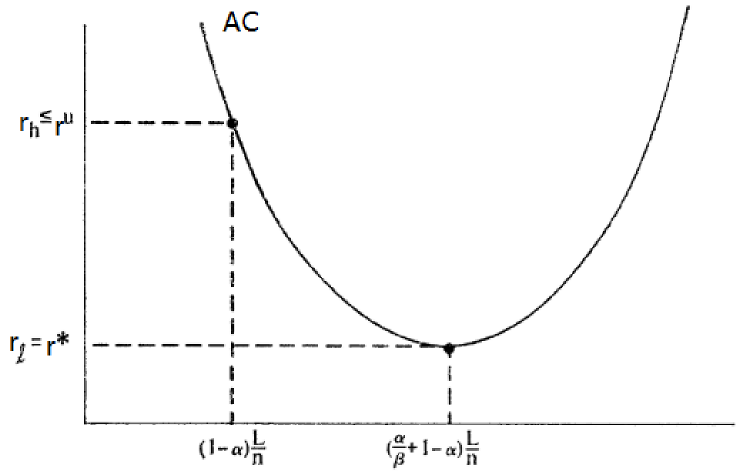


Figure 3. Two Price Equilibrium

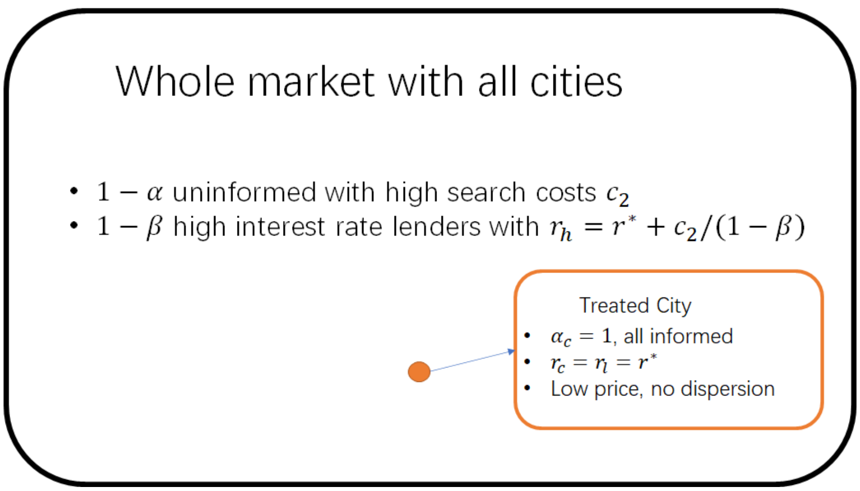
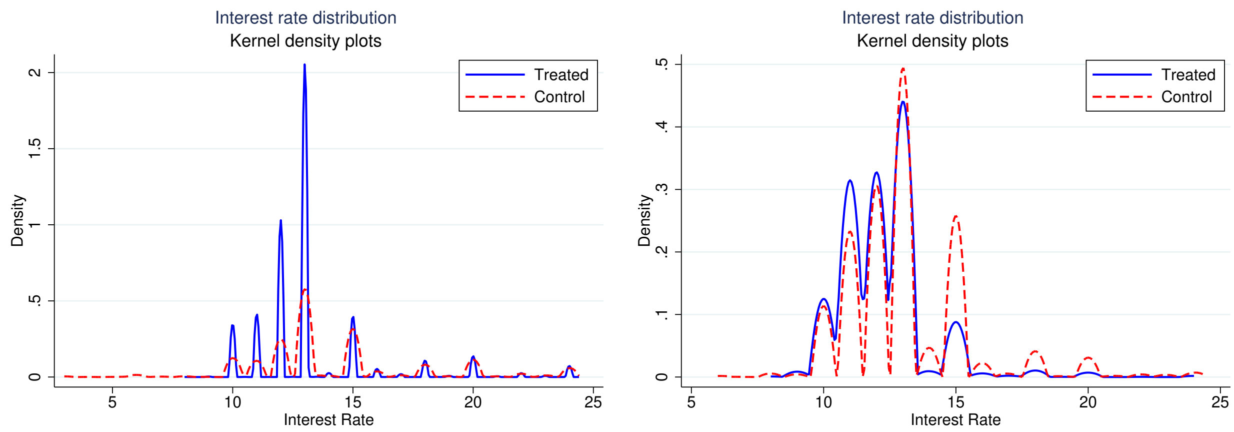


Figure 4. The introduction of PLcentres in a city



(a) full sample

(b) success sample

Figure 5. Interest Rate Distribution

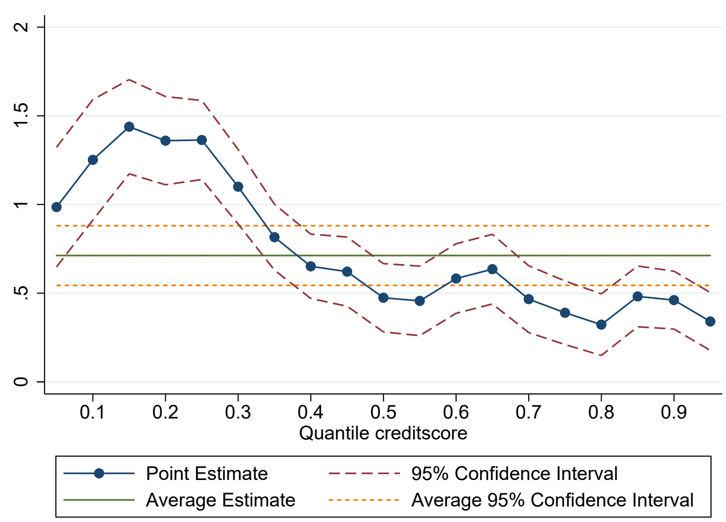


Figure 6. The Effect of Pcenters on Distribution of Credit Score.