Lighthouse in the Dark: Search in Marketplace Lending

SHASHA LI *†

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ABSTRACT

This paper sheds light on the search friction in the Fintech credit market, and examines the impact of public information service centers on marketplace lending outcomes. From 2012, Chinese government gradually introduced private lending registration service centers (PLcentres), essentially public information service centers, in many cities. Exploiting the introduction of PLcentres 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 potential endogeneity, I use a measure of China's political cycle as instrumental variable. PLcentres boost the marketplace lending. Remarkably, PLcentres help borrowers secure lower interest rates from the platform and reduce the dispersion of interest rates. The effect is mainly driven by less sophisticated borrowers. The findings imply that PLcentres reduce search costs, pointing to a potentially important role of informational public goods in Fintech credit.

JEL classification: G14, G23, G28, O16, D83

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I. Introduction

In the wake of the most recent global financial crisis, and the Fintech credit is thriving. Pertinent questions are raised surrounding the efficiency of the global financial system and the necessity of the existence of financial intermediaries such as banks, which has been an institutional solution to the asymmetric information problem in the credit market (Diamond, 1984).[1] Fintech, technology-enabled financial services, allows direct individual lending transactions between borrowers and lenders, brings the convenience of "push-button" loan processing, and thereby improves access to credit for under-served segments. Less experienced individuals and small businesses enter the market.

Nevertheless, similar to the online shopping market (e.g. see the evidence in Lynch Jr and Ariely, 2000), though the internet brings explosive information and convenience, search frictions can induce deviations from market efficiency. The borrowers, as the retail buyers, do not know all types of contracts and lenders in the market. They search for information at a cost, either pecuniary or non-pecuniary. Individuals with high search cost due to lack of financial knowledge or IT skills will not enter the market, or even if they enter, they borrow at sub-optimal interest rates.

Yet, it remains unclear how to reduce the search cost of borrowers in Fintech credit market. Furthermore, what is the best manner to provide information to individuals? Chang and Hanna (1992) suggest that even with more information disclosure, consumer education programs are needed to help less sophisticated borrowers understand the market and reach better outcomes in the credit market. Many studies also stress the importance of financial literacy in Fintech (e.g. Panos and Wilson, 2020). Then, who can educate borrowers? Private firms are reluctant to do so since their competitors can free-ride on their customer training programs.

This paper puts forward a "rational economic planner" solution to reduce the dead-weight cost caused by search frictions: public information service centre 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 that public information service centres can work effectively in reducing the search cost. The experiment I look at

[1]According to the Financial Stability Board (FSB) 's definition, the Fintech credit, one type of non-banks, is all credit activity facilitated by electronic platforms that directly connect borrowers and lenders. The Fintech credit extended globally has swelled from about \$11 billion in 2013 to \$284 billion (Claessens et al., 2018). 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).

is the staggered introduction of private lending registration service centres (PLcentres) by Chinese government in different cities since 2012.

PLcentres gather, process, and disseminate the local private lending information and financial knowledge. Take Wenzhou city's PLcentres as an example. First, PLcentres gather all needed agencies such as marketplace lending companies, notary offices and law firms in one place by providing them almost free office spaces. Second, PLcentres publish local prevailing interest rates of private lending regularly, hold finance knowledge seminars, and provide private loan contract templates. Overall, we can consider PLcentres as public information service centres that offer free information services with the characteristics of public goods: market information disclosure and education of financial knowledge.

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

To guide the empirical investigation, I use a conceptual framework of search cost following Salop and Stiglitz (1977). There is an identical commodity, money, in the market.[3] The borrowers seek money for their consumption or investment and buy it with an interest rate. They can search for complete information at a cost to find the lowest interest rate in the market. Due to knowledge heterogeneity, borrowers very in terms of search costs. Some high search cost borrowers decide to stay uninformed and could borrow at the high interest rate, while 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. PLcentres enter the framework by lowering the search cost of borrowers. The model predicts higher lending amount, lower interest rate and less interest rate dispersion in a wake of lower search cost.

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

[3]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.

One challenge for this staggered DID setting is that potentially PLcentres are not randomly assigned across Chinese cities. Unobserved regional demographic or economic characteristics correlated with the setup of PLcentres may drive the results. To address this problem, I use a measure of abnormal political attention on private lending issues in new mayor periods, in the spirit of the literature on political cycle instrumental variables (see Levitt, 1997; Bian et al., 2017), to instrument the introduction of PLcentres. 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 that this is a valid instrument for the introduction of PLcentres, in the sense that it strongly predicts the opening of the city PLcentres, and it is uncorrelated with online marketplace lending outcomes before the treatment.

The findings of this paper are consistent with the search explanation. First, PLcentres boost marketplace lending. With lower search costs due to the PLcentres, Renrendai's total requested lending amount increases by \$1,711,000, and matched lending amount is up by \$456,000. Moreover, both numbers of monthly loan applications and active borrowers on Renrendai increase by 171. Second, borrowers whose working cities have PLcentres borrow at lower interest rates on average. The annual interest rate of private loans matched through Renrendai is lower by 1.6%. Third, PLcentres reduce the dispersion of interest rate, and the effect is mainly driven by the less financial 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 "Law of One Price" is a sign of market inefficiency. Less varied interest rate implies the market moves closer to the efficiency and PLcentres mediate the search friction. Furthermore, I find there are less extremely low interest rate proposals from marketplace lending borrowers after having access to PLcentres.

To the best of my knowledge, this is the first paper that explores the role of information service with characteristics of public goods in a Fintech credit market. The findings of this paper have implications both for theory and policy. First, it connects the Fintech credit market with search cost framework, which mainly applied in Industrial Organization or Labor Economics, and highlights the similarity between marketplace lending and retail consumer market: individuals or retail buyers with search frictions. Second, it points to a potentially important role of the government in the Fintech credit market: playing the role of a lighthouse by providing public information service. The PLcentres help put all market participants in sight by lowing search costs and thus boost and improve 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 (i.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) used the P2B auction data from a marketplace lending platform and found a sizable deviation from the market efficiency. Grennan and Michaely (2020) show that 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)'s findings suggest financial innovation enable less experienced households to participate in the credit market. Many studies focus on the decisions made by directly participated and less experienced borrowers and lenders. Zhang and Liu (2012) report novel evidence of rational herding behaviour in the P2P lending market. Hertzberg et al. (2018)'s experiment result suggests that 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 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), and especially it's 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 there's price dispersion in a market with identical commodity. Xu (2016) finds persistent interest rate dispersion in the crowdfunding market due to search frictions. Bhutta et al. (2020) document wide mortgage rates dispersion and show that 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 Fintech credit market. The results of this paper that PLcentres reduce the price dispersion by lowering the search cost is consistent with the findings and explanations in 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 financial 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) mentioned 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 since it is unprofitable, but it provides essential public services. Global public goods, including policies and infrastructures that have international externality effects, is an example of public goods that have economic impact (Maskus and Reichman, 2004). However, few paper has studies the role of public goods in the credit market. This paper tries to fill the gap by showing the case of providing market information and financial knowledge as public goods. The public information service provided by PLcentres has the property of public goods: non-rivalrous and non-excludability. When a citizen learns how to write a private loan contract from the PLcentres, the contract template is still there for others to learn (non-rivalrous). No one in the city can be excluded from the access to the PLcentre's information service (non-excludability), and it is free of charge. Though the informational public goods discussed in the paper is provided by the government, there's possibly a space for privately providing public goods (West Jr, 2000; Menezes et al., 2001).

The rest of this paper is organised as follows. Section 2 talks about the institutional background. Section 3 describes data and pre-test. Section 4 displays the conceptual framework of consumer search and generate predictions. Section 5 lays down Difference-in-Difference 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 as 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.[4] Only 1.3% of loans extended by state banks went to private firms (Li and Hsu, 2009). Meanwhile,

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

a large number of 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 Chinese private lending market is estimated at 2.4 trillion yuan (around $357 billion) as 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.[5]. Lenders in the private lending market include friends, relatives, pawn shops 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 facing severe private credit crunch, with many large-scale local private lending networks collapsed, around 100 bosses reported running away from their private debts and 20% of its private businesses ceased 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 (PLcentre)*

Chinese government noticed this private credit crash and its non-negligible damages to the real economy. In late March 2012 Chinese central government set up a pilot financial reform in Wenzhou aiming at boosting and stabilising the private lending market. As part of the pilot scheme, Wenzhou Private Lending Registration Service Center (PLcentres) was inaugurated on April 26 2012.

PLcentre acts as a public information service centre for private lending. Take Wenzhou PLcentres as an example. Local citizens can gain market information and financial knowledge, and complete the whole procedure of private lending in one location through visiting PLcentres. The PLcentres 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 template, and disseminating financial knowledge by holding seminars. Besides, PLcentres offer almost free office spaces to financial intermediaries and consultants such as P2P companies and small loan companies, notary office, and legal consultancy office.[6] It's much more convenient for citizens to compare products of different lenders and consult professionals.

<insert table 1 here>

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

[6]e.g., CreditEase, Renrendai, Sudaibang, Eloan, Fpimc and Zhedaitong had offices in Wenzhou PLcentres.

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

<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 UK-based company Zopa in 2005. China is the largest P2P lending market in the world 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 opens to users ranging in age from 22 to 60, and the amount of funds requested ranging from 3,000 to 500,000 yuan. Renrendai requires borrowers to provide credit report from the central bank, work certificate, income certificate and resident identity card when apply for P2P loans. Borrowers can voluntarily provide other selective materials such as property ownership certificate and marriage certificate to Renrendai for verification as well. 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>

For a borrower to request a loan, first 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 annualised interest rate 13.2% with maturity 24 months for travelling. While creating the listing, the borrower can also provide personal information such as the 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 vice versa. Majority of borrowers in the market is lower-educated as depicted in figure 2. Around 80% borrowers do not have a bachelor degree.

<insert figure 2 here>

Investors (i.e., lenders) observe the loan request listing at the website. They then offer bids (i.e., lend money) to the interested borrowers if agree with the posted contract terms. The bidding is on a 'first come first served' basis. In figure 1, the first lender with nickname 'f*y' offered 1,000 yuan to 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 at maximum duration of seven days. After seven days, if it's not fully funded, the listing closes, and it becomes a failed request. Lenders can diversify the risk by offering bids to different borrowers. And automatic bidding facilities are available to lenders.

Note that other than borrowers directly applying online (denoted as 'credit' type), they're borrowers applying through Renrendai's offline branches (denoted as 'field' type). 'Field' type borrowers visit the offline branches in person with their materials, and the officers will complete the whole procedure of listing online on behalf of the borrowers.[7] 'Field' type has A rating and the interest rate is usually fixed by the offline office.[8]

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, 2016). Several studies suggest that 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 the most important factor for the assignment of a city mayor. Local leaders are more likely to be promoted if they have a good political record. Though officially the head of the local governments are 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 of policy implementation may go to their successor. Thus, mayors are more active in addressing social and economic problems

[7]This paper rules out the 'institution' type and 'auto' type which accounts for 4% of all listings on 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.

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

in their newly assigned year. The new mayor story of China's political cycle is similar with the typical electoral cycle story in political economy literature (see Levitt, 2002, 1997).

There's an old Chinese saying conveying a similar message: a new broom sweeps clean (新官上任三把火). In the context of politics, it means that newly selected leaders are more motivated and active to pursuit achievements than those who have served for long time (Luo and Duan, 2016). For the purpose of this paper, I use a measure of the new mayor's abnormal attention on private lending as an instrument for the introduction of the private lending registration service centre (PLcentre) in a city. When there is abnormal attention on private lending issues in the province, a newly appointed city mayor is more likely to set up PLcentres to gain political achievement in their first year.

III. Data and Description

This section describes the data of marketplace lending and private lending problem news, and results of tests. I also show the existence of search frictions in marketplace lending.

A. *Online P2P lending data from Renrendai*

The online P2P loan data of this paper consists of 639,948 retail listings (san biao in Chinese pinyin), both successful and failed listings, from Renrendai platform in the period of 2010 October to 2015 June, with the 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 PLcentres, this paper only looks at the period before 2015 July.

During the sample period, 118,694 out of 437,534 loan applications successfully got funded through Renrendai.com. In average, borrowers request P2P loans with an amount of $9,050, maturity of 18-month and an annual interest rate of 13.56%. Thus it's mainly a small-sized loan market. According to Tang (2019) in the small loan market Fintech lenders are complements to banks and thus borrowers are less experiences in borrowing. The average borrower is 35 years old with credit score 59 at the lowest credit level HR. The successful loan applications, in average offer an annual interest rate of 12.54% with an amount of $8482 and a maturity of 26-month. The average borrower who successfully got funds is 39 years old with credit score 164 (at the credit level AA).

To estimate the effects of PLcentres on outcomes of online P2P lending, I aggregate the original listing level data by year-month and borrower's working city.[9] It ends up in 15,642 observations.

B. *Private Lending News*

The data of private lending news for each Chinese city is collected from news.baidu.com, which is often called "China's Google", by searching for the keywords "private lending" and "city name" contained 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 China Stock Market & Accounting Research Database (CSMAR), including the economic and demographic variables such as GDP growth rate, Population growth, government expenditure, number of books per 100 citizens and transportation. To construct the political cycle measure, I use the data from Chinese Mayor Database, which is also available in CSMAR.

D. *Pre-treatment Balance Test*

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

On Renrendai, P2P borrowers working in the cities that had PLcentres after 2012 are slightly older and richer than the ones from cities without PLcentre even after 2012. But the difference is not statistically significant at the level of 5%. In both groups, the majority of borrowers are lower educated, male and not working in finance or law industry. Other borrower characteristics such as marriage status, income level, credit rating, and whether had loan before are quite similar in two groups.[10]

<insert table 3 here>

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

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

E. *Search Cost in Online P2P Market*

On Renrendai, borrowers post loan requests online and lenders invest in the interested loan requests. Since the borrower and lender directly interact with each other, the online P2P market works very similar to retail consumer market. Borrowers buy money to finance their investment or consumption with attractive prices (interest rates). While 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 subscription of the analyst's report and spend time reading Fintech credit market report. Moreover, borrower's search ability varies due to knowledge heterogeneity. Usually high-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 often in the literature, researchers use price dispersion as a proxy of 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 low-educated borrowers and borrowers who do not work in finance or law industry are more dispersed, consistent with the literature. In this paper, I use standard deviation as a measure of dispersion. As we can see in table 4, there's a negative correlation between education and interest rate dispersion. Borrowers with at least bachelor degree face less search cost. Also consistent with the intuition, it's less costly for borrowers working in finance or law industry to gather information. Table 4 reports the result of maturity dispersion and amount dispersion as well.

<insert table 4 here>

IV. Conceptual Framework and Predictions

Before turning to empirical analysis, this section shows that 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 one of L borrowers wants to buy a unit of money with an interest rate not higher than r^u.

In the economy, there are n private lenders who have spare money and each lender charges a 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 out, and each unit of money are considered as an identical commodity.

Assume that the borrower knows what are the acceptable interest rates by lenders $\underline{r}$ but s/he does not know which private lender charges which interest rate.[11] 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 there are two types of borrowers with different search costs. αL of the L borrowers are knowledgeable borrowers with a low search cost c_1, and the rest $(1-\alpha)L$ are naive borrowers with a high search cost of c_2, where $c_2 > c_1 > 0$. For example, more financially sophisticated borrowers can collect interest rates of P2P loans from different platforms and do statistic analysis to find the best interest rate. In contrast, less financial sophisticated may take a long time to learn how to get and use the information, and they usually do random buy.

Assume every private lender have identical U-shaped average cost (AC) curve. The cost of the lender includes the time it spends to understand the market and the money to buy the computer. For example, to start lending out money, a private lender has to spend much 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 to each unit of lending and then rebounds. The rebound is reasonable since if the private lender has much money, it might be more profitable for him/her to do some high-return business instead of lending out the money and bearing the default risk. Assume private lenders know the distribution of borrowers' search costs, and L is large enough such that private lenders face no uncertainty.

Furthermore, assume the borrower decide an optimal search strategy to minimize the total expected expenditure, $r^i + c^i$. If s/he searches, the interest rate s/he paid is r^{min}, the lowest interest rate in the market, but bearing a search cost $c^i > 0$. Otherwise s/he randomly borrow 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, i.e. $c^i < \bar{r} - r^{min}$. And the borrower will enter the market if and only if his total cost does not exceed the reservation

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

interest rate, r^u, i.e. if and only if

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

Consistent with the intuition, knowledgeable borrowers are more likely to search and enter the market than the naive borrowers. Remind that the majority of the market participants in the marketplace lending are naive individuals who are lack of financial knowledge and search skills. So the search friction in the market is not trivial.

It is assumed that 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 that the entry of private lenders occurs as long as profits are positive.

B. Equilibrium, Search Cost and Interest Rate Dispersion

Given the setup, a equilibrium in this market is defined by a 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 that gather information that obey 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.

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

As proved in Salop and Stiglitz (1977), there are two types of equilibria in the economy, Single Price Equilibrium (SPE) with a single price of r^u and Two Price Equilibrium (TPE). Since the evidence shows there is price dispersion in the online P2P lending (see table 4), this paper only focuses 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 αL knowledgeable borrowers decide to search and hence borrow from a r_l private lender. And the $(1-\alpha)L$ high information cost borrowers choose to stay uninformed and borrow randomly. This equilibrium property contains the possible interest rate dispersion.

<insert figure 3 here>

The two interest rates equilibrium (TPE) is summarized as follows, [12]

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

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

Denote the competitive quantity as $A(q^\star) = p^\star$. From equation (2) we have

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

Where α is the proportion of informed borrowers and β is the proportion of low-priced lenders.

The average market interest rate is $r_m = \dfrac{q_l}{q_l+q_h} r_l + \dfrac{q_h}{q_l+q_h} r_h$.

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 weaker version of rational "economic planner" into the framework.

Now there is a pubic information service centre established by the government. The public information includes dissemination of private lending information and financial knowledge. Visiting the centre can help the borrower lower the search cost by Δc. For example, in the context of this paper, a local borrower can find a better interest rate by consulting the PLcentre for market information or attending PLcentre's seminars.

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 centre 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

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

consumers' search costs. Since conducting a course is costly, the average cost of this private lender goes up. It means this private lender can never provide the lowest price since 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. Comparative Statics and Predictions

To guide the empirical investigation, we derive the main comparative statics. The proofs are in the appendix. The first comparative statistic indicates lower search cost especially c_2 should boost trading volume in the market.

Prediction 1. PLcentres will boost total lending amount since following a search cost decrease trading quantities goes up, $\frac{\partial(q_l + q_h)}{\partial c_2} < 0$

With this prediction, we expect to see 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 PLcentres, in average borrowers will get lower interest rate in marketplace lending since $\frac{\partial r_m}{\partial c_2} > 0$.

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

Relating to the multi-priced equilibrium, we can also expect to see a lower interest rate dispersion with lower search costs as stated in prediction 3 below,

Prediction 3. Changes in search cost caused by PLcentres should be followed by changes in interest rate dispersion $\frac{\partial sd(r)}{\partial c_2} > 0$. There will be a lower interest rate dispersion.

Ideally, if the market is efficient and if there is no search friction, the identical commodity should have the same price. If "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 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 PLcentres, marketplace lending should experience higher lending amount, lower interest rate, as well as 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 has opened PLcentres in year-month t. $X^c_{c,t}$ is the city control variables such as government spending and the number of book per 100 citizens. $X^b_{c,t}$ is the borrower and loan characteristics, to better fit into 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 proportion of manual bids (denoted as normal), to better fit into 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 (i.e. interest rate, interest rate dispersion) and other marketplace lending outcome variables (i.e. 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 PLcentres. The opening of PLcentres may be correlated with other unobserved variables that could affect the online marketplace lending outcomes as well. Some people may suspect that local governments decide to open the PLcentres 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, to 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 new mayor's career concern on private lending issues, denoted as $NewmayorPLP_{ct}$, to instrument the introduction of

PLcentres, $Treated_{ct}$.

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

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

where the dependent variable $Treated_{ct} = Treat_c \times Post_t$ equals one if the borrower's working city c has the PLcentre opened at time t. The instrumental variable is $NewmayorPLP_{ct}$, which is the number of times the city c has a new mayor with career concern on 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 on 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 has close attention on private lending issues, the city mayor gets motivated to gain achievement in private lending (opening PLcentres 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 Instrument Variable on marketplace lending outcomes, I use same province's other cities' abnormal 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 on private lending.

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

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

To address the concern that new mayor may conduct policies other than opening PLcentres that affects 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 originally all listings and only successful applications. Both Cragg-Donald Wald F statistic and Kleibergen-Paap rk Wald

F statistic are largely greater than 10.

<insert table 5 here>

This measure of new mayor's career concern on private lending is a valid instrument for the establishment of PLcentres, in the sense that it strongly predicts the introduction of PLcentres (as shown in table 5) and only affect the marketplace lending results through PLcentres, 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 2012 April when there is even no PLcentre, but replace the primary independent variable as the IV. If the new mayor's career concern on private lending issues, $NewmayorPLP$, affects marketplace lending through channels other than PLcentres, we expect to see a significant effect of $NewmayorPLP$ on marketplace lending interest rates based on this restricted sample. However, Table reports no significance, which implies a politician's career concern on private lending affects the P2P lending through PLcentre after controlling for city variables.

<insert table 6 here>

There is another concern 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 whether there is a new mayor or not does not depend on the economic condition of the city. 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 PLcentres on Marketplace Lending Outcomes

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

Result 1. PLcentres boost the marketplace lending

First, Table 8 indicates that PLcentres push up the online P2P lending, as predicted by the search cost model in the last section. The variables of interest are the total lending amount of application and 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 PLcentres.

<insert table 8 here>

Table 8 in column (1) and (5) shows that the effect of PLcentres on the total amount of lending is positive and significant. PLcentres push up the total amount of credit extended through Renrendai by \$455,500 per month, and total requested lending amount by \$1,711,800 per month. For actual loans, both numbers of loans and borrowers increase by around 60 per month, as shown in column (6) and (7). And those of applications and applicants increase by 170 per month. The significant positive effect is in line with Prediction 1.

Also, PLcentres 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 at year-month t. Column (4) of table 8 reports that PLcentres increase the success rate by 4.5%.

Result 2. PLcentres Lowers the interest rate

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

It is a more efficient outcome since a competitive market with an identical good should have only one price, the lowest one. Due to the search friction caused by limited knowledge and lack of search skills of borrowers, the interest rate is higher than the competitive interest rate (lowest). When there is a private lending centre 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 decrease can help the private firms lower the cost of capital and in turn, enable the firm to make investment and management decisions closer to the optimal ones. The public information service as public goods not only benefit the low-educated individual borrowers but also may stimulate the economy.

<insert table 9 here>

Result 3. PLcentres reduce the dispersion of contract terms

As foreseen by Prediction 3, this section finds that the dispersion of interest rate goes down after having the PLcentres 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 column (1) to (4) of Table 10, the analysis based on both all listings and successful applications of sample period consistently finds a significant negative coefficient of treatment dummy. It indicates that the introduction of PLcentres reduces the variation of interest rates in the marketplace lending. Borrowers with access to PLcentres' 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, the PLcentre reduce the standard deviation of interest rate by -0.71.

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

With the search cost framework in mind, I conjecture the effects of PLcentres mainly go through the inexperienced. If PLcentres 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) reports the result of the group of borrowers who work in finance or law industry, the experienced group, and the rest columns (3) and (6) is the result of the inexperienced group. The negativity and significance of the coefficient of interest only appear in the experienced.

<insert table 10 here>

The distribution of interest rates before and after the introduction of PLcentres show in figure 4 suggests that there are less extremely low interest rates after having the PLcentres. 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 interest rate will be deficient. However, with PLcentres, this super high search cost problem is mediated.

<insert figure 4 here>

VI. Conclusion

The scale of flows and the direct participation of individuals in the Fintech credit market is stirring concerns(FSB, 2018). This paper focuses on the search frictions in the marketplace lending and explores how the introduction of information as the lighthouse, public goods, affects the market. I put the marketplace lending in a context of 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 PLcentres introduced in China.

Results show that PLcentres boost marketplace lending in terms of lending volume. The interest rate in the market significantly goes down, and more remarkably PLcentres reduce the dispersion of interest rate. The effect is mainly driven by the group who do not work in finance or law industry (less experienced). The findings are in line with the explanation in search cost framework, where borrowers' search cost and interest rate level, 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. It has an important policy implication for mediating search frictions, financial literacy and market efficiency.

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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 of 333 Chinese cities before 2011 December from Renrendai.*, **, 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 listings of Renrendai loan requests. The success sample comprises successful applications.

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

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. 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) Treated	(2) Treated
NewmayorPLP	0.0497***	0.0553***
	(26.20)	(16.49)
GovExpenditure	0.00000475	-0.0000140
	(0.55)	(-1.28)
Bookper100	-0.0000220	-0.0000235
	(-0.91)	(-0.78)
Constant	0.0540**	0.135***
	(2.54)	(3.94)
City FE	Yes	Yes
Year-Month FE	Yes	Yes
BorrowerControls	Yes	Yes
LenderControls	Yes	Yes
R^2	0.475	0.598
F	48.38	20.05
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 of Renrendai loan requests 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
R^2	0.444	0.466
Observations	3154	870

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 of Renrendai loan requests. 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
R^2	0.191
Observations	9900

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 of Renrendai loan requests (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. 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***	170.2***	0.0572***	455.5***	56.20***	56.20***
	(15.73)	(15.95)	(15.95)	(2.62)	(5.56)	(6.43)	(6.43)
Marriage(1=Married)	-19.25	-0.354	-0.354	0.0235***	13.36	1.738	1.738
	(-0.96)	(-0.18)	(-0.18)	(5.85)	(1.18)	(1.43)	(1.43)
Incomeindex	21.87***	-1.817**	-1.817**	0.000536	-5.158	-0.719*	-0.719*
	(2.63)	(-2.23)	(-2.23)	(0.32)	(-1.30)	(-1.70)	(-1.70)
Gender(1=F)	31.74	2.151	2.151	-0.00687	17.63	1.505	1.505
	(1.20)	(0.83)	(0.83)	(-1.30)	(1.19)	(0.95)	(0.95)
Age	5.943***	0.268*	0.268*	0.00140***	2.003***	0.170**	0.170**
	(3.92)	(1.81)	(1.81)	(4.62)	(2.72)	(2.16)	(2.16)
CreditRating	235.3***	24.37***	24.37***	0.0209***	31.64***	2.459***	2.459***
	(22.10)	(23.35)	(23.35)	(9.81)	(6.33)	(4.61)	(4.61)
Degree(1=Bachelor)	-50.05**	-4.734**	-4.734**	0.0245***	-19.41*	-1.630	-1.630
	(-2.22)	(-2.14)	(-2.14)	(5.41)	(-1.84)	(-1.45)	(-1.45)
Industry(1=Fin/Law)	-26.91	-3.142	-3.142	0.0105	5.890	0.750	0.750
	(-0.57)	(-0.68)	(-0.68)	(1.11)	(0.24)	(0.29)	(0.29)
LoanType(1=Consump.)	35.61***	4.375***	4.375***	0.00807***	24.38***	3.150***	3.150***
	(4.25)	(5.33)	(5.33)	(4.81)	(4.42)	(5.35)	(5.35)
HaveLoan	102.1***	7.018***	7.018***	0.0406***	32.88***	0.783	0.783
	(4.10)	(2.87)	(2.87)	(8.12)	(3.19)	(0.71)	(0.71)
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
LenderControls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CityControls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13057	13057	13057	13057	6296	6296	6296
R^2	0.076	0.114	0.114	0.627	0.476	0.474	0.474

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 of Renrendai loan requests (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. 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	-0.979**	2.100**	0.490	-1.559***	1.975	0.0154
	(-2.25)	(2.54)	(0.36)	(-2.86)	(1.29)	(0.02)
Marriage(1=Married)	-0.293***	0.116	0.118	-0.342***	0.268	0.00548
	(-3.66)	(0.77)	(0.47)	(-4.53)	(1.26)	(0.05)
Incomeindex	-0.0188	-0.822***	3.995***	-0.148***	-0.311***	0.664***
	(-0.54)	(-12.42)	(38.11)	(-5.48)	(-4.10)	(16.74)
Gender(1=F)	-0.338***	1.213***	-0.351	-0.338***	0.622**	0.519***
	(-3.19)	(6.05)	(-1.05)	(-3.42)	(2.24)	(3.50)
Age	-0.00851	0.0243**	0.209***	-0.000201	0.0286**	0.0924***
	(-1.40)	(2.11)	(10.95)	(-0.04)	(2.05)	(12.54)
CreditRating	0.170***	1.185***	-0.297**	-0.135***	0.183*	0.104**
	(3.95)	(14.66)	(-2.19)	(-4.05)	(1.95)	(2.08)
Degree(1=Bachelor)	-0.371***	-0.414**	1.451***	-0.392***	0.0302	0.158
	(-4.11)	(-2.42)	(5.10)	(-5.59)	(0.15)	(1.50)
Industry(1=Fin/Law)	0.0970	-0.246	0.707	-0.512***	1.100**	-0.109
	(0.52)	(-0.69)	(1.20)	(-3.18)	(2.43)	(-0.45)
LoanType(1=Consump.)	0.0602*	0.194***	-0.332***	-0.0239	0.501***	-0.0348
	(1.80)	(3.05)	(-3.14)	(-0.65)	(4.85)	(-0.63)
HaveLoan	-0.388***	1.097***	1.169***	-0.190***	0.415**	-0.0651
	(-3.88)	(5.79)	(3.71)	(-2.77)	(2.16)	(-0.63)
Maturity	0.0128***		0.343***	0.0999***		0.0451***
	(2.73)		(23.67)	(22.50)		(6.52)
Avg.A	0.0122***	0.123***		0.0378***	0.158***	
	(4.33)	(23.59)		(4.38)	(6.54)	
R		0.0445***	0.122***		0.806***	0.0898***
		(2.63)	(4.37)		(22.62)	(4.53)
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
LenderControls	Yes	Yes	Yes	Yes	Yes	Yes
CityControls	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.061	0.177	0.179	0.085	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 of Renrendai loan requests. 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. 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	-1.040***	-0.975***	-1.118	-0.711*	-0.786*	0.255
	(-3.49)	(-3.27)	(-1.34)	(-1.72)	(-1.71)	(0.13)
Marriage(1=Married)	-0.0149	-0.0381	0.0850	0.164*	0.120	0.00196
	(-0.24)	(-0.61)	(0.73)	(1.93)	(1.37)	(0.01)
Incomeindex	-0.0200	-0.0265	0.0892	-0.0704**	-0.0696**	0.0861
	(-0.74)	(-0.99)	(1.50)	(-2.44)	(-2.37)	(1.58)
Gender(1=F)	0.0218	-0.0605	-0.137	-0.168	-0.141	-0.167
	(0.26)	(-0.72)	(-0.98)	(-1.58)	(-1.30)	(-1.14)
Age	-0.0132***	-0.0140***	-0.00418	-0.00428	-0.00400	-0.00747
	(-2.90)	(-3.07)	(-0.48)	(-0.76)	(-0.69)	(-1.45)
CreditRating	0.0565*	0.128***	0.0497	0.0259	0.0379	-0.266*
	(1.76)	(3.38)	(0.40)	(0.71)	(1.02)	(-1.85)
Degree(1=Bachelor)	-0.0445	-0.0439	-0.0585	-0.118	-0.107	-0.0589
	(-0.64)	(-0.62)	(-0.55)	(-1.50)	(-1.30)	(-0.54)
Industry(1=Fin/Law)	-0.219			-0.165		
	(-1.49)			(-0.93)		
LoanType(1=Consump.)	-0.0720***	-0.0343	0.113**	0.0155	0.0332	-0.00648
	(-2.58)	(-1.22)	(2.06)	(0.39)	(0.80)	(-0.11)
HaveLoan	0.180**	0.117	-0.130	0.0704	0.0779	0.0285
	(2.34)	(1.51)	(-1.00)	(0.94)	(1.01)	(0.30)
Maturity	-0.0710***	-0.0704***	-0.0578***	-0.0271***	-0.0255***	-0.0644***
	(-19.58)	(-19.11)	(-9.81)	(-5.60)	(-5.16)	(-7.19)
Avg.A	-0.00289	-0.00318	-0.00435	-0.00187	-0.00217	0.00953
	(-1.34)	(-1.48)	(-0.96)	(-0.19)	(-0.21)	(1.08)
minR		-0.0259	0.146	-0.258***	-0.265***	0.253**
		(-0.37)	(0.95)	(-5.41)	(-5.46)	(2.14)
minR		0.0706***	0.0111	0.113***	0.116***	-0.0410
		(3.91)	(0.30)	(8.10)	(8.24)	(-1.09)
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11971	11885	2261	3829	3711	411
R^2	0.035	0.043	0.045	0.079	0.076	0.441
BorrowerControls	Yes	Yes	Yes	Yes	Yes	Yes
LenderControls	Yes	Yes	Yes	Yes	Yes	Yes
CityControls	Yes	Yes	Yes	Yes	Yes	Yes

Graphs

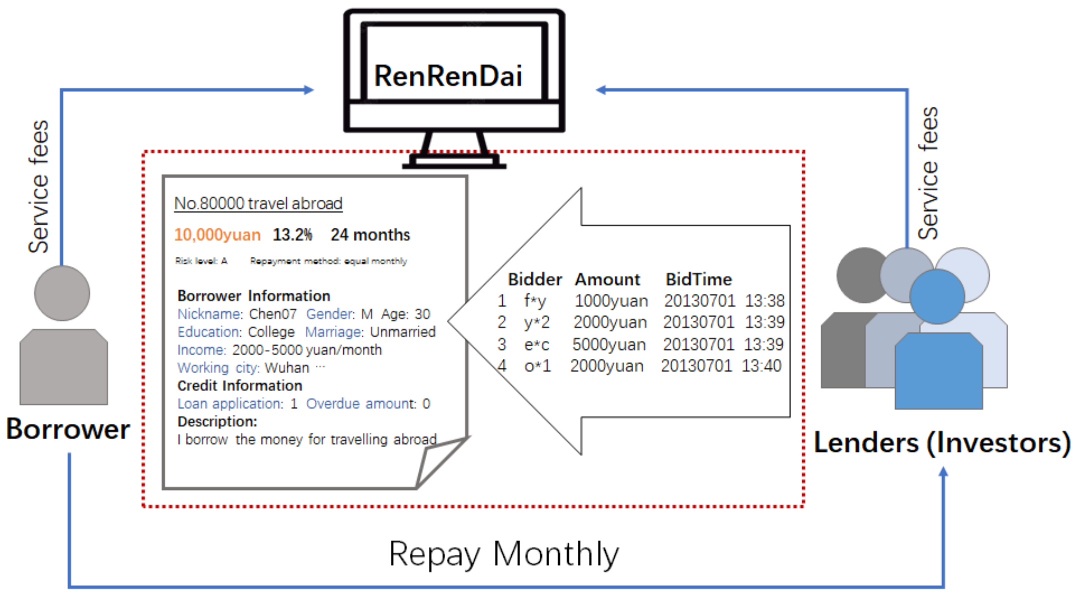


Figure 1. Renrendai loan bids.

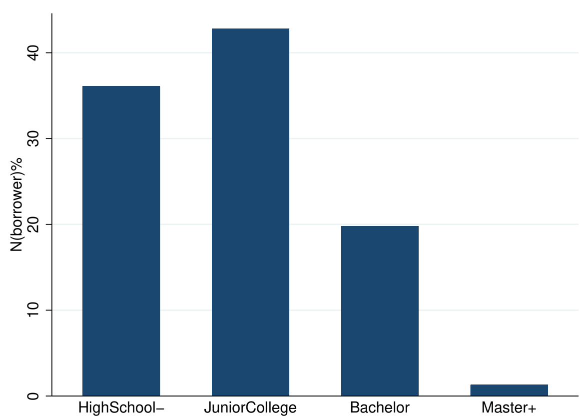


Figure 2. Renrendai Borrowers' Education.

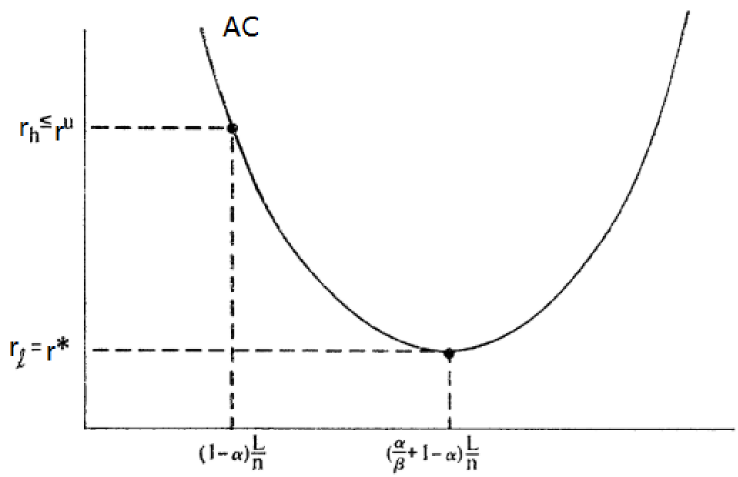
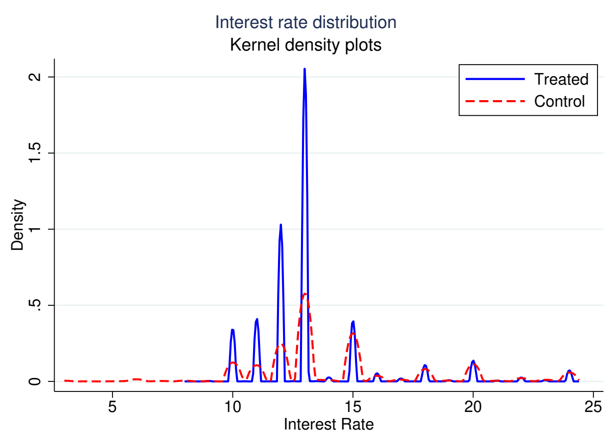
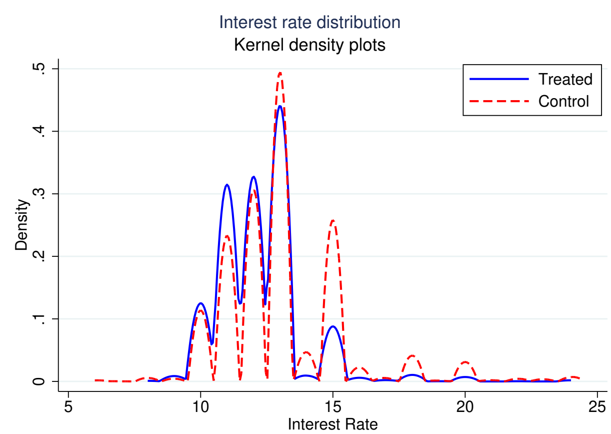


Figure 3. Two Price Equilibrium



(a) full sample



(b) success sample

Figure 4. Interest Rate Distribution