SOCIAL NETWORKS CENTRALITY MEASURES ON HERDING BEHAVIOR IN P2P LENDING: AN EMPIRICAL EVIDENCE IN CHINA

A PREPRINT

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April 28, 2019

ABSTRACT

Considered as a flourishing finance platform, there are still plenty of unprofessional investors in P2P Lending market. Previous researchers provided evidence of herding behavior among P2P lenders. Since the similarity exists between social media and P2P lending platform, we consider employing social network centrality measure to investigate the herding behavior in P2P lending. We apply a networks model on loan data from Renrendai.com, one of the leading P2P platforms in China. Firstly, we build combinations between each individual investors, recording the bid information. Secondly, we employ centrality measure to investigate the influence of each investors, constructing a network with nodes and edges. Our analysis results in a high-centralized network, which indicates that leaders or experts with higher centrality may significantly affect invest strategies of followers who have lower centrality. Super leaders may change followers' potential decision.

***K*eywords** Peer to Peer Lending · Social Networks Analysis · Herding Behaviour · Big Data · Financial Technology

1 Introduction

Introduction of this paper.(Under Draft)

Peer to peer lending market provides a platform in which individual investors could invest loans from multiple individual borrowers.

2 Literature Review

2.1 Herding Behaviour

2.2 Rational vs Irrational Herding

2.3 Information asymmetry

2.4 Social Networks Analysis

2.4.1 Degree centrality

Degree captures the number of ties to a given point, which is defined as the number of links that a node has with other nodes. The fomular is shown as following:

$$C_D(n_i) = d(n_i) \tag{1}$$

where d_{ni} is the degree of node n_i.

For networks with directions, there are two separate types of degree centrality, which are in-degree and out-degree. In-degree measures the number of links directed to the node, out-degree counts the number of links directs to other nodes. Fomulas are shown as below:

$$C_in(v_i) = d_in(v_i) \tag{2}$$

$$C_out(v_j) = d_out(v_j) \tag{3}$$

where $d_in(v_i)$ and $d_out(v_j)$ are the corresponding in-degree and out- degree centralities of nodes v_i and v_j.

2.4.2 Betweenness centrality

Betweenness centrality captures how many times for a particular node to play as a bridge on the shortest path between two other nodes. Acting as a bridge indicates the given node is capable to control the communication between others in the network. The betweenness equation is shown as below.

$$C_B(v_i) = \sum_{j=1,k\neq 1} \frac{g_{jik}}{g_(jk)} \tag{4}$$

where g_{jik} is all geodesics linking node j and node k which pass through node i; g_{jk} is the geodesic distance between the vertices of j and k.

2.4.3 Closeness centrality

Closeness measures the average length of shortest path are required for a particular point to access every other point in the network. It could be considered as a counter to record the speed for a given node to pass a signal to all other nodes. Generally it could be employed to identify which nodes are suitable to spread information into the whole network. The formula for it is shown as below:

$$C_c(v_i) = \sum_{j=1}^{N} \frac{1}{d_(v_i, v_j)} \tag{5}$$

where C_c is the closeness centrality of a node v_i.

2.4.4 Eigenvector centrality

Eigenvector centrality extends the degree conception. All nodes are in same importance and equal credits under the degree centrality. However, in reality, it is difficult to construct a network with all importance-equaled nodes. Every nodes plays different roles which may differ in the importance. Hence, eigenvector centrality separates high-scoring and low-scoring nodes which a given node is connected to, providing a relative score for the given node depending on the scoring type of connections. Given a graph $G = (V, E)$ with n nodes, adjust the A to be the eigenvalue of adjacency matrix of G and λ.

$$C_e(v_i) = \frac{1}{\lambda} \sum_{j=1}^{n} d_i a_{j,i} C_e(v_j) \tag{6}$$

3 P2P marktet in China and Renrendai.com

3.1 P2P marktet in China

Peer-to-peer lending provides a platform for individual or business investors and borrowers in which they could borrow and lend directly to each other, matching borrowers and investors through online services. In February 2005, the first P2P lending platform, Zopa was founded in the UK, then Prosper and Lending Club appeared in the US. Chinese investors had not been waiting for long time, first P2P lending platform PPDai.com introduced P2P markets to China in 2007. Growing rapidly with the online service development and prosperous macro-economy in China, although faced the online micro-loan regulation in 2015 and massive shake out in 2018, there were 1185 active providers operating in the market at the end of 2018, this number in 2011 was only 50. Besides the providers number, the market size of P2P lending in China experienced a significant flourish during the past 11 years, which reached 7690 billion in total accumulated loan amount RMB by December 2018. The prosperous growth might be the result of several reasons. Firstly, P2P lending provides a convenient solution for people who have more difficulty to have access to bank loans with limited credit record. Secondly, banks prefer to provide funding with large business with high potential to repay and cover, which set worse barrier for small business owners to enlarge the scale. Thirdly, small investors have been seeking a better place than stock market and bonds market to maximize returns on their investment. Although the expected annual returns experienced a reduction from over 20 percent to around 12 percent from 2014 to 2016, the development tendency kept during past two years over 2016 to 2018, enthusiastic investors still funded borrowers and small businesses who needed to be funded.

During the initial stage, P2P lending platforms in China appealed to borrowers without high credit records and investors lacking impeccable professional investment acknowledge, leading to higher risk of default and massive losses of investors. In order to rectify the P2P lending market order, the financial regulator issued guidelines in July 2015, which required online P2P lending platforms must be registered as "information agency" firms under the regulation from authorities. Meanwhile, in order to certify the trade transparency and funding ownership, a institution was introduced to required platforms operate funding collected from investors through a third-party depository account in an authorized bank. With the constrictive regulation and intervention, there are a large amount of platforms closed their businesses or transformed to different types of industry. 01caijing.com, a database provider which manages platform information and aggregate data from P2P lending market in China, reported the downward tendency among the number of active platforms in normal operating status decreased from 5890 to 1185 over 2016 to 2018.

3.2 Renrendai.com

Established in October 2010, Renrendai.com is one of the biggest P2P platform in China. By the end of October 2018, about 170000 registered investors fund more than 90000 borrowers on Renrendai.com. Meanwhile, this platform reached 10 billion total lending amount with over 1 million loans which have been confirmed. Although P2P market in China experienced turbulence during 2018, the number of investors on Renrendai.com kept increasing substantially due to the lower default risk and stable expected returns. Panel A of Figure 1 describes monthly changing tendency of the number of investors lend per hour on Renrendai.com. It is obvious that active investors with lending behaviour have been tremendously increasing between 2010 and 2018. Panel B of Figure 1 captures the bidding activities in one-day period, displaying the most active period between 10:00 until 14:00. Meanwhile, at the borrowers side, it could be found that the average amount of loans have been dramatically increasing due to more and more new borrowers are attracted to register and the phenomenal vibrant investors activity.

We investigate the procedure of the platform as follows. In order to apply for a loan, the borrower need to create a listing with explicit amount of funding needed, which ranges from 3000 to 500000 RMB. Renrendai.com allows each listing to be posted on the platform in maximum 7 days (168 hours). On average, a listing would be filled in less than 5 hours since being posted. However, some others may take longer since the standard deviation is approximately 18.5 hours, so we pay more attention to the first 60 hours in this paper. To create a loan listing, the borrower need to upload a statement which explains the funding purpose and provides employment, debt and income information. According to the materials uploaded, the platform separates borrowers into different credit ranking, which contains AA, A, B, C, D, F and HR, where AA stands for the top grade and HR presents the High Risk. Credit grades are associated with personal identity, educational level, property ownership, car ownership, personal mobile and bank account under real-name registration system. Normal repayment from a borrower would help to improve the credit grade, default or overdue would decrease it.

Browsing the platform, relevant information of every prospective loan listing is visible to investors. Also, the risk could be diversified by offering multiple bids to different borrowers. The loan proceeds are credited into the borrower's bank account from which repayments are automatically withdrawn. Once the bid amount fully reaches the requested amount, the loan is created and the loan request is removed from the listings website. In contrast, if listing expires without full funding within seven days, all lenders receive their contributions.

4 Data

Observing Renrendai.com, one of the biggest P2P lending platforms in China, we collected loan data during the period between October 2010 and October 2018. With 1 million loan observations, in order to simplify the calculation in the preliminary results, we generate a sub-sample which contains 25000 loans information during October 2010 and February 2012. Renrendai.com offers three types of bidding services for individual investors. Investors could make their own bid decisions by manual bidding, however, automatic bidding only provides investors with decisions from the system. Another service allows investors manually bid and use auto-bidding at the same time. Since this paper focus on herding behaviour from human natural instincts, we employ only manual bidding from the first and second service. Therefore, the automatic bidding effect could be excluded.

The database is built from two sources. Firstly, we collected loan information which contains borrower characteristics for each loan listing. Then, we captured bidding data for every loan transaction, identifying which specific investors bid to fund a particular loan application. With a combination between listing and bidding, we generated a database which contains 1 million observations. For a particular Loan ID, there are annual interest rate, credit score given by the platform, loan amount and maturity. Meanwhile, the characteristics of borrowers are also recorded, which covers borrower ID, income, age, employment, location, educational level, property ownership and application history. In addition, the lender ID, bidding amount, bidding time are gathered into every listing as well. Then, we built panel data for every listing for manual bidding per hour. Finally, in order to investigate lenders bidding behaviour in every hour, we construct a hourly dummy panel data on lenders.

5 Empirical Model

There are two questions for individual investors: which loan to invest and how much to bid. Investing decisions on how to choose target loan and decide bid amount may depend on the expected return on the loan and the risk from the loan. Previous researchers focus more on daily cumulative bids, however, we apply hourly cumulative data for each loan which contains all bids that lenders invest. It is because that on Renrendai.com loan applications would be completed in short time as we mentioned in the data description. We generate the cumulative hourly bidding data for every loan listing from the opening hour to 60th hour.

Applying lagged panel analysis, we construct a preliminary model as follow to investigate the sequential correlation:

$$\begin{aligned} Bid_{it} = {} & \alpha_1 ExpertBidAmount_{it-1} + \alpha_2 FollowerBidAmount_{it-1} + \alpha_3 ExpertBids_{it-1} \\ & + \alpha_4 FollowerBids_{it-1} + X_{it}\beta_1 + Z_i\beta_2 + e_it \end{aligned} \tag{7}$$

Bid_{it} is on behalf of the funding amount which loan i receives at time $t = 1, 2, ..., 60$. Although technically loan applications could survive up to 7 days (168 hours), we still record listings without full filled funding when T= 60 hours as unfunded and exclude it from our analysis. The reason why we choose this standard is that listings without full funding at $60th$ hours are rarely to be filled by 7 days. In order to investigate the sequential correlation, we introduce $ExpertBidAmount$ and $FollowerBidAmount$ to measure lagged funding from experts and followers respectively that a list has received during the previous hour. If α_1 is significantly more positive than α_2 there will be an evidence in favor of sequential correlation.

Our naive model considers the number of lagged bids from experts, $ExpertBids$, as well as the number of lagged bids from followers,$FollowerBids$ respectively. The model also employs vectors X_{it} and Z_i to measure the time varying and time invariant. For X_{it}, $\%Needed_{it-1}$ presents the percentage of the amount requested by loan i which is left unfunded at the end of hour $t-1$. In order to investigate the effect from the different bidding time on certain hours of a day, we introduce Hour of Day, H_{it-1}, and Day of Week,D_{it-1}, which are fixed for each particular hour. Vector Z_i is employed to details the time invariant loan characteristics, including Requested-Amount, Maturity, Credit Risk

Dummy, Debt-to-Income-Ratio and Property-Ownership Dummy. $IntRate_{it-1}$ captures the the interest rate that a particular loan listing would provide with investors at the end of $t-1$. The $StartDay$ is also be included in Z_i to measure the opening date for the loan listing. Since there are manual bidding and manual-auto-hybrid bidding services, we introduced lagged $PercentAuto - Bidding$. Finally, the e_{it} denotes the error term.

Model (1) provides a method to detect the evidence of sequential correlation among our database. However, the naive model could not confirm the existence of herding behaviour, it is because that sequential correlation could be the result from unobserved heterogeneity across loan listings, payoff externalities among investors. In addition, the investors' rational or irrational herding behaviour could not be separated by applying our naive model. In order to make it feasible to investigate unobserved heterogeneity among the loans, we introduce mu_i, fixed effects from the borrowers characteristics which would be consistent during the loan processing period. Meanwhile, anothor interaction indicator, $Lag(TotalBidAmount) \times PercentageNeed$ is introduced to disentangle the payoff externalities. The following model represents the effects from borrowers characteristics:

$$\begin{aligned} Bid_{it} &= \alpha_1 ExpertBidAmount_{it-1} + \alpha_2 FollowerBidAmount_{it-1} + \alpha_3 ExpertBids_{it-1} \\ &+ \alpha_4 FollowerBids_{it-1} + X_{it}\beta_1 + Z_i\beta_2 + \mu_i + e_it \end{aligned} \tag{8}$$

We next we include interactions between the lagged total amount and listing attributes to identify rational herding from irrational herding behaviour. Hence, the model takes the following form: Then, we take the interactions between $Lag(TotalBidAmount)$ and $PercentageNeed$ to extract rational herding from total investors' herding behaviour. The following model contains the interactions:

$$\begin{aligned} Bid_{it} = \alpha_1 & ExpertBidAmount_{it-1} + \alpha_2 FollowerBidAmount_{it-1} \\ &+ (ExpertBidAmount_{it-1} + FollowerBidAmount_{it-1}) \times Z_i\beta_2 \\ &+ \alpha_5 (ExpertBidAmount_{it-1} + FollowerBidAmount_{it-1}) \times (ExpertBids_{it-1} + FollowerBids_{it-1}) \\ &+ \alpha_3 ExpertBids_{it-1} + \alpha_4 FollowerBids_{it-1} + X_{it}\beta_1 + Z_i\beta_2 + \mu_i + e_it \end{aligned} \tag{9}$$

6 Results

6.1 Sequential Correlation

6.2 Rational Herding

6.3 Perspactive of Investor

7 Conclusion

Since the first P2P lending platform appeared in China, it has been 12 years that online P2P platforms service people's life funding loans to borrowers who have difficulty in financing through traditional financial institution. Since there are great amount of people who need financial help, herding behaviour is expected to support more efficiently to the market operating. Our research focuses on the data from Renrendai.com, one of the biggest online P2P lending platforms in China. Providing super fast automatic bidding service which allows investors enjoy convenient bidding experience. Taking the automatic bidding apart, generally, a successful loan would be completed in 5 hours on average basis. There are three fixed different post times on the platform per day: morning, afternoon and evening. The effect from time group and automatic bidding are also taken into account in our investigation.

Bibliography