Determinants of survival of peer-to-peer lending platforms in China

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Abstract

With the rapid development of the Internet, people's understanding of financial product innovation is also deepening. If the operation mode of peer-to-peer network lending can be optimised, the development of network finance can not only promote the development of small and medium-sized enterprises, but also enhance the innovation of financial products and serve ordinary investors. Therefore, this paper starts with researching literature and operation mode of peer-to-peer lending, and proposes to further explore the decisive factors of peer-to-peer reception. After that, we choose 10 problematic peer-to-peer lending platforms and 10 normal operation platforms to study the influencing factors of peer-to-peer lending scale, and whether there was a significant difference in yield. Later, in order to further study the influencing factors of peer-to-peer network lending in China, we selected the relevant monthly data from January 2014 to March 2019, and established a regression model with econometric methods, and conducted the influence of different macro factors on peer-to-peer lending development.

Keywords: peer-to-peer lending platforms; internet finance

1. Introduction

The emergence of peer-to-peer is a product of the financing needs of small and medium-sized enterprises and the investment needs of individual investors. In recent years, China's peer-to-peer lending platforms have blossomed all over the place, and they are also facing challenges of bankruptcy. On July 16, the chairman of Yatang Holdings and others surrendered on suspicion of illegal crimes. In November 2017, Qianbao.com was inspected. In July, Tang Xiaoseng and Lincomb both went bankruptcy. At this point, Qianbao.com, Yatang Holdings, Tang Xiaoseng and Lincomb – the ‘Big 4’ peer-to-peer lending platforms in China are all bankrupt. By the end of December 2018, the number of normal operating platforms in the P2P online lending industry had dropped to 1,021, down 1,219 from the end of 2017. By the end of December 2018, a total of 5,409 platforms had been shut down or in trouble, and 6,430 platforms in the P2P lending industry had been shut down.

With the rapid development of the Internet, people's understanding of financial product innovation is also deepening. If the operation mode of P2P online lending can be optimied, the development of online finance can not only promote the development of small and medium-sized enterprises that cannot benefit from China's formal finance, but also make use of the advantages of the Internet to increase the innovation of financial products and serve ordinary investors. Therefore, this paper starts with the literature research, analyses the current research status and operation mode of P2P network lending, and proposes to deeply explore the determinants of survival of P2P reception, on this basis, reveals the development process and status quo of China's P2P reception, and puts forward some disadvantages of China's P2P development. After that, we used macroeconomic data to study the factors affecting the scale of P2P lending, and then found out the key factors. On this basis, we made theoretical analysis and in-depth exploration of the micro and macro factors affecting P2P lending, focusing on the performance, causes and influencing factors of P2P network.

2. Review of Existing Literature

2.1 Determinants of peer-to-peer lending

In identifying the determinants of peer-to-peer lending the central issue was the determining factors that affect bidding strategies of lenders and loan funding success rate. In this regard, prior literature analysed such factors as user credit information, loan characteristics, demographic information, and soft information (Feng et.al. 2015). Puro et al. (2010), Freedman & Jin (2008), Lin et al. (2013) highlighted such factors as interest rate, size and maturity of loans that have a significant impact on funding success probability. Iyer et al. (2009), Freedman and Jin (2008), and Yum et al. (2012) indicated that borrowing history and credit rating mainly determine the probability of successful funding. Another study concentrated around demographics in lending process and indicated that "women seem to tolerate a lower interest rate from both the borrowing and the lending sides; younger borrowers are in general more successful; and there exists a racial disadvantage in both the funding success rate and the interest rate paid" (Feng et.al. 2015, p-245). The studies of Wei and Lin (2016) looked into interest rate determination, probability of funding and probability of default in peer-to-peer lending. The study analysed the case of Prosper.com with the dataset containing the listing of more than 13,000 loans. It firstly developed the model of market mechanism for the posted prices and auction bidding processes. These models guided the author to a number of hypotheses that are empirically tested in the second part of this paper.

Determining factors of default within peer-to-peer lending market has been the focus of another group of studies. In this regard, Serrano-Cinca et.al. (2015) employed loan book dataset from Lending Club (USA) and used logistic regression for analysis. According this study, grades assigned by the peer-to-peer platform were central for forecasting loans defaults. Another study compiled by Emekter et al, (2015) highlighted that "credit score, debt to income ratio, FICO score, and revolving line utilization play an important role in loan defaults". Herzenstein et al. (2011) and Lee (2012) concentrated around the 'herding behaviour' were the behaviour of few investors are followed by others. Lin & Viswanathan (2016) and Duarte et al. (2012) highlighted the importance of so called 'home bias' and 'trust'. These two factors were significantly affecting default probabilities. Greiner & Wang (2009) and Freedman and Jin (2014) put forward the social network effect as a significant factor that explains the default probabilities among peer-to-peer lenders. Social network was a specific aspect of online lending practices, where investors put much weight on such factors as the number of friends in online networking platforms.

Behaviour of lenders of peer-to-peer lending platforms in China were also the focus of researchers during the last years. The study of Chen et al. (2014) surveyed peer-to-peer lending platforms in China and highlighted the significant effect of 'trust' in determining the investor's propensity to lend. Another study of Chen and Han (2012) was comparative by essence and contrasted peer-to-peer lending markets of USA and China. Peer-to-peer lending markets in China and the USA were analysed via classifications based on so called 'hard' and 'soft' credit information. Chinese lenders were found to put more trust on 'soft' information whereas their counterparts in US do not. Applying OLS regression in the study of Li & Zhu (2013) yielded importance of such factors as borrowing history, amount of listed loans and credit rating in determining the successful loan interest rate. Zhang et.al. (2015) employed OLS regression and proposed that "bidding record has a greater influence on online Chinese P2P lending compared to other factors, and that Chinese users rely heavily on social capital". Hence, prior literature generally agreed on insignificant dissimilarity when peer-to-peer lenders in China and other countries are compared.

Greiner and Wang (2009) using Prosper more than two and a half years of sample data, analysed more than 200,000 loan application and 27,500 loans, of for-profit private capital in the role of the lending market network are studied, the results show that this kind of folk capital allows the borrower's credit status is improved, thus more preferential interest rates for borrowers. Lin (2009) believes that online lending refers to unsecured loans directly provided by individuals to individuals without intermediaries such as Banks. It relies mainly on the presence of social networks, which can provide important information about borrowers. The author conducts an empirical study on whether and how the network influences peer-to-peer lending transactions. The results show that the online social network can help alleviate the problem of information asymmetry in the loan process, and a key factor for the success of the lending platform is that it can make good use of the information embedded in the social network. Shen et al. (2010) studied the influence of social factors on the decision-making of creditors in online lending. Using data collected on U.S. websites, they propose theoretical models based on preferred attachment to portray the bidding behaviour of lenders. The results show that the lender has a significant herd effect when making investment decisions.

No research to date specifically highlighted the importance of macroeconomic indicators and included these indicators in regression models. The study of Wei and Lin (2016), mentioned earlier, considered linking market mechanisms to inter-platform competitions to be a promising area for future research. Based on these shortcomings in the existing literature this study concentrates around the specific determinants of peer-to-peer lending with specific emphasis on inter-platform competition.

2.2 Analysis on operation mode of online lending platform

The operation modes of different platforms represent different trading mechanisms and risk control mechanisms, and there are different research perspectives on the operation modes of online lending platforms at home and abroad. Foreign research mainly focuses on those websites that are successful in the field of online credit, such as Prosper, Zopa and Kiva. Such as Greiner and Wang (2009); Lin and Prabhala (2013)'s research shows that Prosper's credit system is relatively perfect, and its pre-loan auditing and post-loan management are relatively perfect. In 2009, Greiner took the loans completed by the lending platform as the research object and analysed the characteristics of borrowers' self-selection and bidding transactions on the Prosper platform. It found that not only the borrowers' credit conditions were improved, but also the borrowing rate was mutually beneficial and win-win. Michael has conducted a detailed and comprehensive analysis of Zopa as an important case when studying social network relational lending (Michael K Hulme, 2006). He believes that Zopa provides more authentic and transparent financial services. Also noted is the lower bad debt rate.

Although the problem of asymmetric information of network platforms is more serious, as long as the risk control measures are in place, the risk will be lower than that of traditional financial institutions. According to Seth Freedman (2010), peer to peer lending platforms are different from traditional lending markets in two aspects. Firstly, although peer-to-peer lending providers face certain credit risks, they have no incentive to investigate borrowers like banks before lending. Secondly, peer-to-peer lending platforms can use social network to estimate the credit and default probability of borrowers, emphasise the importance of information, and use the social network of borrowers to achieve good risk control. Michal Herzenstein (2008) conducted an empirical study based on the data of peer-to-peer lending platforms. He believed that peer-to-peer lending platforms deserve attention for two reasons. Secondly, peer-to-peer lending platforms combine the process of online auction valuation and bidding to improve the transparency of information.

In recent years, the research of foreign scholars on peer-to-peer lending platforms focuses on the empirical research on peer-to-peer lending. Lin (2013), Kumar (2010), Freedman and Jin (2011), Puro (2010) and many other scholars analysed a series of influencing factors of peer-to-peer lending platform and lending business, mainly analysing borrowers. From the perspective of social capital, financial status, risk rate and rate of return, the researchers divided the information of both parties into two categories: hard information and soft information. Lin (2013) pointed out that in both the spread of the objective information such as age, gender, marital status, education level, credit rating, loan interest rate, loan period will be affected to some extent both trading behaviour, general peer-to-peer lending platform has specific requirements on information disclosure, the scholars will such information as the "hard information" were analysed. Through a large number of empirical analyses of "hard information", scholars have reached the same conclusion, that "hard information" has a significant impact on loan success rate, loan interest rate and loan default rate. Klafft (2008) found that the credit rating of the borrower has the greatest influence on the level of borrowing rate, while in the lending business, the debt income of the borrower has a significant but little influence on the borrowing rate. On the other hand, whether the borrower has a bank account is the main factor affecting the success of this loan business. Lin and Prabhala et al. (2013) found that loan business projects with high success rate on peer-to-peer lending platforms all have one feature: borrowers of the loan project can provide their own reliable financial information. Peer-to-peer lending platforms carry out credit rating based on borrowers' disclosure information. Borrowers with high credit rating get significantly higher expected earnings than those with low credit rating. Herrero and Lopes (2009) also obtained the research conclusion that the two are positively correlated through the proof. Iyer et al. (2009) further studied the relationship between borrower's credit rating and borrowing risk level.

The study found that when borrowers' credit ratings changed, so did a range of borrowing elements. Compared with the borrowers with low credit rating, the borrowers with high credit rating have lower borrowing rate, higher borrowing success rate and lower loan default rate. All this shows that credit rating has an important influence on the borrower and the loan project. Some scholars also studied the correlation between the physiological characteristics of borrowers and trading behaviour. Under the requirement of information disclosure, borrowers need to fill in specific personal information and loan project information on peer-to-peer lending platform, and the peer-to-peer lending platform publishes loan information after being audited. Investors can inquire about loan projects and borrower information after registration on peer-to-peer lending platform. Duarte et al. (2012) proposed that lenders could filter other information such as borrowers' credit information through software query tools to help lenders make optimal investment decisions. Researchers such as Ravina (2008), Barasinska (2009) and Pope and Sydnor (2008) further studied the relationship between the appearance, gender and other physiological characteristics of borrowers and their borrowing behaviour under the same "hard information". Barasinska (2009) found that the borrowing and trading behaviours of men and women were different, and men participated in peer-to-peer lending more than women. Men tend to prefer high-risk, high-reward loan programs, while women do the opposite. They also found that borrowers with a beauty advantage were more likely to be successful at borrowing money, although less influential. In the aspect of "soft information", foreign scholars also have a lot of research. They believe that the "soft information" of borrowers in peer-to-peer lending platforms can, to some extent, be seen as an evaluation of the reputation of borrowers in real life. To some extent, the "soft information" of the borrower reflects the social capital information of both parties. In the transaction of loan business, "soft information" will certainly exert an invisible constraint on both borrowing and lending parties. To some extent, peer-to-peer lending and lending parties can reduce the investment risk according to the constraint of "soft information". In this respect, foreign scholars mainly use social capital theory to analyse the factors that influence lending behaviour. Markowitz and Gorski et al. (2012) analysed the influencing factors of borrowing behaviour and the components of social capital in the social network relationship between borrowers and lenders. They first studied the social capital information of borrowers and believed that the social capital information of borrowers could be used as a supplementary reference element for lenders' credit rating of borrowers. Freedman (2008) points out in the research that social capital information does not influence the borrowers with high credit rating on peer-to-peer lending platforms, but the borrowers with low credit rating do not. For borrowers with lower credit rating, investors pay more attention to the social relations and social capital information of borrowers. They hope to conduct a more comprehensive assessment of the default risk of borrowers through the social capital information of borrowers, so as to help them make the optimal decision. Lee and Chae (2012) used social capital information as supplementary information to "hard information" of borrowers. Iyer et al. (2009) further studied the significance of borrowers' social capital information and came to the same conclusion that the "soft information" of borrowers could help lenders to select high-quality loan projects and borrowers from multi-dimensions. Secondly, some researchers also studied the influence of social capital. They considered the social capital information of borrowers and the factors influencing the success rate and interest rate of borrowing. Ashta and Assadi (2009) and Lin et al. (2009) pointed out that social network relationship can reduce information asymmetry to a certain extent. Ashta and Assadi (2009) found that peer-to-peer online lending platforms can improve the communication efficiency of their own platforms through the widespread use of social networks. Combined with the application of technologies such as big data technology and cloud computing, peer-to-peer lending platforms can provide faster and more efficient services at a lower cost. The research of Greiner (2009) found that the social relationship of borrowers would affect the interest rate and success rate of borrowing. Borrowers with more information about social networks have higher success rates and lower interest rates. Borrowers who disclose less or do not disclose information about social networks do the opposite. Lin et al. (2009) also pointed out that individual social network information can be used as valuable signals when studying network social theory. This kind of social signal can alleviate the problem of information asymmetry to some extent, while the influence degree of information asymmetry depends on the authenticity, reliability and verification of the borrower's social signal. Foreign scholars usually use quantitative analysis method for research. They conducted systematic quantitative analysis of borrowers' social information, and divided the parameters from high to low into five levels. The study again shows that borrowers with more information about social capital have higher borrowing success rates, lower borrowing rates and lower default rates. This result proves that the relevant social capital information of the borrower has real value in the loan transaction. Finally, in the aspect of "soft information" research, many scholars have analysed and studied the borrowers' group information. Everett et al. (2011) pointed out that the members of the borrower's group have a certain degree of information similarity, and each borrower in the group reflects the social capital information of the group member borrowers. As there is mutual comparison and supervision among group members, this influence can control the group's borrowing success rate, borrowing interest rate and default rate. When a new borrower joins a group, the default rate changes. Berger et al. (2009) and Barber (2012) also reached similar conclusions in their own research. Berger et al. (2009) believed that groups can establish their own private information, thus reducing the impact of information transmission and information asymmetry. The mutual restriction of the group of borrowers can control the risk and default to a low level. Meanwhile, the endorsement of the group leader can reduce the interest rate of borrowing, because the members with the group leader endorsement or guarantee are more trusted. But the Barber (2012), Collier and Benjamin (2010) study, organization, leadership, group guaranteed borrowers can obtain higher credibility, in this type of group, borrowers can obtain lower loan interest rates and higher borrowing rate, but the group members and borrowers default rate correlation is not very obvious, even some of the lower credit rating borrowers can through active participation in the group and is trusted by investors. Yum, Haewon and Lee (2012) conducted group information analysis on data of Zopa platform but got different results. They argue that group borrowers are less productive than non-group borrowers. The mutual influence of group borrowing members is the main reason for restricting group investment return. But with third-party guarantees, the interest rate and default rate of borrowers can also be low. Although a large number of studies have been conducted by foreign scholars, Chaffee and Rapp et al. (2012) believe that scholars mainly conduct statistical analysis of data of Zopa or Prosper platform, and these results have some limitations, and their research methods and objects are relatively single.

3. Peer-to-peer development process and current situation

3.1 Peer-to-peer development process

Under the general trend of "Internet +" development, the number of peer-to-peer online lending platforms is soaring, and the development trend is extremely hot. The greatest advantage of peer-to-peer lending is that borrowers which are hard to cover by traditional banks can fully enjoy the efficiency and convenience of loans in the virtual world.

However, as the fastest growing industry in the field of internet finance, in recent years, peer-to-peer online lending industry has also been faced with the status quo of continuously exposed credit risks, intensified industry competition and tightened regulation.

Since the establishment of Zopa in the UK in 2005, the network lending model represented by Zopa has been rapidly emerging in developed countries such as Europe and America, and then spread to the world soon after, forming four major operating models (Zopa model, Prosper model, Lending Club model and Kiva model). However, due to relatively complete construction of various investment and financing systems in foreign countries, online lending only exists as an operation mode, with small transaction scale, small audience group and limited role in the financial system. Therefore, it has not been valued by foreign individuals and institutions.

The development mode and operation mode of China's network lending are greatly different from those of foreign countries. The development scale and speed of peer-to-peer network lending are both growing rapidly. Therefore, this section mainly summarises the development process of China's peer-to-peer network lending. In 2006, the first lending website in China was founded, and the individual-to-individual online lending market has been booming since then. The number of participants has increased dramatically as the number of operators has multiplied, the scope of operations has been expanded, and the scale of funds has been expanded. The emergence and prosperity of the online lending model has expanded the investment channels of private capital, promoted the prosperity of private lending, and to some extent eased the difficulties of SMEs in financing. However, a series of events, such as the closure of "Ha Ha Loan", which had been officially operating for only one and a half years, and the suspected fraud of "Youyi Loan" at the end of 2012, have pushed China's online lending business to the forefront, making it controversial and bringing the development of peer-to-peer online lending to the bottom.

In 2013, known as the first year of China's internet finance, peer-to-peer online lending experienced explosive growth in 2013, with the number of platforms surging from more than 200 to more than 800, and the scale of loan transaction surged from more than 10 billion to more than 100 billion. The surge in the number of platforms and transaction volumes reflects the huge pent-up demand for investment and financing. In terms of transaction volume, the biggest transaction volume in 2013 was 7.7 billion yuan of Wenzhou Loan. In 2013, the total transaction amount exceeded 1 billion yuan, including Wenzhou Loan, Shengrong online, Jujinsuo, Zhongbao Investment, Renren loan, 808 credit, 365easy Loan, and Wanhui Investment and so on, a total of 12. Even the newly established lending platform has seen a rapid increase in the scale of loan transaction. Take Huanrong, a peer-to-peer online lending platform, as an example. The platform was launched on July 18, 2013.

Online lending platforms have also gained considerable operating income while meeting the investment and financing needs of both parties. According to the third party network lending platform ‘net house’s data of 2013, the platform operating income is the highest in the treasure to investment, business income reached 52.66 million yuan, the platform in the treasure of a turnover of more than 10 million investments, 808 credit, 365 easy Loan, ShengRong online and so on, a total of 13.

However, under the current conditions of the number of peer-to-peer online lending platforms and the scale of transaction volume, China's potential investment and financing needs still have a huge gap, which needs to be filled. In 2013, the total number of investors in peer-to-peer online lending was more than 200, 000.

3.2 Peer-to-peer current situation

By the end of 2017, the accumulated transaction volume of peer-to-peer online lending industry reached 6 trillion yuan, breaking the 6 trillion mark for the first time. According to the turnover trend of peer-to-peer lending industry in each month in 2017, the monthly turnover is stable at over 200 billion yuan, and the transaction scale of the industry will be stable in 2018. It is estimated that the total transaction volume of peer-to-peer lending is about 3 trillion yuan in the whole year of 2018.

In terms of the number of platforms, although the overall size of the industry is increasing, the number of platforms is gradually decreasing. By the end of 2017, the number of normal operating platforms in the peer-to-peer lending industry had decreased to less than 2,000, nearly 500 fewer than at the end of 2016. Judging from the number of normal operating platforms in each month of 2017, the number of peer-to-peer lending platforms is decreasing gradually. It is estimated that by the end of 2018, the number of online lending platforms will remain around 800. In the next year, benign exits such as suspension of business and transformation will remain the main exit mode of the platform. As of the end of June 2018, there were 7,503 peer-to-peer online lending platforms in China, a record high. Among them, 2,163 peer-to-peer lending platforms are operated normally. A total of 3,593 problem platforms such as active closure, cash withdrawal difficulties and lost contact ran away. In June alone, there were 71 new platforms, 3 more than the previous month, up 4.41%, and 21 more than the previous year, up 36.00%.

In the first half of 2018, the transaction volume of peer-to-peer online loans in China reached 1345.335 billion yuan, with the month-on-month and year-on-year declines of more than 30%, down 31.58% and 30.26% respectively. The average daily transaction volume was 7.433 billion yuan, and the growth rate was also significantly reduced, down 30.44% and 30.26%, respectively.

From the perspective of platform turnover, 39.51% of platform turnover is between 10 million and 100 million, and the number is about 1,047. It was followed by platforms whose turnover was between 100 million and 500 million, with about 682, accounting for 25.74%. The number of platforms whose turnover was less than 10 million yuan also accounted for more than 20 percent, reaching 536.

In terms of regional distribution, in the first half of 2018, the top three total transaction amount of peer-to-peer lending platforms in China were Guangdong province, Shanghai city and Beijing city, with the total transaction amount of the three provinces exceeding 920.632 billion yuan, exceeding 68% of the national total. Guangdong accounted for the largest share with a turnover of 314.338 billion yuan. In Guangdong province, Shenzhen city accounted for more than 80 percent of the transaction volume, with 19.54 percent in the country, ranking fourth.

From the development experience of the online lending industry, from 2007 to 2018, a variety of online lending business models have been explored and developed in practice. With the growth and decline of peer-to-peer lending platforms, a variety of experiences conducive to the development of peer-to-peer lending platforms are constantly summarised, and a variety of risks leading to the decline of peer-to-peer lending platforms are constantly exposed. For a long time to come, the number of peer-to-peer lending platforms will continue to decrease, the merger and reorganization of peer-to-peer lending platforms will further deepen, and the rate of return of peer-to-peer lending platforms will decline. The compliance of peer-to-peer lending industry will be further realised, which is undoubtedly good news for millions of peer-to-peer lending investors.

3.3 Comparative analysis of peer-to-peer platforms

The most important thing in the survival of peer-to-peer lending platform is that the default borrowing exceeds the profit space of the platform, while the credit risk assessment of peer-to-peer online lending is an important measure of the borrower's default. When the borrower defaults, most peer-to-peer online lending platforms, due to the lack of a complete collection mechanism, make debt collection work more formal. Limited by the number of employees and the cost, the platforms often choose to collect by phone or by text, which is inefficient and ineffective.

In peer-to-peer network lending industry, many borrowers are difficult to obtain financing from traditional financing channels, which reflects the limitations of traditional financing channels on the one hand, and on the other hand, the poor or difficult judgment of credit conditions of these financiers. For example, small and micro business owners, lack of standardised financial records and adequate collateral, are often rated as low credit rating among traditional financial institutions, and thus excluded from the loan object. Compared with large and medium-sized enterprises, the financing channels of small and micro enterprises and individuals are limited, so it is difficult to get other sources of funds to repay the loan in time when the expected repayment sources are in trouble. Peer-to-peer online lending platforms mainly provide financing services for small and micro businesses and individuals, which determines that lending activities are bound to face higher credit risks.

Peer-to-peer online lending provides financing services to borrowers through the model of crowd funding, and a loan is usually completed by several dozen co-investors. The investors come from all over the country, and most of them contribute a small amount. When the loan is in default, the dispersed and small investors bring great inconvenience to the rights protection activities. Firstly, investors are scattered all over the country, most of them are far away from the borrower, and it is inconvenient to safeguard rights. Secondly, most investors have a small amount of capital, and it is not economical to go to the location of the borrower to protect their rights. Thirdly, decentralised investors also have a great impact on the progress of case handling. Before handling the case, the judicial department spends a lot of time to investigate and collect evidence from investors from all over the country, which seriously affects the efficiency of case handling. For these reasons, many lenders have to abandon their own rights protection activities, making it impossible for the borrower to pay the price for his default and to generate incentives for the borrower to keep his promise.

The low default cost of borrowers in peer-to-peer lending industry is also an important contributor to borrowers' default. In peer-to-peer online lending industry, it is difficult for the borrower who default to receive collection requirements and litigation directly from the investor, and the collection activities of peer-to-peer online lending platforms are often limited to form, making it difficult for the borrower to fulfil repayment obligations under pressure after the default. As peer-to-peer online lending platforms are not financial institutions and cannot be connected with the credit investigation system of the central bank, the default information of borrowers in peer-to-peer online lending cannot be incorporated into the credit investigation system of the central bank, which cannot further deter the borrowers in default and reduce the enthusiasm of borrowers to perform their obligations. Due to the need to protect customer resources, peer-to-peer online lending platforms have no enthusiasm for information sharing of borrowers, and borrowers who have defaulted have turned to other lending platforms for further financing. All of these provide convenience for borrowers to default and reduce the risk of borrowers to default.

The author selected 10 problematic peer-to-peer lending platforms and 10 normal operating peer-to-peer lending platforms, and made a comparative analysis of the loan size and rate of return of the platforms, to study whether there is significant difference in the loan size and rate of return of the two types of platforms.

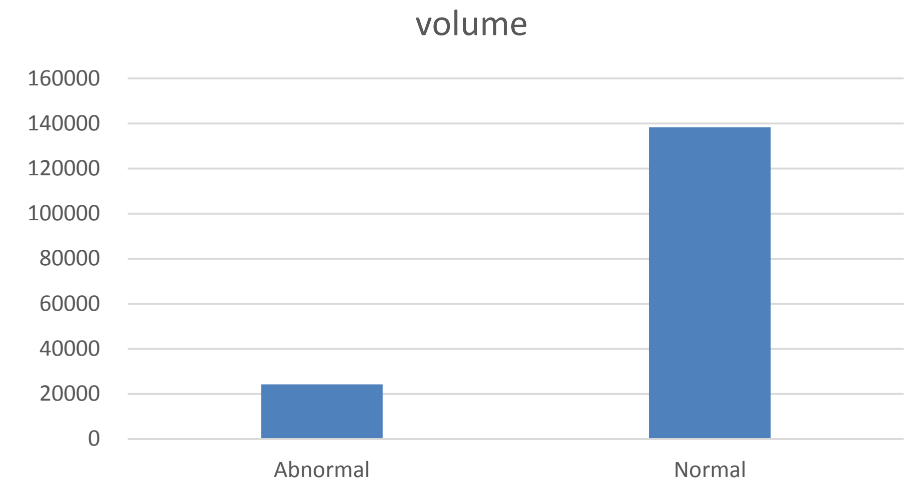

Figure 1 Comparative analysis of total borrowing

As shown in Figure 1, the total loan amount of the normal operation platforms is much higher than that of the operation abnormal platforms. It indicates that the peer-to-peer lending platforms can be effectively lower than the non-performing loan in a larger scale, improve the ability of the platform to withstand risks and survive better.

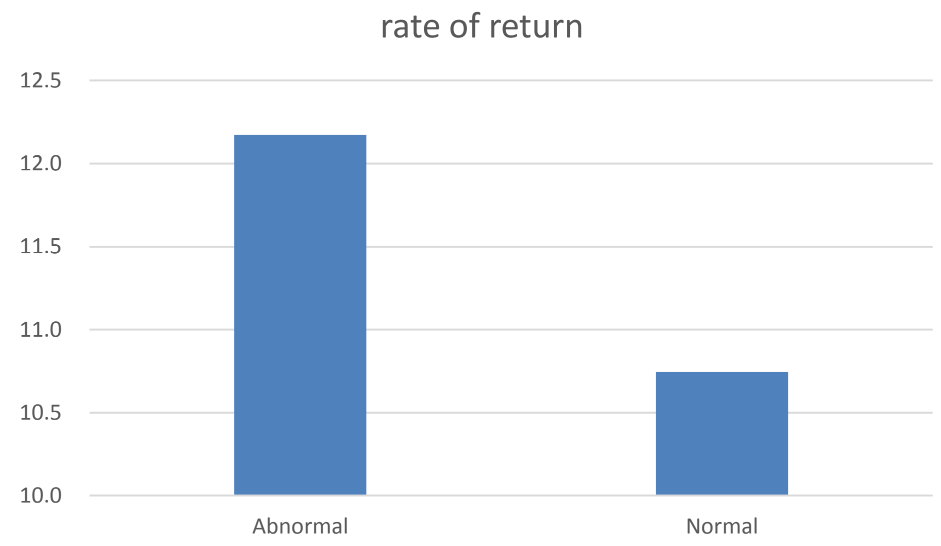

Figure 2 Comparative analysis of yields

As shown in figure 2, the rate of return of normal operation platforms is far lower than that of abnormal operation platforms, which indicates that many peer-to-peer lending platforms tend to pursue excessively high interests, thus ignoring the existence of credit risk. Higher yield and interest rate are inevitably associated with a higher risk which determines that lending activities are bound to face higher credit risk.

4. Methodology

4.1 Data source

Data will be collected from secondary sources including global alternative investment marketplace platforms, associations, the national bureau of statistics and some third parties. Most of the dataset contain a number of characteristics for individual platforms such as platform's turnover, default rate and late loans etc., we set platform's turnover as dependent variables in the later research results. Considering the data is collected for each months and for each platform, it allows running scale panel data regression with significant expected results. The data is collected from the platforms and as most of them are not public companies there may arise the problems with authenticity of data. However, the data also to be enriched by obtaining the data from other authentic databases such as the national bureau of statistics.

We choose 10 problematic peer-to-peer lending platforms and 10 normal operation of peer-to-peer lending platforms to study the influencing factors of peer-to-peer lending scale, and whether there was a significant difference in yield. Using these datasets or by combining several available datasets for both operational and closed platforms this study may get additional support by conducting survival analysis.

4.2 Selection of data indicators

As the transaction volume of peer-to-peer lending platforms is the leading indicator of the overall scale change of the industry and reflects the overall development of the industry, this paper selects the turnover of peer-to-peer lending platforms as the dependent variable.

For the choice of independent variables, we mainly consider the macro and micro effects. First of all, any economic subject should be affected by the economic environment, and peer-to-peer lending is no exception. Therefore, GDP is selected as the indicator to measure economic development. Secondly, because the real estate industry is a pillar industry of China, the development is rapid since 2007 to a high return drive more people to invest in real estate, and the two years of data show that real estate industry relative excess capacity, so find the part of investment, which is likely to flow into the emerging and the peer-to-peer lending industry of high income, so the real estate development comprehensive prosperity index uses to measure the current situation of the real estate industry. Thirdly, as an innovation of traditional finance, peer-to-peer network lending is mainly engaged in lending business. Therefore, it is affected by the deposit and loan of financial institutions and the loan of private lending companies. Therefore, domestic loans of financial institutions are selected, and the loan balance of individual deposits and small loan companies of financial institutions are taken as the corresponding measurement indexes. Finally, different from traditional finance, peer-to-peer lending is based on internet technologies, the influence factors of it in addition to the economic environment and the influence of the financial system internal factors, and to a large extent influenced by technology, in view of the technological progress is bad to quantify, but traders must through the internet to complete the transaction, therefore to adopt the internet broadband user as independent variables, measure of technology development. The variables and their definitions are shown in Table 2:

Table 2 Index interpretation table

Variables	Classification	Variable name	Code
Dependent variables	P2P scale	Platform turnover	P2P

Independent variables	Economic environmental factors	Gross domestic product	GDP
		Real estate development comprehensive prosperity index	PI
	Technical factors	Broadband Internet access users	IP
	supply and demand factors	Domestic loans	DL
		Personal savings	PS

The index data adopted in this paper are from global alternative investment marketplace platforms, associations and the national bureau of statistics and some third parties. Because peer-to-peer lending platform data release time is limited, so this article selected data from January 2014 to March 2019, part of the missing value is used for filling, because GDP is quarterly data, so the first thing to seasonal adjustment of it to make the sequence is more smooth, microfinance loan balance only quarterly data, so it is transformed into monthly data. As the original data is different and the value is large, taking the logarithm can not only make the data smooth, but also overcome the degree of heteroscedasticity and avoid the unnecessary influence. So we take the logarithmic transformation of all the original sequences.

4.3 Model description

Considering that the industry is at its very early stage, regression model was chosen accordingly, with decent level of flexibility. The model mainly aims to identify the determinants (mainly economic factors) of peer-to-peer lending platforms' volumes and quality. Review of existing literature indicated that both theoretical and empirical literature is not enough for building full methodological foundations of this study. Even the most recent studies have neither empirical modelling framework nor extensive cross-country analysis. The only known study (Dushnitsky et.al. 2016) is limited to considering the number of existing crowd funding platforms as dependent variable. The same study acknowledges this limitation and identifies economic performance of platforms as an area for future research. Therefore, this dissertation project will base its model framework from the closest available industry sector, namely venture capital and angel investments. Research studies in the area of venture capital investments have been developing during the last two decades. As such, these studies have the solid conceptual framework proven via robust empirical analysis. Prior studies on both crowd funding and peer-to-peer lending rely on theoretical framework derived from venture capital, too (eg. Mollick 2013, Iyer et.al. 2009, Lukkarinen et.al. 2016). In this regard, Black and Gilson (1998) provided one of the early theoretical models that connected country specific variables with the behaviour of venture capitalists. Later studies of Gompers and Lerner (2001), Felix et.al. (2009) and Cherif and Gazdar (2010) empirically tested further and improved the same model. Variables that were prevalent in these models such as GDP growth is further explained below with discussion of the variables.

Another model to be relied upon is the models relating entrepreneurship to economic development. Studies of Acs & Audtresch (1994), Armour & Cumming (2006) and Cumming et.al. (2014) stated that countries with higher economic growth tend to have more advanced entrepreneurship environment. Later papers on venture capital investments used the same proposition for building their model. Empirical model of this study also to be drawn from this concept and expect countries with higher economic indicators to have larger volumes of peer-to-peer loans.

The models of traditional finance may also be applicable for the case of alternative investments as indicated in Lukkarinen et.al. (2016). The most prevalent and applicable theories are financial accelerator (Bernanke & Gertler, 1989 and Kiyotaki & Moore, 1997) and life cycle consumption models (Lawrence, 1995) that relate business cycles with financial intermediation. These models relate both overall lending volume and probability of default to economic activity. These models have been empirically tested in both US (Keeton & Morris, 1987 and Gambera, 2000) and European markets (Klein, 2013 and Skarica, 2014).

On the other hand, the role of inflation rate has also been prevalent in financial literature. High inflation periods, for example, are considered as the periods with the distortion in lending, borrowing and saving decisions. Periods with high inflation are characterised by ambiguous returns on firm-level investment and where companies decrease accumulation of capital. As such, it might bring reduced level of borrowings from both financial markets and institutions (Apergis & Eleftheriou, 2002 and Wongbangpo and Sharma, 2002).

The last aspect of the conceptual framework for this project to be drawn upon the theory of asymmetric information. Most of the research papers on peer-to-peer lending referred to this theory as the backbone of interest rate and funding success determination. The theory that was theoretically conceptualised by Akerlof (1970) refers to signalling as the mitigation mechanism for asymmetric information. In alternative financing markets such as peer-to-peer lending signalling is significantly important, as each of the platforms brings together complete strangers into financing activity. From the investors' perspective, signalling tools has been widely examined in terms of determination of interest rates and funding success for borrowers in peer-to-peer lending platforms (Lin & Viswanathan 2016, Wei & Lin 2016 and Freedman & Jin 2017). However, no study explored platform success from the perspective of agency theory. If the platform success is considered agency theory takes the central stage as most of the traditional financing practices operate under signalling mechanisms such as regulation, credit rating, public financial reporting, etc. As such, peer-to-peer lending platforms offering more transparency by being publicly listed or regulated could have better performance.

Asymmetric information also creates ‘moral hazard’ problem where agents are to undertake activities that are not at the best interest of principal. In the case of peer-to-peer lending, agents (lending platforms) may increase riskiness of their loan portfolio if faced with the poor quality. Investors (principal) being unaware of these hazardous activities may suffer from poor investment decision (‘adverse selection’). This proposition has been largely investigated in traditional financing services and indicated that banks tend to increase their non-performing loans when faced with low credit quality (Keeton & Morris, 1987, Messai & Jouini, 2013). This study, relying on this theory will also consider default loans and late loan payments as dependent variable. Credit ratings of borrowers and economic indicators are used as independent variables.

Based on the number of theoretical models the rough model for the regression may be presented as in equation [1]. The rationale behind each of the variable under consideration is elaborated accordingly. Proposed model mainly aims to identify the determinants of peer-to-peer lending platforms’ volumes. STATA software is used for analysis. Generally, rough model for the regression may be presented as in equation (1).

$$lnP2P_t = \alpha + \beta_1 lnGDP_t + \beta_1 lnPI_t + \beta_1 lnIP_t + \beta_1 lnDL_t + \beta_1 lnPS_t + \varepsilon_t \qquad (1)$$

Where, α is the intercept term, β_i is the correlation regression coefficient, represents the relative influence degree of independent variable on dependent variable, and ε_t is the random error term.

5. Empirical analysis

5.1 Descriptive statistics

Firstly, scatter plot analysis is carried out for each independent variable and dependent variable.

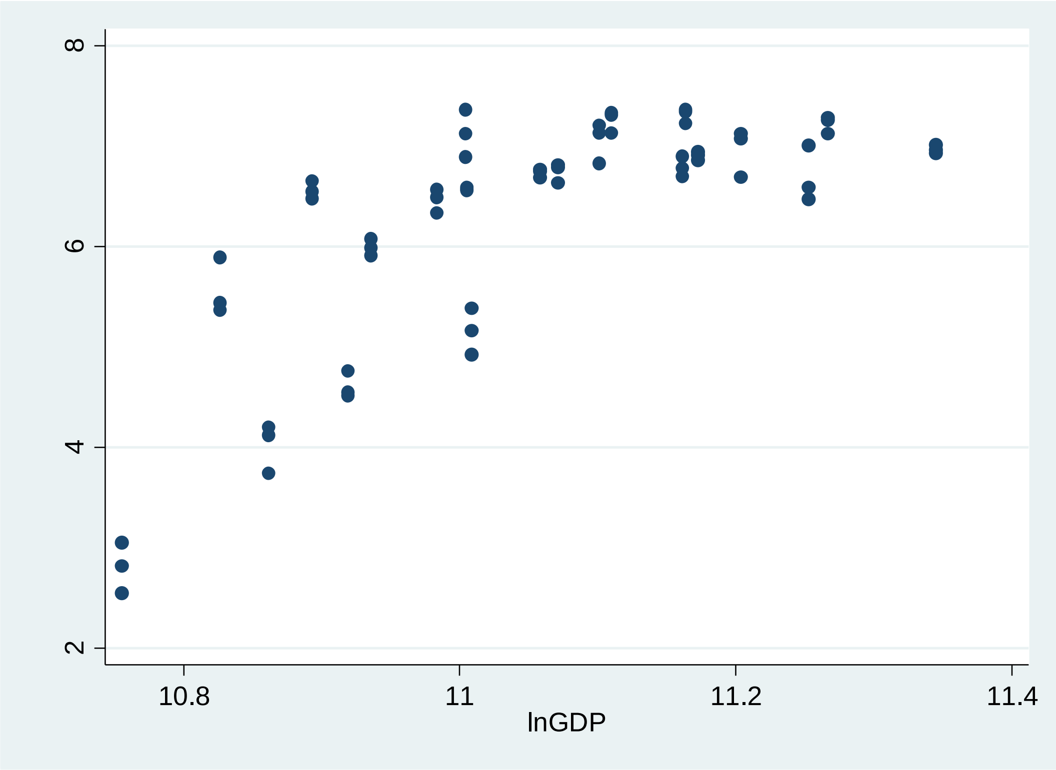

Figure 3 Scatter plot of lnP2P and lnGDP

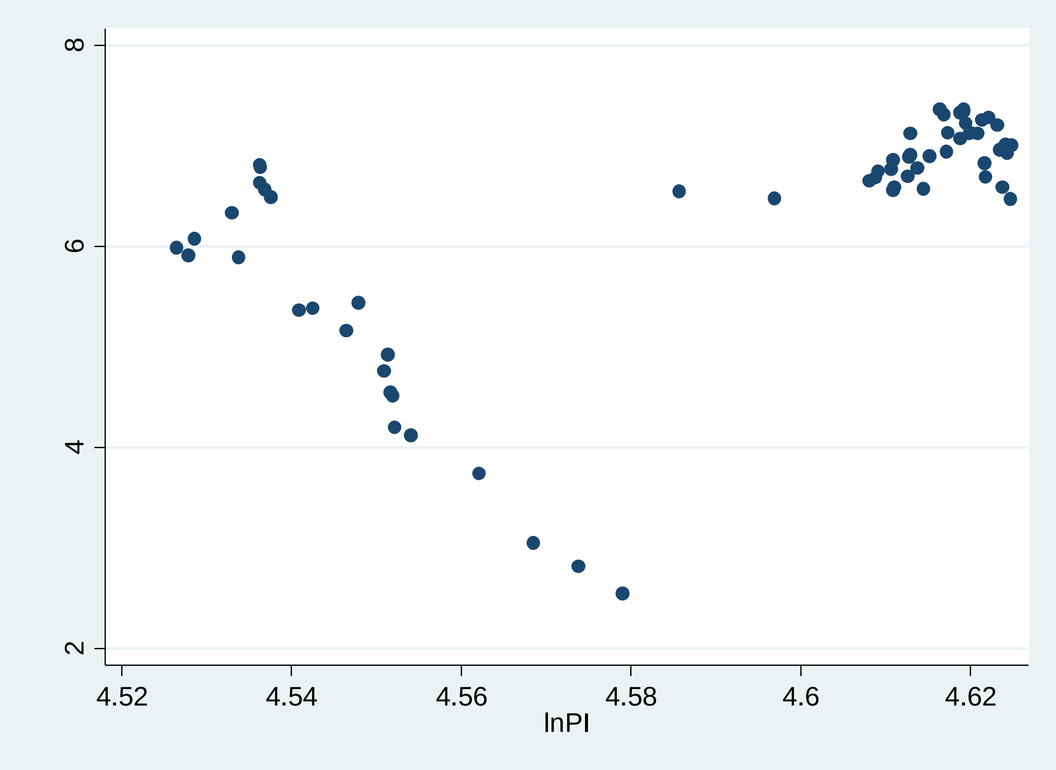

Figure 4 Scatter plot of lnP2P and lnPI

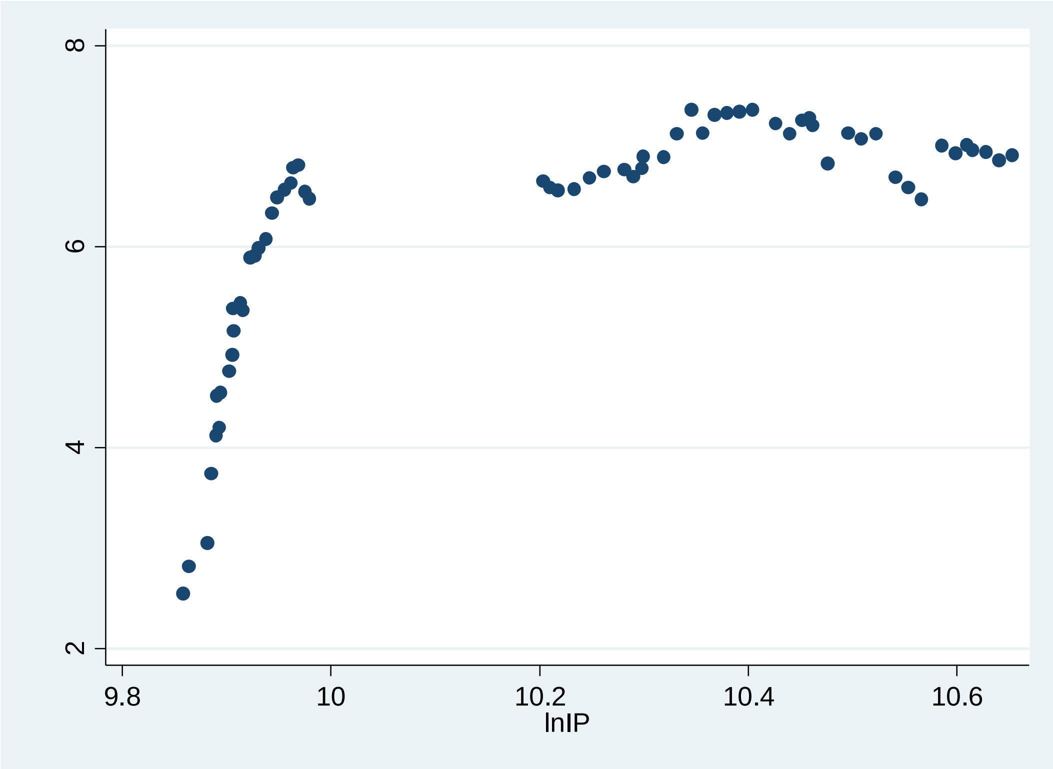

Figure 5 Scatter plot of lnP2P and lnIP

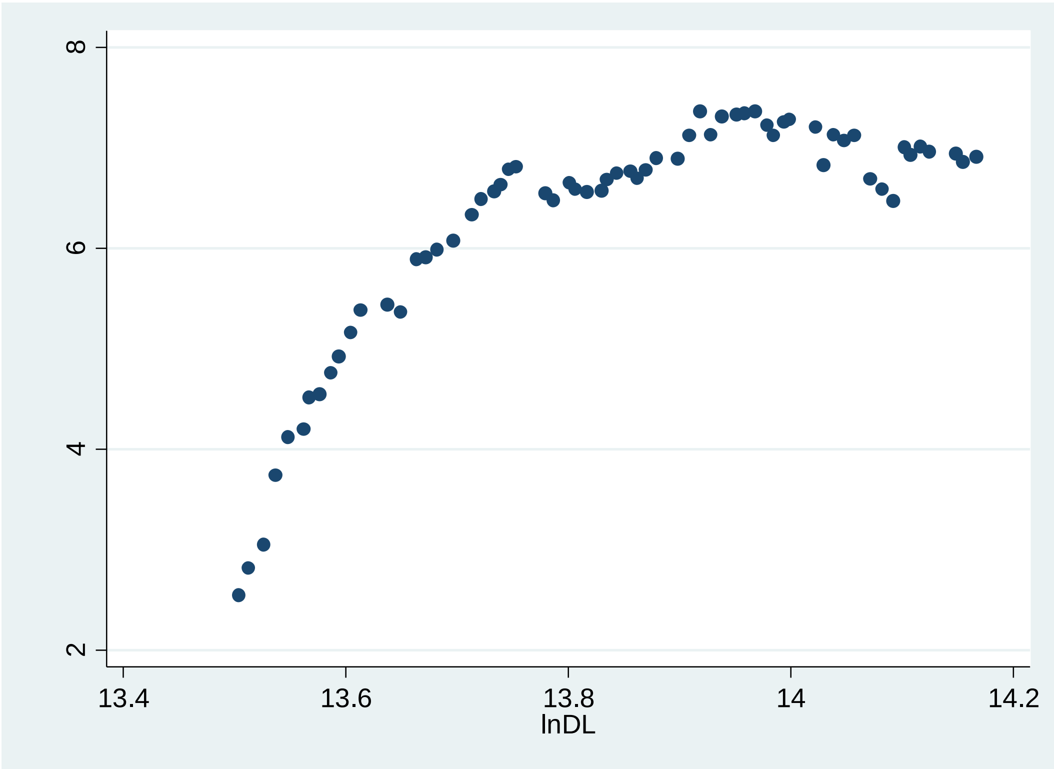

Figure 6 Scatter plot of lnP2P and lnDL

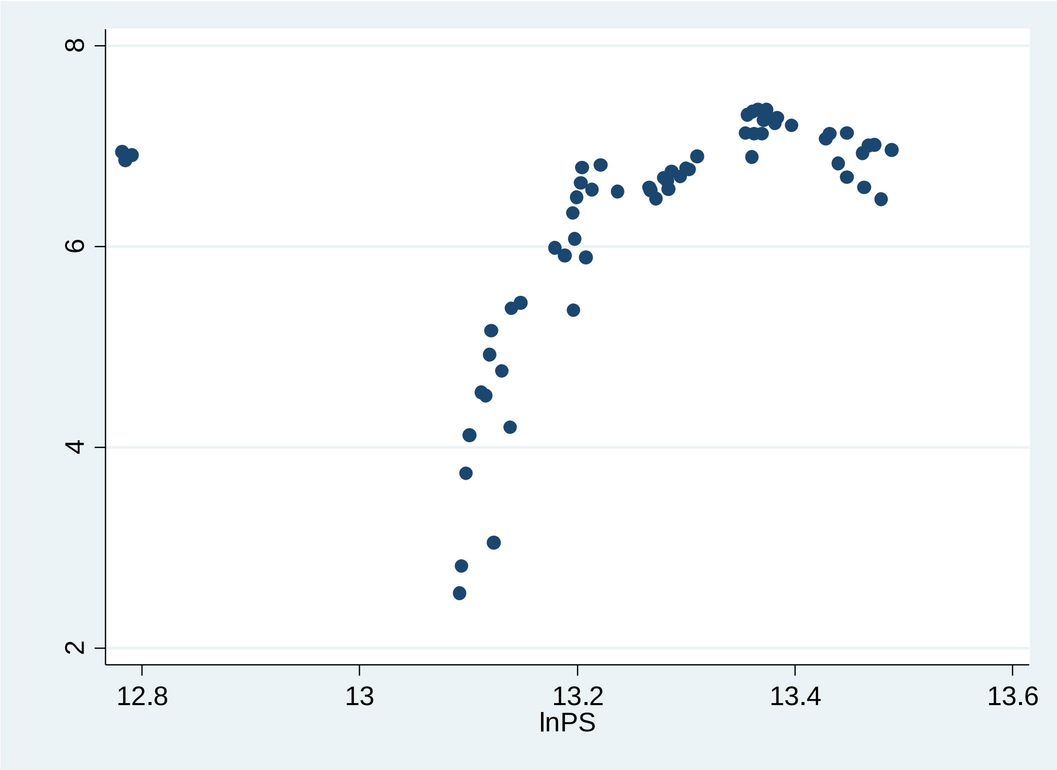

Figure 7 Scatter plot of lnP2P and lnPS

Before the discussion about the relationship between data, firstly, we need to determine whether the correlation between variables is linear or non-linear, so as to determine the linear model and the nonlinear model. For the above independent variables and dependent variables, we establish the scatter diagram. From Figure 3 to Figure 7, it can be seen that the overall linear relationship between lnP2P and the respective variables is presented, so a linear regression model can be established.

5.2 Regression analysis

Table 3 Regression model

lnP2P	Coef.	Std.Err.	t	P>|t|	95% Conf.	Interval
lnGDP	1.456	1.068	1.360	0.178	-0.684	3.595
lnPI	9.103	5.703	1.600	0.116	-2.318	20.52
lnIP	-9.088	1.862	-4.880	0.000	-12.82	-5.360

lnDL	14.57	1.930	7.550	0.000	10.71	18.44
lnPS	0.971	0.565	1.720	0.091	-0.160	2.103
cons	-173.3	28.19	-6.150	0.000	-229.8	-116.9
Source	SS	df	MS	Number of obs	=	63
Model	69.61	5	13.92	Prob>F	=	0.000
Residual	16.83	57	0.295	R-squared	=	0.805
Total	86.44	62	1.394	Adj-R2	=	0.788

Table 3 analyses the regression results of the multivariate linear model, in which R squared measures the goodness of fit of the model. The larger R squared is, the better the model fitting effect is. The R squared in the result is 0.805, and the model fitting effect is good, but the P value of lnGDP, lnPI and lnPS in the statistical result is relatively large, so the equation is continued to be tested to find out the reason. Since the model estimation is based on the classical hypothesis, the error term needs to be tested by autocorrelation and heteroscedasticity.

5.3 Autocorrelation and heteroscedasticity test

Table 4 Breusch-Godfrey LM test for autocorrelation

F-statistic	df	Prob > chi2
0.835	1	0.432

Table 5 Whitetst

F-statistic	df	P-value
0.696	9	0.721

The p value of LM test statistic in Table 4 is 0.432 significantly greater than 0.05, so the original hypothesis cannot be rejected, that is, there is no sequence autocorrelation. The p-value of the heteroscedasticity test statistics in Table 5 is 0.721, which is significantly greater than 0.05. Therefore, the original hypothesis cannot be rejected, that is, there is no heteroscedasticity. However, it can be seen from Table 3 that the R squared of the model is larger, which is 0.805, indicating that the overall fitting effect of the model is good, which can be seen intuitively from Table 3. However, the t-statistic value of the regression coefficient estimator is generally low.

5.4 Multicollinearity test

The above analysis indicates that there may be multicollinearity, resulting in the insignificant coefficients of the model variables. Therefore, the correlation analysis is carried out. The correlation coefficients between independent variables are given in Table 6.

Table 6 Correlation analysis

	lnP2P	lnGDP	lnPI	lnIP	lnDL	lnPS
lnP2P	1					
lnGDP	0.739	1				
lnPI	0.566	0.673	1			
lnIP	0.716	0.863	0.886	1		
lnDL	0.808	0.876	0.812	0.975	1	
lnPS	0.501	0.499	0.512	0.443	0.442	1

As can be seen from Table 6, the correlation coefficient between the respective variables is very high, with a minimum of 0.442. Therefore, there is a highly linear correlation between the variables. Next, VIF test is performed on the model.

Table 7 VIF test

Variable	VIF	1/VIF
lnIP	53.83	0.0186
lnDL	29.65	0.0337
lnPI	8.780	0.114
lnGDP	5.600	0.179
lnPS	1.710	0.584
Mean	VIF	19.91

From the VIF test in Table 7, we can see that the VIF test values of the two variables of lnIP and lnDL are all greater than the critical value 10, indicating that multicollinearity does exist in the model, so it is necessary to deal with multicollinearity.

5.5 Stepwise regression analysis

Common methods to deal with multicollinearity include merging variables, removing secondary variables and stepwise regression. The stepwise regression method is adopted to establish the model, and table 8 reflects the estimation results of the model.

Table 8 Stepwise regression analysis

Source	SS	df	MS	Number of obs	=	63
Model	68.69	3	22.90	Prob>F	=	0.000
Residual	17.75	59	0.301	R-squared	=	0.795
Total	86.44	62	1.394	Adj R-squared	=	0.784
F(3, 59)	=	76.09		Root MSE	=	0.548
lnP2P	Coef.	Std.Err.	t	P>|t|	95% Conf.	Interval
lnDL	-13.50	1.625	-8.300	0	-16.75	-10.24
lnIP	6.703	1.164	5.760	0	9.033	4.374

lnGDP	1.493	0.487	3.070	0.00300	0.519	2.467
cons	-131.8	12.12	-10.88	0	-156.1	-107.6

The estimation results show that the R squared of the final model is larger 0.795, and the adjusted R squared is 0.784, indicating that the independent variable has a higher fitting degree to the dependent variable. The statistics of F is 76.09, and the corresponding P value is close to 0, indicating that the overall significance of the model is significant, and the explanatory ability of all independent variables is relatively high. In addition, the coefficients of the independent variables all pass the significance test, so the model estimation effect is better.

5.6 Results analysis

The coefficient in front of the independent variable represents the elasticity of platform transaction value to the respective variable. LnGDP's former coefficient is 1.493, which indicates that the platform trading and economic present positive correlation, in the case of other variables constant, GDP grew one percent, each will promote peer-to-peer lending industry average turnover growth of 1.493%, shows that the platform has strong role in promoting economic, its mechanism of action for when the economy is on the line, people's disposable income increase, to stimulate consumption, and expand consumption driven manufacturing and investment is the source of production to expand, thus stimulating people's investments, and improve the turnover of platform;

The coefficient before the lnIP is 6.703. Platform trading and technical progress present positive correlation, in the case of other variables constant, whenever the internet broadband user increases by one percent, the volumes will promote peer-to-peer lending industry average growth of 6.703%, that pull function on the platform is very large, its reason is closely related to the inherent characteristics of peer-to-peer lending, because peer-to-peer platform is an online platform, business calculation combined with pure online or offline mode, traders must realise the investment and financing through the network, so the internet broadband user increases, the internet increases, thus increase customer group, trading opportunities increase, and finally the platform transaction volume is greatly increased;

Before lnDL's coefficient is -13.50, and suggests that platform transactions and negative correlation between financial institutions within the territory of loans, in the case of other variables constant, financial institutions within the territory of each loan growth one percent, will make peer-to-peer lending industry average turnover fell 13.50%, credit policy of financial institutions in the platform has very big effect, when the economic downturn, the financial institutions to lend, credit decrease, performance for domestic loans decreased, then financing difficulties will become the factors restricting the development of part of the economic subject, so they will seek other financing channels, and peer-to-peer lending platforms are quick in financing due to the high rate, it will attract some fund raisers to finance on the platform, thus increasing the transaction volume of the platform.

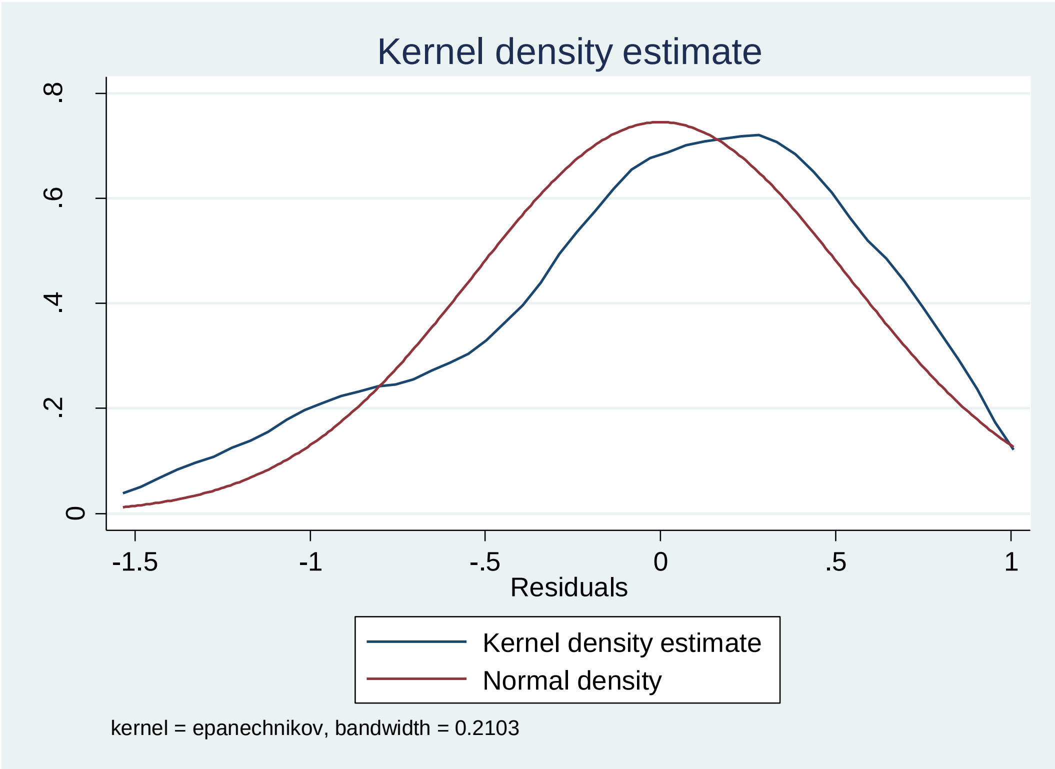

Figure 9 Fitting situation

Figure 9 shows the fitting effect of the model. It can be seen that the overall fitting effect of the model is good. Therefore, the trading volume of the platform can be predicted based on the data of independent variables.

6. Research Conclusions

This paper applies the method of combining theoretical analysis and empirical analysis, from the research literature of internet financial, detailed understanding of the development of peer-to-peer lending platforms and macro and micro factors influencing them, then analysed the development of peer-to-peer lending in China and other countries and the current situation of the development of peer-to-peer lending at the present stage in China and choose 10 problematic peer-to-peer lending platforms and 10 normal operation of peer-to-peer lending platforms, this paper compares and analyses the two kinds of platform loan scale and whether there was a significant difference in yield. Later, in order to further study the influencing factors of peer-to-peer network lending in China, the author selected the relevant monthly data from January 2014 to August 2018, and established a regression model with econometric methods, and conducted in-depth research and calculation on the influence of different macro factors on peer-to-peer lending development.

The conclusions of this paper mainly include the following aspects:

Firstly, the scale of peer-to-peer online lending in China is controllable and develops rapidly, and the risk has not been expanded. Peer-to-peer network in China, the scale of the borrowing compared with the traditional financial product number and size, also has the very big disparity, and because recently the Chinese government has started to notice the peer-to-peer lending risks, and adopted a series of measures, and has played a certain limit to the infinite amplification for peer-to-peer network borrowing. We can think that Chinese government is able to control the scope of peer-to-peer lending, but from the point of increment, the development of peer-to-peer lending increases very quickly in China, and the emergence of a variety of innovative business brought certain difficulty to regulation, because there are many shareholders with state-owned enterprise background in peer-to-peer lending platforms in China, which plays a certain role in stabilising the internet market and optimising peer-to-peer online lending products.

Secondly, the total loan amount of peer-to-peer lending platforms in normal operation is much higher than that of operational abnormal platforms, indicating that peer-to-peer lending platforms can avoid non-performing loans effectively after a relatively large scale, improve the platform's ability to resist risks and better survive. On the other hand, the rate of return of normal operating platforms is far lower than that of abnormal operating platforms, which indicates that many peer-to-peer lending platforms tend to pursue excessively high rate of return, thus ignoring the existence of credit risk and determining that lending activities are bound to face higher credit risk.

Thirdly, through the analysis of the influencing factors of peer-to-peer total loans, we understand that economic development plays a strong role in promoting the platform, technological progress increases the accessibility of customer groups, opportunities for transactions increase, and finally the transaction volume of the platform is greatly improved. And loans in financial institutions, personal savings and real estate development investment have the opposite effect for the survival of peer-to-peer lending platforms. when the economic downturn, the financial institutions to lend, credit decrease, the real estate industry overcapacity, part of the investment goes into peer-to-peer lending platforms, will attract part of the issuer in financing platforms, and improve the trading platforms.

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