Risk studies on peer-to-peer lending in China

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Declaration for PhD thesis

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Abstract

In November 2020, China's P2P online lending platform completed a complete liquidation. P2P online lending platforms emerged in China in 2010. From rise to prosperity, to regulation, to the final liquidation of the industry, this short process has meant that investors and the industry have paid a painful price. Therefore, this paper aims to study the risks and influencing factors of online lending industry platforms, consider the crux of the lack of past development, and provide references for future Internet financial innovation and risk management in innovation.

This paper studies the behaviour characteristics of P2P platforms and the default risk of platform loans. Starting from the development status of P2P platforms, this paper systematically studies the introduction of P2P platforms, the development of P2P platforms and the causes of P2P risk research. Then, based on the characteristics of China's P2P lending behaviour and the risk assessment of China's P2P lending, a progressive research method is adopted. A clear theoretical mechanism is established to analyse the macro, meso and micro risks of P2P platforms.

The first topic is mainly studied from the perspective of lending platforms. Considering the risk of lending platforms and the factors affecting the loan volume ofthe platform, it is concluded that the loan volume of the platform itself is affected by lending sentiment, herd effect and speculation. In the second topic, we selected three representative companies of Renrendai, PPDai and Yirendai, and obtained the impact of four characteristics, namely borrower characteristics, borrower credit characteristics, borrower working characteristics and borrower asset characteristics, on the loan default rate. The third topic is mainly studied from the perspective of P2P online lending platform problems, and it is concluded that registered capital, whether it is a private background, repayment guarantee, creditor's rights transfer, regional competition, platform survival time, or access bank deposit has a significant impact on P2P online lending problem platforms.

Key words: P2P platform, network loan impact, platform risk

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Chapter 1: Introduction

1.1 Motivation

P2P online lending platform is a new financial platform created by the government under the continuous introduction of policies to encourage and guide, in order to help small and medium-sized enterprises to solve the financing problems in the development, expand financing channels, and reduce financing costs. It is a kind of person-to-person, point-to-point credit. P2P network lending uses modern network information technology to carry out lending business on the Internet, and is a form of private lending. The entire lending process is carried out online. P2P online lending platforms do not participate in the transactions between lenders and borrowers, but only act as information intermediaries and charge certain business management fees or information service fees to both sides of the transaction, similar to direct financing, which is the biggest difference from traditional financial institutions such as banks. Due to its low investment threshold and high yield, it is quickly welcomed by investors. However, due to the imperfect system and immature development of P2P online lending industry in China, some P2P online lending platforms have difficulties in withdrawing cash, closing down, and running away due to problems such as illegal operation or weak risk control ability. Since 2017, China has successively introduced relevant policies to regulate the development of the P2P online lending industry, but due to the lack of supervision in the early stage, the P2P online lending platform running away and liquidation events are still common.

By the end of 2020, all P2P platforms in China had disappeared. The once-brilliant P2P platforms no longer existed, signalling the end of an era. P2P went from once being brilliant to the present industry being entirely wiped out, which incurred serious risks.

In 2007, PPDai was officially established as the first P2P online lending platform in China, firing the first shot in China's P2P online lending industry. However, the industry did not continue the trend of rapid development, nor did it receive large amounts of capital. It was not until the gradual increase in the number of platforms four years later that the P2P online lending industry ushered in the era of rapid development. In the following three years, due to the frantic expansion of the platform and the absence of regulation, the industry ushered in a wild growth period. According to the data of third-party platforms, the number of online lending platforms soared during the wild growth period. In 2013, the number of online lending platforms was around 800, and in 2015, it skyrocketed to 3,437. The year 2017 can be said to be the heyday of P2P. There were 5,970 P2P platforms in China that year, and a number of P2P platforms successfully went public in the US. By the end of 2020, P2P finally retired.

In the wild growth period, the increase in the number of platforms was accompanied by the intensification of industry risks. When the risks have accumulated to a certain extent, the industry will enter the risk outbreak period. The gradual explosion of platforms has attracted the attention of regulators. On the one hand, relevant policies should be introduced to guide the benign exit of poorly operated platforms, so as to maximize the interests of the regulatory authorities, platforms and lenders, so that a large number of non-compliant platforms can minimize the negative social impact when they are liquidated and withdrawn. On the other hand, the filing pace of the compliance platform was accelerated.In the second half of 2019, the pilot registration and filing of online loan platforms was carried out in some developed regions, and the experience was extended to the whole platform to ensure the healthy and orderly development of the platform after the filing.On March 15, 2022, the China Banking and Insurance Regulatory Commission announced that P2P illegal online lending platforms must be completely closed down that year.

According to the data disclosed by Zero One think tank, due to the introduction of policies such as tightening the supervision of P2P platforms and guiding the benign exit of platforms, problem platforms have shown explosive growth: as of the end of 2019, there are 6,056 platforms with problems due to transformation, exit, registration and other reasons, while only more than 300 platforms remain in normal operation, and the number of normal operating platforms is lower than the level in 2013.According to incomplete statistics, in 2019, there were more than 700 platforms experiencing a crisis in their business process. Among these platforms, about one quarter were forced to shut down due to poor management, which was the first reason. In second place was "winding-up" at about 17 per cent. This was followed by "benign exits" at about 10 per cent.

With the super-strong tightening of P2P platform supervision, a large number of difficult service platforms went bankrupt, some service platforms had benign exit, and some P2P service platforms entered the road of transformation. On the premise of establishing "will be back, should be closed to the full", the "Suggestions on classification and risk prevention and control of online lending institutions" also points out three directions for the transformation and development of online lending: Internet small loans, with financial companies or lending institutions. This shows that the pace of innovation of Internet finance will not stop with the liquidation of the P2P industry. Therefore, this thesis aims to study the characteristics of P2P platforms, and the influencing factors of borrowing and risk research, in order to establish the crux of non-benign development in the past, and provide a reference for the future innovation of Internet finance and risk management in innovation.

1.2 Research Objective and questions

Given that a large number of P2P platforms in China have been withdrawn or transformed at this stage, the purpose of this paper is to study the risk influencing factors of P2P platforms in China from three perspectives: the influencing factors of loan amounts of P2P platforms, the influencing factors of default loans from the perspective of borrowers and the influencing factors of withdrawal of P2P problem platforms, in order to provide new insights from our results and analysis. It will play a valuable reference role for the new innovation model of P2P platforms in the future. First of all, this paper uses innovative and advanced research methods to link the two risk links of P2P platform lending risk and P2P borrower risk, and carries out a strict robustness test on the research results. Regarding the risk of lending platforms, the factors affecting the loan amounts of the platforms are considered, and the loan amounts of the lending platforms are studied in detail. Whether the loan amount of the lending platform is affected by lending sentiment, herding and speculation, this paper is to reveal the influencing factors of P2P platform risk by studying the influence of the above three behaviours. Then, from the perspective of borrowers, this paper analyses the impact of borrower's characteristics, borrower's credit characteristics, borrower's work characteristics and borrower's asset characteristics on the loan default rate, their credit history, their work situation and their assets on the loan default rate. Further, based on the historical data of P2P platforms, the borrower credit risk assessment model is established to study which P2P platforms have strong risk control ability, to establish the common characteristics of P2P platforms with strong risk control ability, and then to determine if the acquisition and assessment of a borrower's background information is the best risk control means for online lending platforms. It is hoped that the risk assessment model of Renrendai can provide a reference for the transformation of other P2P platforms. Finally, with regard to P2P lending platforms, this paper analyses the relevant factors that affect the withdrawal of the problem platforms, and determines the influence of each factor on the withdrawal of P2P online lending platforms.

1.3 Summary of findings

In Chapter 2, we give an overview of China's P2P online lending platforms, and discuss the main reasons for the emergence of China's P2P online lending platforms, including the support of government policies, the development of China's network technology and the lack of traditional financial institutions to serve the real economy. This thesisconsiders the development stages of P2P platform, i.e. the bud stage, initial development stage, rapid expansion period, outbreak period and policy adjustment period. This thesisconsiders the supervision and regulation of P2P network lending platform, andconsiders six kinds of classification standards of P2P network lending risk.

In Chapter 3, the loan risk is mainly studied from the perspective of lending platforms. With regard to the risk of lending platforms, the monthly information of 918 P2P platforms from 2015 to 2019 is selected, considering the factors that influence the amount of loans on the platforms, and an in-depth study is made on whether the amount of loans on lending platforms is affected by lending sentiment, herding effect and speculative behaviour. Specifically, P2P lenders reacted positively to the lending sentiment (good news) in the P2P industry. We interpret this result as P2P lenders showing stronger lending sentiment in the wake of more positive news about P2P. It is worth noting that this emotional effect is also likely to be felt by other participants in the P2P lending market, including investors and borrowers. On the other hand, the influence of herd effect on P2P is also significant and effective. Specifically, when the total lending volume of other P2P platforms increases, P2P platforms will have a follow-on effect and expand their own lending scale. This result suggests that herd behaviour is an important feature of P2P lending in China. An analysis of speculation finds that rising commercial property prices positively explain the amount of P2P lending (speculation). This suggests that P2P lending in China is likely to be driven by a bubble in the real estate market, as formal financing channels in China are restricted from investing in the real estate market, so some investments in the real estate sector have to be financed through shadow banking activities, which is best embodied by P2P online lending in the Internet sector.

In Chapter 4, based on the systematic study of borrower characteristics and risk control literature, the background information of 30,000 borrowers from the three P2P lending platforms of Renrendai, PpDai and Yirendai in the past five years is collected, and the Logit model is established with large samples for analysis. By analysing the impact of the borrower's characteristics, their credit history, their work situation and their assets on the loan default rate, the study found that under the background of increasingly strict supervision, gender, age, education, marital status, credit score, credit limit, number of offences, income, working hours, real estate information and automobile information have a significant impact on loan default, while borrower mortgage information and automobile loan information have no significant impact on loan default. Among them, the older the borrower, the more educated they are, the more stable their marital status, the higher their credit score, the higher their credit limit, the higher their income, the longer their working hours, the less likely they will default. The borrower that can produce property and vehicle information is also less likely to default. However, the borrower with more past offences is more likely to default. In addition, in the third sub-topic, we assess the risk of borrowers through the historical data of P2P platforms, and establish credit risk assessment institutions based on the characteristics of borrowers on P2P platforms. Factor analysis was carried out on the above 11 borrower characteristic indicators, and the risk control level of the three P2P platforms of Renrendai, PpDai and Yirendai was evaluated. It is found that Renrendai has strong risk control ability. Through the actual investigation, it is found that the information disclosure of Renrendai is relatively transparent. It will publish quarterly operating data to anticipate and avoid risks. The project funds are deposited by China Minsheng Bank. Especially for P2P loans, borrowers will receive about 4 times as many basic information inquiries, about 5 times as many public information screenings, 8 times as many telephone checks, 35 as many scorecard data entries, a 100% information association check, and more than 30% of quality inspection coverage to ensure the safety of loan funds. This further proves that the acquisition and evaluation of borrower background information is the best risk control method for online lending platforms. It is also hoped that the risk evaluation model of Renrendai in this thesis can provide a reference for the transformation of other P2P platforms.

In Chapter 5, risk platforms are studied, 521 specific problem platform data are selected, a logit model system is used to study the main characteristics of problem platforms and the main factors affecting the failure of problem platform, and various outcomes of P2P online lending platforms are divided into general exit platforms, serious problem platforms, major problem platforms and big problem platforms. Then, the econometrics method of the multiple Logit model is used to study the various influencing factors of each category. The main conclusions are as follows: first, the registered capital is in all the problem platforms; the platform background is in the platform of serious and large problems; Factors such as the registered capital of the platform with major problems such as ICP operating license and bank deposits cannot represent the background strength level of the platform, and relevant information does not play its due role.Second, in terms of risk control, certain repayment guarantees (third-party guarantee, real estate and vehicle mortgage, risk reserve fund, etc.) is conducive to the P2P online lending platform to control the risk of high bad debts, improve the credit degree, truly enhance the risk control strength of the platform, and help reduce the occurrence of problem platforms. Third, the transfer of a creditor's rights is conducive to the turnover of investors' lending funds, which increases the platform's requirements for liquidity, but also improves the platform's control of risks from the side and reduces the proportion of platform problems. Fourth, the response of serious problem platforms and major problem platforms to regional competition is not significant, but the response of major problem platform to regional competition is significant. Fifth, the earlier the platform goes online, the longer the survival time, the richer the business experience, and the less likely it is to have problems exiting the platform. Sixth, the access of bank deposits can effectively reduce the occurrence of serious problems and major problems, but it cannot reduce the occurrence of irregularities and illegal platforms.

In Chapter 6, we summarise our findings and discuss the implications and limitations of our findings.

1.4 Contributions

As an innovative financial model, online lending mainly provides diversified financing services for small and medium-sized enterprises and individuals. However, China's traditional financial institutions have not solved the problem of financing difficulties and high financing costs for small and medium-sized enterprises, and the lack of effective supervision of private lending has led to the accumulation of risks. As an innovative financial model, the emergence of P2P online lending puts forward a way to fundamentally solve the financing difficulties of small and medium-sized enterprises. Transactions on Internet platforms will also effectively curb the phenomenon of illegal high-interest loans and help the government better regulate interest rates.

From the analysis of the behavioral characteristics of P2P lending, this paper concludes that P2P lending in China is affected by lending sentiment, herding effect and speculative behavior of P2P platforms, indicating that herding behavior is an important feature of P2P lending in China, public opinion has a significant impact on the development of P2P platforms, and P2P investors' investment behavior is a phenomenon of bandwagon investment. It is consistent with the research conclusions of Herzenstein(2010),Matthew (2007) and Shen(2010), and on this basis, it is further concluded that investors are more likely to suffer from adverse selection and moral hazard in P2P platforms without fund custody mechanism. At the theoretical level, on the basis of normative analysis, this paper strives to provide a theoretical research direction for the academic community to study online lending, especially the P2P risk impact theory, lending sentiment, herding behavior and speculation.

As one of the important carriers of financial innovation, the study of Internet financial innovation theory has become a research hotspot for scholars around the world after the global financial crisis. From the perspective of influencing factors of P2P loan default, this paper finds that 11 borrower characteristic information variables, such as gender, age, education level, marital status, credit score, credit limit, overdue times, income, working hours, real estate information and automobile information, have a significant impact on loan default. This is consistent with the conclusions of Xuchen(2017),Powell(1997), Greiner(2009),Emekte(2014),Magee (2011) and other studies. However, borrowers' mortgage and auto loan information have no significant impact on loan default. This is related to the unique emotions of Chinese people towards cars and houses. On the one hand, houses and cars may represent that borrowers have certain economic strength and are not prone to default; But on the other hand, it may also be caused by the high pressure of repayment of borrowers, which is different from the research conclusion of Li(2016). On this basis, this paper further uses factor analysis to analyze the risk level of each lending platform, and evaluates the default risk level of the three lending platforms, which is the innovation of this paper. This study also has practical guiding significance for the healthy development of P2P.

Due to the lack of social awareness and distrust of online lending companies, the lack of reliability of online lending platforms and the lack of effective legal supervision, it is easy to engage in illegal fundraising, malicious loan fraud, dishonesty and other activities, which seriously affects the image of the entire online lending industry, and this behavior hinders the healthy development of the industry. From the analysis of P2P problem platforms, this paper concludes that platform background, repayment guarantee, creditor's rights transfer, regional competition, platform survival time, ICP operating license, bank deposits, whether there is a regulatory background and other factors have a significant impact on the problem platform. Consistent with several rounds of research such as Smith(2016),Jiang(2019),Klafft(2007),Prescott(2013),Shaw(1960),Matthew(2007), etc., registered capital is not the key factor affecting the survival time of problematic P2P online lending platforms. This is different from the fact that the registered capital of a platform can significantly reduce the exit probability of a P2P online lending platform (Yum(2012)). The reason why the registered capital has no significant impact on the survival time of a platform is that the registered capital of a platform cannot accurately reflect whether the platform has abundant funds. On this basis, this paper innovatively selects registered capital, regional competition degree and platform survival time to further conduct ANOVA and other tests, and the robustness results also fully prove the accuracy of the above conclusions.

In the long run, if social trust is not improved in the future, the resulting risks will bring a fatal blow to the online lending industry. Therefore, studying the impact of P2P platform risk from the perspective of platform risk and lender risk can effectively promote the transformation and upgrading of P2P platform. Based on the actual situation, this paper makes an in-depth analysis of the risks of online lending, which is of great practical significance for the later transformation of China's online lending and the promotion of the reform of China's financial system.

1.5 Data

The data set used in this thesis mainly comes from three sources. The first is the data of P2P platform, which comes from the home of online lending. Founded in October 2011, WangDaizhijia is the first authoritative P2P online lending portal in China. It contains raw data from all P2P platforms in China. The data, reports and opinions released by Wangdaizhijia are generally regarded as the most influential in China's online lending industry. The second is macro-level and industry-level data, which mainly comes from the WIND database, which is provided by WIND, a leading financial data service provider in China. The WIND database is an internationally recognised database and has been widely used in Chinese academic research. The data of P2P platform and macro (industrial) data of WIND database are mainly used for the risk data analysis of P2P online lending platform in Chapter 3. The third is P2P borrower data, which is not open to the public. We use web crawler tools to collect data of online loan houses. After data cleaning, each lending platform selects 2,000 pieces of data every year. P2P borrower data is mainly used in the fourth chapter of borrower risk analysis. The fifth chapter analyses the data of P2P online lending platforms mainly using the data of P2P platforms.

Chapter 2: China's P2P lending platform

2.1 Introduction to the Chinese P2P lending

A P2P online lending platform refers to an intermediary that uses Internet technology to provide financial information and facilitates direct lending by individuals and individuals according to certain lending rules. Compared with the credit intermediary function of traditional financial institutions such as banks, a P2P online lending platform is an information intermediary in the lending process. P2P online lending platforms originated from small loans. In the early stage of the development of small loans, small loans mainly adopted the traditional "offline" lending mode; its purpose was to support the poor, so as to provide financial services of capital lending to low-income and vulnerable groups. But with the advancement of science and technology and the spread of the Internet, many changes have taken place in microlending. Under these circumstances, P2P online lending platforms have emerged at an historic moment. P2P online lending platforms have the characteristics of low capital threshold and high efficiency, which is an effective supplement to the traditional financial system. In general, there are three main reasons for the emergence of P2P online lending platforms.

2.1.1 Chinese Government Policy Support

At the beginning of the rise of P2P online lending, China was in the process of urbanization. The state encouraged the development of small and medium-sized enterprises and encouraged more people to participate in entrepreneurship. Many enterprises had huge capital needs, forcing the state and regulatory authorities to support this new financing and lending mode of P2P online lending, which allowed many enterprises and individual businesses to obtain large amounts of funds.In the process of the rapid development of China's P2P industry, the country has given great help and support, and successively promulgated policies to support the development of the P2P industry. For example, in 2013, the Implementation Opinions on Financial Support for the Development of Small and Medium-sized Enterprises and Several Opinions on Promoting Information Consumption and Expanding Domestic Demand both mentioned that Internet finance plays an irreplaceable role in helping enterprises realise the expansion of financing channels, and Internet finance innovation should be promoted. In 2014, the Opinions of The State Council on Employment and Entrepreneurship under the New Situation stated that it was necessary to increase the innovation of Internet finance and formulate scientific, reasonable and feasible development plans. In the same year, Premier Li Keqiang put forward the concept and role of Internet finance for the first time in the Government Work Report, and made it clear that the role of Internet finance is irreplaceable for other industries, especially in promoting the rapid development of China's small and micro enterprises and rural finance. At this point, Internet finance, represented by P2P network lending, ushered in unprecedented development opportunities. With the rapid development of the Internet finance field and increasingly significant achievements, the country has gradually introduced relevant documents and policies. The Opinions of The State Council on

Further Improving Employment and Entrepreneurship under the New Situation issued in April 2015 clearly indicated that Internet finance could enrich and expand channels for venture capital investment and financing, and stressed that Internet finance should be actively explored and standardised. In addition, in the Guiding Opinions on Promoting the Healthy Development of Internet Enterprise Finance issued by the Central Bank and other four departments in 2015, it can be seen that the words "online lending" and "encourage" are used more frequently, reaching 11 times and 22 times respectively, meaning that the country has fully recognised the role of online lending in various industries and fields. In the 2015 Government Work Report, Premier Li Keqiang further clarified the significance and value of promoting the scientific development of Internet finance, claiming that the active promotion of Internet finance cannot only help small and medium-sized enterprises solve their financial problems, but also play an important role in promoting the innovation and reform of traditional finance. As one of the most important models of Internet finance, P2P online lending is the product of the organic integration of traditional folk lending and the Internet. In the process of development, "thunderclap" is common. How to ensure its healthy and stable development has become the focus of the current financial regulatory authorities. In the process of strengthening the standardized development of the P2P online lending industry, the government issued the "one method and three guidelines" in 2016. They are the Interim Measures for the Management of the Business Activities of Online Lending Information Intermediaries, the Guidelines on the Filing and Registration of Online

Lending Information Intermediaries, the Guidelines on the storage of Online Lending Funds, and the Guidelines on the Disclosure of Business Activities of Online Lending Information Intermediaries, and the "One Approach and three Guidelines" together constitute the regulatory framework of the P2P industry. It has achieved remarkable results in protecting the legitimate rights and interests of lenders and borrowers and promoting the healthy development of the P2P industry.

2.1.2 The development of network technology

The rapid development of Internet technology has made people more closely connected with each other. In the beginning, people only used non-instant chat tools such as email. Now, a large number of instant chat tools and social networking sites have appeared. Data generation, data mining, search engine technology and data security based on Internet technology provide a strong support for the development of Internet finance. Search engines, social networks, third-party payment, e-commerce, etc. have formed a huge database, the emergence of cloud computing and behavioral analysis theory makes big data mining possible, and data security technology ensures the smooth progress of transaction payment and privacy protection.

The popularity of the Internet provides a platform for the development of P2P online lending. Modern information technology has greatly improved the speed and coverage of information transmission, reduced the cost of information transmission to the maximum extent, and provided a quick communication platform for both lenders and borrowers, so that they can understand each other through the network and reach the intention of borrowing. With the development of Internet technology, more and more financial businesses are shifting from offline to online, which also makes financial transactions more convenient and efficient. The development of information technology such as cloud computing and big data analysis can more accurately and efficiently reflect the changes in market supply and demand information, opening up a way for the development of the P2P industry. By integrating information technology, Internet channels and financial products and services, the network can directly facilitate lending behavior. At the same time, P2P network lending has the advantages of a wide range of transaction objects, fast speed, simple process and so on. It can greatly improve the efficiency of transactions. At the same time, the Internet, as an online operation channel, can reduce the cost of P2P online lending platform, so that the original P2P credit mode can be reconstructed into a modern P2P model, that is, person-to-person credit based on information platform. Therefore, the development of Internet technology has laid a certain foundation for the development of P2P online lending.

2.1.3 Traditional financial institutions are not enough to serve the real economy

In the past, traditional financial institutions mainly targeted large corporate clients and big projects, which typically had thicker capital, less risk and higher profit margins. However, credit services for individuals and micro, small and medium-sized enterprises are relatively scarce; Such groups have a weak capital base and strict loan approval procedures of commercial banks, making it difficult to obtain loans from commercial banks, which has also contributed to the rise of China's private lending market. P2P lending relies on Internet channels. This initiative can not only scientifically and effectively comprehensively deal with and solve the financial problems faced by small and medium-sized enterprises, but more importantly, provide a new investment platform for small and medium-sized investors, so as to obtain higher returns.

Different from the traditional financial model, P2P online lending is a direct contact between borrowers and lenders through P2P online lending platforms. The borrowers announce their borrowing needs on the P2P online lending platform, and the lenders choose the borrowing needs according to their risk tolerance, and finally decide who to lend the funds to, breaking away from the traditional capital medium. On the other hand, compared with the complicated approval procedures of traditional bank loans, the approval procedures of P2P online lending are relatively simple. As long as both lenders and borrowers reach an agreement, the transaction can be completed immediately. For some borrowers with short-term lack of capital turnover and urgent need for capital, P2P online lending is the best choice, avoiding the cumbersome procedures of bank lending and saving time. And raised much-needed funds. The emergence of P2P online lending has filled the gap in the credit market, and its emergence has a certain inevitability. Due to the support of

Internet technology, the development of P2P online lending breaks through the restrictions of geographical location, the participation group is relatively wide, and the participation method is more flexible, which promotes the rapid development of China's P2P online lending market.

From the perspective of three reasons for the emergence of P2P online lending platforms, it can be seen that the rapid development of P2P online lending platform not only benefits from the policy support of the Chinese government and the financial industrial revolution brought about by information technology, but the most important thing is that P2P online lending platform enables borrowers and investors to break through the restrictions of geographical and identity factors and complete two-way transactions through the Internet anytime and anywhere. It can provide a new and fast channel for the investment and financing of low - and middle-income people and small and medium-sized enterprises, fully reflecting the fairness and universality of the participating groups, and the whole process is simple and direct, and the efficiency is significantly improved. Therefore, P2P platforms should not be directly banned, and the industry transformation and upgrading. Therefore, platforms in the industry should improve their own operational capabilities and focus on preventing related risks. In particular, they need to improve their own risk management capabilities and establish an efficient and reasonable risk management system to cope with the increasingly fierce competition environment, which is also the focus of this thesis.

2.2 Development status of P2P lending

Now that China's P2P lending industry has entered the regulation and supervision period, a large number of problematic platforms have been removed, and the development modes of good and bad have been curbed. However, the reason for the withdrawal of platforms is mainly because in the early stage of the development of the P2P lending industry,P2P lending industry regulations have not been formed.

Reviewing the development of China's online lending platforms, it is not difficult to see that online lending is an "imported product" for China, which copied the operation model of Britain and the United States and other countries at the beginning of its introduction. Therefore, China has no relevant laws to regulate it. From the establishment of the first online lending platform PPDai in 2007 to the announcement of the Interim Measures in 2016, the P2P online lending industry experienced a wild growth period of nearly 9 years. In the vacuum environment with no regulatory body and no regulatory basis, the number of P2P online lending platforms exploded. However, extensive supervision was accompanied by the gradual alienation of the industry, and illegal and criminal activity such as the establishment of capital pools, self-financing and fund-raising of platforms constantly appear, which hit the legal bottom line, triggering the first large-scale explosion. As a result of frequent P2P platform problems, China successively issued relevant regulatory regulations to regulate the development of the industry, but in the critical period of reform, a new round of explosive wave has broken out. The reason is that under the high-pressure policy, some enterprises cannot rectify within the deadline due to long-term illegal operations, resulting in overdue, liquidation, and even running away. This phenomenon shows that there are still some deficiencies in China's current legal regulations on P2P online lending, which need to be further improved.

2.2.1 The embryonic stage, before 2007

Before 2006, it was the embryonic stage of the P2P lending industry in China. Before 2006, there had been a number of entity platforms of the P2P online lending industry in other European countries, but they accounted for a relatively small share of the entity market. In 2005, ZOPA, known as the "originator of P2P online lending", was established in the UK. In March 2005, Zopa, a P2P online lending platform, began to operate in the UK. Zopa is the first P2P online lending platform in the true sense. The website provides services to community small borrowers, matching the loan request of borrowers and the capital supply of investors. After the transaction is successful, it will collect fees from both parties, supervise the subsequent repayment and be responsible for the borrower’s repayment after default.

Prosper, which launched in America in 2006, operates by bidding on loans using an online auction platform. Early online lending platforms had low requirements for borrowers, resulting in adverse selection and a high bad debt rate. Subsequently, as required by the Securities and Exchange Commission, Prosper suspended its trading operations to conduct the process of registering its products as securities. Prosper, after its approval, will comply with the Securities Act by regularly updating corporate reports and becoming much more transparent. However, China's P2P lending started relatively late. At this stage, it is mainly to learn the foreign P2P lending model, and no mature P2P lending platform has emerged in the embryonic stage.

2.2.2 Initial development period, 2007-2009

In August 2007, PPDai, China's first P2P online lending platform, was established in Shanghai. In October 2007, CreditEase launched its online lending platform and launched P2P business— Pleasant Loan. At this time, the threshold of online lending platforms is low, and P2P online lending platforms such as Red Lead Venture Capital and 365 Loan have also been launched, but the overall number is not large. The 2008 financial crisis caused China's commercial banks to reduce liquidity, and commercial banks refused to increase the amount of loans. With the rapid economic expansion, the financial demand of small, medium and micro enterprises has continued to increase. In this context, P2P online lending platforms have begun to attract the attention of social financiers and investors. In 2009, there were 9 P2P online lending platforms in China, so the period from 2007 to 2009 was a slow fermentation period of China's P2P online lending industry.

2.2.3 Rapid expansion period, 2010-2012

With the acceleration of interest rate liberalisation and the development of China's private economy, private lending is becoming more and more common. Some entrepreneurs who have private offline lending experience and are concerned about the development of P2P online lending platforms have tried to open P2P online lending platforms. At the same time, some software development companies developed a large number of relatively mature P2P network platform software templates in order to make profits, and the price of each set of P2P platform software templates was not high, which made up for the technical shortcomings of P2P network loan entrepreneurs. Most western P2P platforms are pure online intermediary platforms, especially in the United States, where P2P platforms such as LendingClub and Prosper adopt the pure online intermediary model, and the loan application, review and lending processes are all completed online, which is due to its perfect personal credit information system and the development of financial technology.Compared with, most of China's P2P platforms adopt a combination of online and offline.Relying on traditional third-party financial institutions, they need to look for investors online and financing terminals offline.Therefore, P2P network lending platforms also entered a period of rapid expansion, with a sharp increase in the number of platforms, but the robustness of the platforms was not high. There have been cases of platform failures and cashing frauds. By the end of 2012, the number of online lending platforms in China grew rapidly from about 20 to about 200, with a turnover of about 30 billion yuan and the number of effective investors was between 25,000 and 40,000.

2.2.4 Outbreak period, 2013-2015

2013 was the first year of China's Internet finance, because the representative models of Internet finance, such as third-party payment, P2P online lending, crowdfunding and other innovative models, entered the explosive period in 2013 after the preliminary brewing and development. For example, the number of users of Yu 'e Bao exceeded 2.5 million in just 18 days after it was launched in June 2013, and the number of users exceeded 100 million yuan a year later. There are also various types of P2P online lending that grew rapidly in 2013. With the rapid development of Internet finance, the P2P industry entered a period of explosion: in 2013, the number of normal operating platforms in China soared from about 200 to about 600, and reached 3,437 in 2015. During the three years, the industry demonstrated explosive growth. The annual turnover increased from 30 billion at the end of 2012 to about 982.3 billion, which increased by 33 times in three years. The number of effective investors increased to more than 5 million. However, with the explosive growth of the number of P2P online lending platforms, industry risks also appear frequently. Since October 2013, some platforms with excessive returns have started to have problems. According to the statistics of Wangdaizhijia, the number of problem platforms exceeded 170 in the fourth quarter of 2014, and the industry ushered in the first large-scale risk outbreak. Analysis of the external environment is mainly due to the downward pressure of China's economy, which increases the possibility of overdue borrowers. On the other hand, with the recovery of the stock market, investors withdraw funds from the platform to invest in the securities market. The internal reasons mainly lie in the lack of industry regulation and the irregular operation of platforms, leading to the surge in the number of problematic platforms.The participants of P2P lending in Western countries are mainly individual investors, especially institutional investors such as investment banks and hedge funds. China's P2P lending participants are mainly individual retail investors, which is related to the country's proposed financial inclusion policy.

Before 2013, there were few laws and regulations related to the P2P online lending industry in China. On the one hand, the number of P2P platforms in China before 2013 was small. On the other hand, there was no large-scale centralised outbreak of platform risks and collective runaway in the embryonic stage of the industry development. Since 2013, with the brutal growth of P2P online lending platforms, the regulatory authorities have gradually realised the importance and urgency of Internet financial supervision.In 2013, the People's Bank of China issued the "Payment Business Risk Alert", warning commercial banks and third-party payment platforms to pay attention to the risks of online credit business, which was the first time that the central bank made a statement on online credit.

In 2015, the Supreme People's Court of China issued the Regulations on Several Issues concerning the Application of the Law to the Trial of Private Lending Cases, which stated that online lending platforms only provide information intermediary services and do not provide guarantees for transactions. If the platform explicitly provides guarantee for both lenders and borrowers on the website or advertisement, the platform provider shall bear the guarantee liability. Loans with an annual interest rate of more than 36% are not valid.

In 2015, the People's Bank of China issued the Guiding Opinions on Promoting the Healthy Development of Internet Finance, proposing to follow the principles of "legal supervision, appropriate supervision, classified supervision, coordinated supervision and innovative supervision", scientifically and reasonably define the business boundaries and access conditions of all business forms, fulfill regulatory responsibilities, clarify the bottom line of risks, and protect legitimate operations. We will resolutely crack down on violations of laws and regulations.

2.2.5 Policy adjustment period, 2016-2019

The rapid expansion of the industry has brought about a decline in the quality of industrial development. In 2012, the number of P2P problem platforms was less than 50. In 2016, the number of problematic platforms reached 1,713. Industry chaos, fraud, lost contact, running away from home, campus loans, usury, violent debt recovery and other events emerge in endlessly; This effect is extremely harmful, as the interests of most investors are severely damaged. It even caused social panic and drew the attention of regulators. P2P is more strictly regulated in Western countries. In the US, for example, P2P is regulated by the SEC (Securities and Exchange Commission), while in the UK it is regulated by the Financial Conduct Authority and the P2P Finance Association. China's P2P industry supervision is relatively lagging behind, therefore, the Chinese government has promulgated a series of policies and systems one after another; Mainly by the CBRC supervision and management, and require the platform to record and information disclosure, the regulatory department began to strictly control the platform operation threshold, severely crack down on illegal bad platforms. On the other hand, the risk control model of P2P online lending platforms in western countries, especially in the United States and other countries, mainly relies on the credit rating system, and reduces risks through the portfolio of creditor's rights projects with different risks. China's risk control model is more complicated, due to an imperfect credit system, platforms usually reduce risks through risk reserves or third-party fund custody.

As shown in Figure 2.1, from 2010 to 2019, the number of platforms rose sharply, with a growth rate as high as 118% in 2015 and a maximum of 3,437 in 2015. However, with the intensification of competition, problems with P2P platforms were gradually exposed.

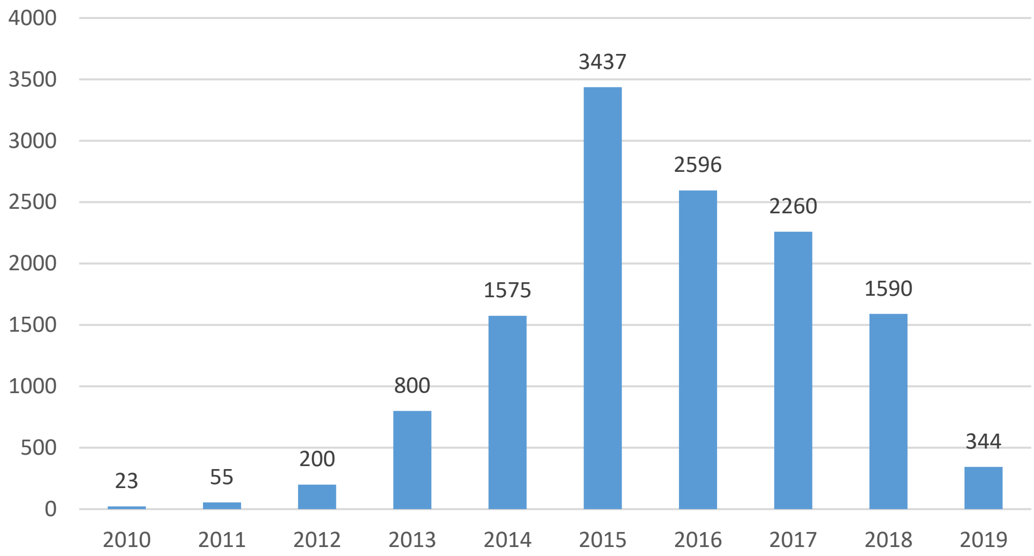


Figure 2.1 Number of P2P online lending platforms from 2010 to 2019 [1]

Judging from the development history of China's P2P platform, China's P2P industry has developed from the first one in 2007 to more than 20 in 2010, and then to a large-scale cleanup in 2020. In less than 13 years, it went through five stages: the embryonic stage, the initial development stage, the rapid expansion period, the outbreak period and the current policy adjustment period. This reflects the process of an emerging industry from the bud to the outbreak to the final industry adjustment. During this period, the P2P industry developed in all countries in the world, but in China, the scale and speed of development were all higher than most countries in the world, the main reason is that the financial market in Western countries is developed, individual and institutional investors have a high acceptance of Fintech, and financial supply is sufficient, and fintech and banks complement each other. In China, due to financial repression and lack of inclusive financial

[1]Data source: Net loan home, https//www.wdzj.com. In the process of data collation, the problem platform is screened and summarised.

supply, Internet finance companies have carried out large-scale regulatory arbitrage in an inclusive regulatory environment. However, due to the irregular operation of some websites, bad information spread throughout the P2P lending market, causing a certain impact on some reputable platforms. During this period, the state has successively introduced policies and political P2P development chaos, and guided the orderly withdrawal of P2P problem platforms,dozens of provincesand cities such as Hunan and Ningxia successively announced the withdrawal policies of P2P platforms, and even adopted "one-size-fits-all" measures for online lending in each province and city,The market was forcefully cleaned up.

In 2016, The General Office of the State Council issued the Implementation Plan for the Special Rectification of Internet Financial Risks, making comprehensive arrangements for the special rectification of Internet financial risks. In the same year, the CBRC, together with the Ministry of Industry and Information Technology, the Ministry of Public Security, the Cyberspace Administration of China and other departments jointly issued the Interim Measures for the Management of Business Activities of Online Lending Information Intermediaries. It defines the regulatory system and mechanism of online lending and the responsibilities of relevant subjects, online lending business rules and risk management requirements, obligations of borrowers and lenders, information disclosure and third-party depository of funds, and comprehensively and systematically standardises online lending institutions and their business activities.

Subsequently, a series of rules and regulations on online lending platforms were issued, such as Guidance on the Registration and Management of Online Lending Information Intermediaries' Business Activities, Implementation Plan for the Special Rectification of P2P Online Lending Risks, and Negative Clearing of Internet Market Access.

In 2017, the CBRC officially issued the Guidelines on Information Disclosure of Business Activities of Online Lending Information Intermediaries, specifying the specific items, time, frequency and objects that should be disclosed in the business activities of online lending information intermediaries, providing standardised standards and basis for all parties involved in online lending business activities to conduct information disclosure.

In 2018, the Office of the Leading Group for the Special Rectification of Internet Financial Risks and the Office of the Leading Group for the Special Rectification of P2P Online Lending Risks jointly issued the Opinions on Doing a Good Job in the Classified Disposal and Risk Prevention of online Lending Institutions, which required speeding up the risk clearance of the online lending industry and doing a good job in the classified disposal and risk prevention of online lending institutions.

In September 2019, the Leading Group for the Special Rectification of Internet

Financial Risks and the Leading Group for the special rectification of Online lending Risks issued the Notice on Strengthening the Construction of the Credit Investigation System in the Field of P2P Network Belt, supporting the P2P online lending institutions in operation to access the credit investigation system, so as to ensure the smooth liquidation of the P2P online lending industry, in order to curb the increasingly fierce phenomenon of debt evasion and cancellation and to punish the deliberate evasion of debt.

Although P2P online lending brings many risks and problems, there is no denying its positive role in the development of inclusive finance. Therefore, it is unscientific to forcefully impose "one size fits all" and remove all P2P platforms; in addition, P2P online lending is a major part of Internet finance. If it is forced to withdraw, it will inevitably have an impact on the entire Internet finance industry and even the entire financial industry. Therefore, China should promote the development of P2P online lending industry compliance, and actively improve the legal regulation of P2P online lending, which cannot only reduce the risks brought by the platform itself, so that it can give full play to its advantages, but also provide a regulatory basis for the healthy development of P2P. Based on the optimisation of the legal regulation of P2P online lending, some ideas are put forward to establish the legal regulation system of the whole Internet finance industry, so that Internet finance will inject more vitality into our economy.

With the improvement of regulatory policies, online lending platforms have played an effective role in governance due to illegal phenomena such as running away with money and closing down. However, the problems of online lending platforms still lie in insufficient platform risk control and untimely identification of borrowers' risks. It is necessary to adjust the online and offline processes of the platforms in a timely and effective manner with the regulations of regulatory authorities. In other words, the basic focus of regulation is to stop the existence of violations in the industry and give the market a harmonious and healthy development prospect. At the same time, the platform also needs to effectively control the platform's own risks and borrowers' risks, so as to further stimulate the development potential of the private lending market and enhance the trading volume and activity of the platform. The purpose of this thesis is to further study the risks of lending platforms and borrowers' default risks on the basis ofoptimising legal regulations, so as to reduce the risks of P2P platforms at the root.

2.3 P2P Risk classification

The fundamental difference between P2P platforms and traditional financial institutions lies in information processing methods, funding sources, risk control and regulatory environment. In terms of differences in information processing methods, P2P platforms conduct information processing and risk assessment through the network and do not need to disclose information to the CBRC on a regular basis; However, traditional financial institutions rely on the traditional credit investigation and approval process, and need to disclose relevant information to the CBRC on a regular basis and accept the supervision of the CBRC, and there are great differences in compliance and information disclosure level. In terms of sources of funds, the funds of P2P platforms mainly come from high-interest financing funds with high cost; The capital of traditional financial institutions mainly comes from low-cost deposits, which have low cost and large liquidity. In terms of risk control, traditional financial institutions have a sound risk management and control system, while P2P platforms are weak in risk control ability and rely on big data and models for risk management, so market risks and operational risks are relatively high. In terms of regulatory environment, traditional financial institutions are subject to strict financial supervision, while P2P platforms are generally not subject to strict financial supervision, which poses certain legal and security risks.Beck (2012) pointed out that P2P online lending is developing rapidly because it can supplement the shortcomings of traditional finance. However, it needs the guidance of regulators to promote the sustainable development of its legal compliance and reduce the risks of the industry.

In the study of online lending platforms, scholars have conducted a lot of research on P2P online lending risks, and classified them according to different classification standards. Based on the current industry status of China's online lending platforms, platform risks can be summarised into the following six types: information disclosure risk, compliance risk, liquidity risk, operational risk, market risk and credit risk. The following section will summarise different types of platform risks, so as to find the risk analysis content that can be quantitatively analysed.

2.3.1 Information disclosure risk

Information disclosure risk is the most general risk of online lending platforms.The risk of information disclosure refers to the phenomenon of information asymmetry caused by the inaccuracy and time delay in the process of information transmission, which runs the risk of misleading decision makers. The Internet Finance Association of China released a draft on information disclosure standards, stipulating the basic principles and contents of information disclosure on platforms. The draft establishes a detailed index system for information disclosure content, and defines and standardisesa number of disclosure indicators, including institutional information, platform operation information and project information. The supervision of the P2P online lending industry has been absent for a long time, and it is still common for many platforms to fail to provide adequate information. Investors are the inferior party of information, and their decision-making will be affected and they will face the risks caused by inadequate information disclosure. The relevant regulations give detailed disclosure rules. According to Freedman and Jiin (2013), investors have a high probability of not knowing the purpose of the borrower's funds. At present, most platforms implement unsecured credit loan models.

In Chapter 4, we evaluate the risk control level of the three P2P platforms, namely Rendai, PPDai and Yirendai, and conclude that the risk control level of Rendai is relatively high. Therefore, this thesis analyses specific cases of Rendai. Take Renrendai as an example. First of all, relevant policies require borrowers to disclose whether they have been involved in lawsuits and have received administrative punishment when publishing the loan object. However, information about the official website of Renrendai shows that there is no information yet and no reasonable explanation has been made. Then, according to the policy, the platform is required to disclose its annual report and quarterly report to the public. Renrendai did make relevant disclosure, but the data disclosed in the annual report is simply business data, and selective disclosure inevitably leads to investors' doubts about the real operation of the platform. Third, the policy stipulates that the information disclosure part of the online loan should have the signature of the legal representative, but the official website of Renrendai has not seen this information; Fourth, according to the annual reports of the past two years, Renrendai's indicators on overdue borrowers include the balance and number of related loans, overdue amount, overdue amount, overdue rate of projects and overdue rate are all zero. Even though the platform is running well, such data is not realistic, so the information disclosure content of Renrendai is obviously inconsistent with reality.

2.3.2 Compliance risk

P2P compliance risk refers to the risk that some P2P platforms, in pursuit of profits, do not abide by relevant laws and regulations and carry out non-compliant operations, thus facing legal sanctions or regulatory penalties.When the above behaviours occur, the role of the platform is no longer the information intermediary defined by the policy. It is just a financing intermediary disguised as an information intermediary. In this case, the funds are not properly allocated, but illegally occupied by the platform, which brings huge risks to all stakeholders.D Shen,C Krumme, and A Lippman (2010) conducted data analysis on a specific platform from the perspective of case analysis, and found that platforms tend to release targets with high profits to attract investors, but there are often hidden risks.

In theory, if P2P lending platforms are fully compliant, investors will choose their lenders according to their wishes and be responsible for their own economic decisions at their own risk. However, when the platform is no longer an information intermediary defined by the policy, but a financing intermediary disguised as an information intermediary, its essence has changed, and it is no longer a lending platform between people. When a borrower or platform fails to pay or defaults, all users of the platform and even the entire industry are affected, resulting in greater risk. In terms of compliance, this chapter chooses the legitimacy of P2P online lending enterprises, ICP operating license and market supervision as the representative variables of platform compliance, and studies the impact mechanism of platform compliance on P2P platform withdrawal in detail.

2.3.3 Liquidity risk

P2P platforms are mainly for small, medium and micro enterprises and individuals, so there is a large demand for capital and a large number of investors and borrowers. The platforms often set up reserve funds to deal with risks. When borrowers fail to repay due to their own economic conditions, the platforms will make rigid payment in order to protect their reputation and investors' interests. Pennacchi (2006) found that negative news would induce investors to redeem, forming a "herd effect", which would increase liquidity risk.A platform with sufficient capital can cover the bottom, but when a large number of defaults occur, the platform will face a liquidity crisis, in which a large amount of the platform's funds will be used for redemption and withdrawal, and the liquidity will be greatly reduced. Lee et al. (2012) pointed out that since P2P online lending platforms serve small and medium-sized enterprises, the purpose of their loans is usually short-term capital turnover, and the amount of money is not large, so there is no need for additional guarantees. However, a large number of targets without guarantees only rely on credit, which means that borrowers need the platform to cover their losses after default. It has brought huge liquidity pressure to the platform.In an extreme case, the platform will use all the risk reserves to meet the investor's redemption requirements, and the capital chain of the platform will be rapidly broken, resulting in inmeasurable liquidity risks. Ultimately, it can make the operation of the platform unsustainable. Some platforms will set up a debt-for-debt (debt transfer) model, that is, creditor holders transfer their claims to other investors through P2P online lending platforms, mainly to split and reorganize the subject matter, and carry out maturity mismatch to increase the liquidity and flexibility of funds. This model is highly risky and requires high liquidity.

Renrendai has also been greatly affected by the "three reduction" policy (the outstanding balance on the platform, the number of lenders and the number of offline stores). Once the issuing of new bids ceases, new business cannot be carried out, and there is no cash flow, which means that the platform can no longer "rob Peter to pay Paul" as before, and payment difficulty is bound to arise sooner or later. Since 2019, Renrendai has begun to vigorously shrink the front line. The number of employees has been reduced from the peak of 10,000 to several hundred. Almost all of its more than 300 offline stores have been closed down, leaving only a dozen important regions to maintain stock assets and existing customers. Frequent P2P thunderstorms also meant that some people took risks after taking out loans. As a result of useless collection, Renrendai has more and more loans that cannot be collected, the capital chain is constantly strained, the platform needs to advance more and more objects, and the liquidity can only be maintained by short-term credit. Therefore, when we study P2P platforms, we also add factors affecting cash flow such as the average lending volume and loan term into the model, so as to consider cash flow risk.

2.3.4 Operational risks

Operation risk is one of the most significant risks of P2P online lending platform. Influenced by the particularity of online lending, platform marketing strategy, financial innovation and other aspects, the platform will face some risks in the operation process. With the increase of the participation of lenders and borrowers and the transaction amount, the operational risk also increases. With the rapid development of big data and the Internet, P2P platform came into being and is the product of financial innovation. It is often combined with traditional lending models (such as insurance, wealth management, trust, financial leasing, etc.). Therefore, the financial products operated by P2P platform are relatively complex, and such a complex product model is more prone to operational risks. This is because it requires higher operational and internal risk control capabilities. Finally, China's P2P industry has a short development history, throughout which thunderstorms have broken out several times and failure cases in risk control have been common. However, there are only a few platforms that can serve as industry benchmarks for new platforms. In the heyday of P2P development, a large number of platforms and practitioners flooded in, resulting in severe market saturation, fierce competition in the industry and increased information barriers between platforms. More acute operational risks were created. Schenone (2004) also believes that P2P platforms are under the supervision system of SEC, which is conducive to improving their security and financing transparency, and further improving the efficiency of lending. In this paper, the impact of operational risk is fully considered in the study of P2P platform withdrawal mechanism, and the market supervision on operational risk is taken into account in the model.

2.3.5 Market risk

Many practitioners see the profit space of the P2P industry, so want to get a share of the market, resulting in the increase of the number of P2P platforms. It is the nature of profit seeking platforms to compete with each other, so all platforms are faced with a certain degree of market risk. Anthony (2010) analyzed the operating data of Prosper platform and found that investors of the platform generally prefer investment targets with higher risks, thus increasing the risk of P2P lending virtually. Therefore, in addition to the above risks, P2P online lending platforms also face risks caused by the impact of external factors, among which competition risk and economic cycle risk are the most common. As mentioned above, the risk of competition is mainly due to the profit-seeking nature of platforms. In the peak period, the number of platforms keeps rising, which brings a lot of competition within the industry. There are many competitors in China's P2P lending industry, and the industry resources and market scale are limited, which are not enough to meet the needs of all P2P platforms. All platforms seize the market one after another to attract investors' funds, thus bringing profits to the platforms. Some platforms have begun to enagage in unfair means that are not in line with the market competition rules, such as setting off a price war and making high-risk investments. These are bad market competition, not only affects the normal operation of the market order, but also affects the reputation of the platform, blackening the impression of investors on the P2P lending platform, but also brings no small competitive risks to other platforms. Economic development is not a smooth process, nor is it always in an upward trend, but there is a cyclical, bust and boom alternately. It takes a long time for the industry to develop into a mature system, and it is easy for it to be affected by external factors in the beginning and middle stage of development. Once the economy fluctuates, a series of chain reactions will affect the development of the industry. If the fluctuation is great, it will bring a fatal blow to the industry, such as when the market enters the stage of economic recession or depression. The decline of borrowers' repayment ability leads to the rise of the bad debt rate of P2P online lending platforms, which will affect the operation of the platforms in severe cases. The epidemic has had a huge impact on Chinese small and medium-sized enterprises in 2020, with 29.58% of them seeing their annual operating revenue drop by more than 50%. In addition, 28.47% of the enterprises decreased by 20% to 50%; 17% of the enterprises decreased by 10% to 20%. In addition, 20.93 percent of the companies were unpredictable. The main investors of P2P platforms are micro, small and medium-sized enterprises. When the market environment changes due to the epidemic, investors' confidence decreases and the platform explodes frequently. Therefore, the epidemic brings great market risks to P2P platforms. In terms of market risk, in Chapter 4, we consider the influence of herding effect and speculative effect on the lending risk of P2P platforms, and in Chapter 5, we also consider the influence of regional competition on the withdrawal of P2P problematic platforms.

2.3.6 Credit risk

Credit risk refers to a risk, also known as the risk of default, where the other party suffers economic losses due to the failure of the two parties to perform their obligations accurately after signing the contract, or the performance of acts not stipulated in the contract.Steelmann (2006) believes that there is information asymmetry in the transaction process of P2P online lending, so P2P online lending in this mode has greater credit risk.According to the provisions of the policy, P2P platform is an information intermediary, responsible for capital allocation and information disclosure. Usually, before lending activities start, the platform needs to conduct risk control in advance; that is, evaluate the credit rating of the borrower, and inform investors that due to the particularity of P2P online lending, investors and borrowers cannot have face-to-face contact. Even investors do not know where their funds flow to, so investors can only rely on the information obtained from the platform and their own discrimination ability to make decisions on their own. If the borrower has moral hazard, the uploaded information is false or concealed, and the platform lacks the auditing ability, the platform will face greater credit risk. So P2P lending is more risky than traditional bank lending. The direct manifestation of the borrower's credit risk is the overdue loan. The period from 2015 to 2016 was the risk outbreak period of the P2P industry, but the growth rate in overdue amounts of

Renrendai platform decreased during this period, indicating that Renrendai platform was a platform with strong risk control ability in the industry in the early stage. In 2017, the delinquency amount for the first time showed a decline, but not significantly, and compared with 2012, the delinquency amount was very large, and the credit risk more prominent. In Chapter 4, we deliberately select "borrower's credit characteristics", which are divided into borrower's credit score, credit limit and default frequency. We study the impact of a borrower's default by examining their credit characteristics.

Among the above six platform risks, information disclosure risk and compliance risk are regulated by numerous laws and regulations, which have been discussed in the previous chapter. However, most online lending platforms do not disclose the working capital of liquidity risk, so it is difficult to conduct qualitative research on liquidity risk. Operational risk and market risk can be considered from the perspective of the P2P platform itself and the industry, and credit risk can be studied from the perspective of the borrower. Therefore, three types of risks, namely operational risk, market risk and credit risk, can be analysed concretely and quantitatively. This paper focuses on the risk analysis of P2P lending platforms and P2P borrowers. The above six kinds of risks are well reflected in this paper. In terms of platform risk measurement indicators, we mainly choose from the perspective of operational risk and market risk, and in terms of P2P borrower risk indicators, we mainly choose from the perspective of credit risk.

Chapter 3: Analysis of behaviour characteristics of P2P lending[2]

3.1 Introduction

The Chinese P2P lending industry has been experiencing a crisis recently. Fraudulent P2P lending cases have been exposed by the media since 2015. In 2016 one-third of China's P2P lending platforms were 'problematic' (Leng, 2016). The Chinese Banking Regulatory Commission (CBRC) statistics also show that about 40% of P2P lending platforms in China were in fact Ponzi schemes in 2016. In 2019, there were only over 300 online lending platforms in normal operation. In response to the crisis, the Chinese government has taken a series of measures to clean up the P2P market since later 2015, which aims to curtail small and medium-sized lending platforms.[3]In 2020, there were zero Chinese P2P platform online loans.

Unlike conventional means of financing, P2P platforms directly connect investors and borrowers through the internet. In mature market economies (hereafter MMEs), P2P platforms mainly function as financial services providers which offer information about borrowers and potential investment projects. They are not financial intermediaries and their financial accounts are separated from those of their clients. However, a striking difference between Chinese P2P lending platforms and their counterparts in MMEs is that many Chinese P2P platforms themselves directly

[2]Another version of this chapter is published in the European Journal of Finance (EJF) as "Shuai Shao & Hong Bo (2022) Behavioural aspects of China's P2P lending, The European Journal of Finance, 28:1, 30-45, DOI: 10.1080/1351847X.2021.1880459.". I would like to thank the co-author and my supervisor, Dr Bo, for her inputs and the referees and editors at EJF for their reviews.

[3]For example, in 2015, the central bank issued guidance on promoting healthy development of internet finance. In August 2016, the Chinese Banking Regulatory Commission (CBRC) issued 'Interim Measures for the Administration of the Business Activities of Online Lending Information Intermediary Institutions'. In June 2017, China issued regulations on internet financial information disclosure, and a series of notices on special rectification, capital management rectification, compliance supervision, and self-regulatory inspection.

initiate loans to borrowers and raise funds from investors, i.e. they do not focus on providing financial services; instead, they are directly engaged in financing and lending activities (Huang, 2018). In this context, the conventional principal-agent problem (Stiglitz, 1974) between investors and borrowers becomes the principal-multiple agent problem. On the one hand, investors are the principal of borrowers. Investors have little information about the creditworthiness of borrowers and they mainly rely on P2P platforms to obtain such information. On the other hand, investors are also the principal of P2P platforms that directly raise and manage funds on behalf of investors. The relationship between investors and P2P platforms in China is therefore more complicated than that in MMEs. Due to information asymmetry, investors are not able to judge the quality of P2P platforms; hence moral hazard and adverse selection behaviour of P2P managers will hurt investors' interests. In addition to the relation between investors and P2P platforms, information asymmetry exists between P2P firms and borrowers. In this relationship, P2P platforms are not able to distinguish between good and poor-quality borrowers and one would also observe the moral hazard and adverse selection behaviour of borrowers. This suggests that P2P firms risk not being able to get loans back. Obviously, there should be strong mechanisms to guarantee that P2P platforms do not deviate from the interest of their investors, and that borrowers are capable of repaying loans. In MMEs, these mechanisms are in place in the form of laws and regulations on P2P lending, government guarantee schemes, independent third-party credit evaluation institutions, and sophisticated credit information systems. It should be noted though that formal regulations on P2P online lending were absent in China before 2015. In addition, unlike MMEs where P2P fund suppliers are often institutional investors, P2P capital providers in China are mostly individual investors who seek short-term capital gains, so both P2P platforms and their investors have astrong intention to use the P2P online lending market as a speculative investment tool (Yoon, et al., 2019). On the demand side, P2P borrowers are very risky in China. They are often privately-owned small and medium-sized enterprises (SMEs) and individual consumers who are not able to obtain funds from sources of formal financing. Chinese national credit information system is still underdeveloped too; when carrying out due diligence, P2P lending platforms in China have to rely on their own small-scale individual credit assessment and risk control mechanisms. Risks embedded in Chinese P2P borrowers are reinforced by higher interest rates charged by P2P lenders, especially privately-owned P2P platforms (Lo, et al. 2020). This can be summarised in the quotation: “P2P platforms comprise one of the riskiest and least regulated slices of the shadow banking system in China” (Bloomberg, January 2, 2019).

In 2013, the Central bank proposed at a joint meeting of nine ministries and commissions that P2P online lending platforms should establish a fund custody mechanism for third-party payment enterprises and commercial banks. On July 18, 2015, the "Guiding Opinions on Promoting the Healthy Development of Internet Finance" was issued, which stipulates that payment institutions shall not handle cash access, credit, financing, financial management, guarantee, and currency exchange services for customers or in disguise. On August 17, 2016, the Interim Measures for the Management of Business Activities of Online Lending Information Intermediaries required that online lending information intermediaries must select qualified banking financial institutions as the depository institutions of lenders and borrowers. With the clarity of regulatory policies, third-party payment institutions cannot implement P2P depository, and only banks can carry out P2P depository. However, due to the advantages of payment companies in system docking and industry cognition, the joint depositary mode of third-party payment and bank came into being. Under this model, third-party payment institutions are responsible for payment settlement and technical services, while banks are responsible for fund management and supervision. In February 2017, the CBRC issued the Guidelines on Online Lending Fund Depository Business, clarifying the detailed rules and requirements for P2P depository of commercial banks. The joint depository mode is no longer compliant, and gradually transitions to the direct bank management mode, that is, the investors and borrowers of the platform open accounts in the bank account system, and the real funds are deposited in the special account for fund transactions opened by the platform in the depository bank.

Due to severe information asymmetry and lack of regulation, P2P investors and platforms in China face high uncertainty when making investment and lending decisions. P2P platform has the risk of borrower default, and investors cannot effectively monitor P2P platform. High uncertainty exacerbates the moral hazard and adverse selection issues between P2P platforms and investors. In this context, we can expect P2P lending decisions to be heavily influenced by the behavioral factors of P2P company managers. In the P2P online lending market, the main investment group is the low-income long-tail group, whose investment concept is not mature, investment experience is relatively lacking, and they cannot fully meet the conditional assumptions of rational people. They are easy to be affected by the investment sentiment in the market to make irrational decisions and take irrational behaviors, and the frequent negative news in the online lending industry is very representative. At the same time, because on the P2P lending platform, potential investors can easily observe the bidding status of other investors, investors' behavior decisions are not completely based on their own known information, and they will make their own decisions according to the behavior of other participants. For example, investors are more inclined to choose to invest in the near completion of the underlying loan order. All these situations are the manifestation of limited rationality of investors, appearing herding behavior. In the final analysis, the emergence of these behaviors is due to the existence of investment mistakes in the original herd, but these problems have not been corrected and the impact of the enlarged collective has been enlarged, resulting in the amplification of investors' emotions in the market and the decline of investment rationality. In addition, investors often refer to the interest rate choices of other investors when choosing the target of borrowing. When the interest rate of a certain loan target is set higher, investors will think that it is a "high yield" target, so they choose the target for investment. Such interest rate setting speculation can lead to distortions in market interest rates, making it difficult for high-quality borrowers to obtain reasonable borrowing costs, while high-risk borrowers obtain funds at high interest rates, increasing the risk of the market. If this is the case, then we can observe that P2P lending in China is responding to behavioral factors, such as lending sentiment, herding, and speculation.

At present, the researches on investment sentiment, herding effect and speculative effect in online lending are limited, especially no scholars can focus on the factors of online lending behavior. In the existing research, the direction mainly focuses on the existence of herding effect. For example, Lee and Lee (2012) confirmed that there is a significant herding effect in Korean P2P online lending and its diminishing marginal utility to investors, but they did not consider the performance of herding effect under the interference of external factors, especially investment sentiment and excessive speculation.

In this context, based on a sample of 918 P2P platforms from 2015 to 2019, this paper studies the behavioral factors of P2P lending in China. The research method is to combine quantitative analysis with qualitative analysis, analyze the influence of emotional factors, herd effect and speculation factors on investment decisions of P2P online lending from the perspective of investors, and find out the behavioral factors of current P2P platforms from the results of empirical analysis. In China, the debate about P2P lending has been centered on the risks it poses to the country's financial system, and the primary goal of China's P2P industry's return to health is to reduce the risks of P2P lending. Considering that these risks are likely to be the result of behavioral factors in P2P lending decisions, we ask the following research questions: To what extent can P2P lending in China be explained by behavioral factors in P2P platforms?

The empirical results show that after controlling the fixed position effect, there are significant lending sentiment, herding effect and speculative behavior among Chinese online lending investors. P2P lenders will show stronger loan sentiment towards P2P positive news and increase the total amount of loans; Herding behavior is an important feature of P2P lending in China, which is driven by the bubble of the real estate market. Moreover, the results of these behaviors are still valid after the robustness test of the model, excluding the highly endogenous variables of loan sentiment, herding effect and speculative effect. In the in-depth study, the lending activities of P2P platforms that do not adopt the fund custody mechanism are more likely to be affected by behavioral factors, mainly because for P2P platforms that do not adopt the fund custody mechanism, investors are more likely to suffer from adverse selection and moral hazard, and P2P platforms are more likely to be irresponsible and risky. This makes it more vulnerable to borrowing sentiment, herd behaviour and speculation.

The research conclusion of this paper has certain practical significance. On the one hand, this paper concludes that P2P lender behavior is influenced by borrowing sentiment, herding and speculation. This gives us a comprehensive understanding of the different types of behavioral factors that influence P2P lending in China. To our knowledge, there are no studies that have examined the multiple behavioral factors associated with P2P lending in China in one study. On the other hand, one of the causes of lending sentiment, herding effect and speculation is information asymmetry and adverse selection. Therefore, for government departments, it is urgent to introduce relevant policies as soon as possible to strengthen the information disclosure mechanism of lending. For P2P platforms, improving and optimizing target review process and target display mode can help alleviate the information asymmetry faced by investors, thus attracting more investors to invest. However, this paper also has certain defects. For example, due to data collection limitations, it uses a single index to measure borrowing sentiment, herding effect and speculation behavior, which is still far from the comprehensive measurement of Lee and Lee (2012) and other detection models based on the existence of borrowing herding effect. In addition, the influence of behavioral factors is limited to whether they have an influence or not. On the basis of the influence, Freedman S.M and Jin GZ(2013) et al. further verified the diminishing marginal utility of behavioral factors on investors. This is also the content that will be further focused on later.

3.2 Literature review

Existing studies on P2P online lending based on MMEs mostly focus on the conflict between investors and borrowers, which is underpinned by the asymmetry information theory (Akerlof, 1970; Stiglitz and Weiss, 1981). Their central argument claims that the degree of information asymmetry is higher for P2P lending as compared to traditional financial intermediaries, such as banks. This is because financial intermediaries can provide research, evaluative, and monitoring services more efficiently than individual investors in the market (King and Levine, 1993). P2P lenders are less able than formal financial intermediaries to invest in systematic mechanisms in collecting information and monitoring borrowers. Therefore, information asymmetry becomes more severe for P2P lending. This explains why many existing researches on P2P lending based on P2P platforms in MMEs focus on how to reduce borrowers' risks faced by both investors and P2P platforms. More specifically, there are three sub-streams of research on a borrower's creditability in the standard literature. Firstly, some studies examine how demographic characteristics of borrowers affect P2P lending (e.g.Herzenstein, et al., 2008). Secondly, some scholars emphasize the role of borrowers' social connections in P2P lending (e.g. Lin, et al., 2013; Lu, et al., 2020). Thirdly, some studies specifically focus on the credit scores of borrowers (e.g. Duarte, et al. 2012; Emekter, et al., 2015). In sum, the standard literature on P2P lending in MMEs has chiefly focused on the creditworthiness of P2P borrowers.

Existing literature on China's P2P lending is very thin. Overall, the focus of very few researches is different from that based on P2P lending platforms in MMEs. The central research question regarding China's P2P lending is the extent to which P2P platforms are trustworthy to their investors. Huang (2018) points out that the business model of Chinese P2P lending platforms is different from that in MMEs in which the 'client segregated account model' is adopted. In that model, P2P platforms are services providers, they facilitate P2P transactions, but they are not a part of the transaction. However, in the Chinese P2P lending industry, the most popular model before 2016 is the 'platform lender model' (Huang, 2018). In this model, P2P platforms are directly involved in transactions. They originate loans to borrowers and manage a pool of funds on behalf of investors through a collective investment scheme.

The above-mentioned business model of China's P2P lending industry suggests that moral hazard and adverse selection problems are very serious in China's P2P lending industry. This explains why many P2P platforms in China are in fact Ponzi schemes[4]. Studies mainly focus on the characteristics of P2P platforms that may make P2P platforms more trustworthy. For example, Lan, et al. (2018) document the importance of social capital owned by P2P platforms for their survival. They measure P2P platforms' social capital through the use of online posts on their websites and online communication activities of the P2P platform. Yang, et al.

[4]Ponzi scheme： is the term used for investment fraud in the financial sector. It uses the money of new investors to pay interest and short-term returns to old investors, in order to create the illusion of making money and obtaining more investments.

(2017) use data from a survey of 358 Chinese P2P platforms in 2016 and find that investors' trust of the P2P platform encourages them to invest in the P2P platform repeatedly. In addition, Li and Yang (2019) examine whether ownership background of P2P platforms affect P2P transaction volume. They find that P2P firms owned by venture capitalists, state-owned enterprises (SOEs), listed companies, and banks would lend more than privately-owned P2P firms because private ones are riskier as perceived by investors and borrowers. Jiang, et al. (2019) also document that SOE-affiliated P2P platforms in China fare better during market downturns and they have higher trading volumes, attract more investors, and offer lower interest rates as compared to non-SOE-affiliated P2P platforms.

Given that moral hazard and adverse selection problems are more severe in China's P2P industry, one can conjecture that P2P platforms (lenders) are more likely to take risks and speculate in making lending decisions. Yoon, et al. (2019) provide indirect evidence that China's P2P lending market is speculative in the sense that more revenue from the gambling industry is positively associated with a higher default risk of P2P platforms. More recently, Allen, et al. (2019) study another element of China's shadow banking system: entrusted loans. They demonstrate that about half of non-affiliated entrusted loans flow into the Chinese real estate industry and these loans are more likely to have problematic performance afterwards. Since China's real estate industry has accumulated a lot of bubbles over the years and there have been regulations that restrict financing of the formal banking sector from lending to the real estate industry, the result provided by Allen et al. (2019) can be seen as evidence that lenders of non-affiliated entrusted loans have been chasing higher returns in the Chinese real estate industry. If this is the case, we would expect that China's P2P lenders to behave similarly to non-affiliated entrusted loans lenders. In fact, there is likely to be an ovrlap between P2P lenders and lenders of non-affiliated entrusted loans in China.

When making decisions facing severe information asymmetry and high uncertainty, economy agents tend to follow the other people's decisions, hence the localised conformity of behaviour can be observed (Birkhchandani, et al., 1992). There are a few studies that discuss herding behaviour in P2P lending based on P2P platforms in MMEs. For example, Herzenstein, et al. (2010) discuss herding behaviour among Prosper's lenders. They find that lenders are likely to bid in the presence of more existing bids, meaning that a loan application that has already received lending offers is more likely to attract more offers. Zhang and Liu (2012) provide evidence of rational herding among Prosper's lenders and show that lenders not only mimic peers' lending decisions, but also make use of publicly observable borrowers' characteristics in making their own decisions, hence it is 'rational herding'. Lee and Lee (2012) examined a large sample of P2P daily transactions and provide strong evidence of P2P lenders' herding behaviour in Korea. Recent studies on herding bahaviour based on Chinese P2P platforms have emerged. For example, Caglayan, et al. (2019) investigate investors' bidding behaviour based on transactions data from *RenRenDai*during October 2010-October 2018. They demonstrate that investors herd in bidding in the sense that they prefer projects that had already attracted strong interestin previous periods. The authors find that investors who have been active in the platform only for a short duration of the bidding process and more experienced investors are more likely to herd. In another study, Jiang, et al. (2018) argue that automatic bidding can reduce investors' herding behaviour as compared to manual bidding. Using transactions data from *PaiPaiDai* in 2015, they suggest that automatic bidding weakens investors' herding behaviour. Moreover, automatic bidding produces a rational herding because the outcomes of automatic bidding are very similar to the observed pattern of loan amount and loan period.

Apart from herding behaviour, lending decisions are also often influenced by P2P lenders' perception of the industry. A growing body of recent literature suggests that industry information from news articles and other information can adequately explain the return ability of the stock market. According to Shiller (2000) investors follow the printed word even though much of it is pure hype, suggesting that market sentiment is driven by news content. Along this line of argument, Calomiris and Mamaysky (2018) use the aggregate news at a monthly horizon from the Thomson Reuters Machine Readable News Archive to derive measures of word flow. They find that these news measures have predictive powers in explaining stock market risks and returns. Moreover, Garcia (2013) constructs investor sentiment from media contents by counting the number of positive and negative words from two financial columns published in the New York Times. The author finds that positive words embodied in the news help predict stock returns. Moreover, this news effect is more profound during economic recessions. In summary, the above-mentioned studies justify that it is meaningful to derive a measure of lending sentiments from news contents. In the empirical analysis of this thesis, we use positive P2P news release to derive a measure of lending sentiments and examine whether it affects P2P online lending in China.

3.3 Research hypothesis

In the P2P industry, if the investment sentiment is in a positive state, the financing efficiency will be at a higher level, and more borrowers will be attracted to the target; If the investment sentiment is in a negative state, the financing efficiency will be at a low level, the efficiency is low, and the loan demand of lenders can not be solved. If the investment sentiment is relatively neutral, the financing efficiency will be relatively stable. In China, P2P online lending industry, as an innovative financial management method, is still in the emerging stage, and the market-related operating mechanism and transaction system still need to be improved, which cannot meet the conditional assumptions of an efficient market. Especially at this stage, not all registered P2P platforms only play the role of information intermediary in the real sense. Due to the existence of a large number of non-compliant platforms, P2P has a large amount of investors' funds. Once the information asymmetry occurs and the platform has problems, the situation of explosion will occur. Investment funds will be reduced or even required to withdraw funds, the number of old investors, new investors and investment amount will decrease, making lenders unable to quickly obtain funds, the full time will increase, and the volatility of financing efficiency will decrease. Emotional reflection affects investment amount, investment rate and so on in behavioral decision-making, and finally affects financing efficiency. Lending decisions are often influenced by peer-to-peer lenders' perceptions of the industry, and a growing body of recent literature suggests that news media has a significant impact on peer-to-peer lending. Fang (2009) believed that the media provided a broader channel for the information dissemination of P2P platforms and provided guidance for investors to make decisions. Matthew (2007) also introduced the P2P online lending business in detail, and explained that public opinion has an important impact on the development of P2P platforms, and there is a correlation between the amount of news and the turnover when no conditions are controlled. Based on the above views, this thesis proposes the following hypotheses:

Hypothesis 1: The loan sentiment of the P2P platform will prompt the P2P platform to expand the loan volume.

In the P2P online lending market, herding behavior shows that investors are influenced by other investors' behavior in the decision-making process and tend to imitate others' investment decisions while ignoring their own information and judgment. Herding behavior in P2P online lending market is manifested as investors blindly following the trend in bidding behavior, interest rate setting, credit evaluation and market bubbles. Especially in the bidding behavior, investors tend to choose the loan object with fast bidding progress and large number of bidders. This choice is not based solely on the borrower's credit rating and risk-return analysis of the loan project, but is influenced by the behavior of other investors. When the bidding progress of a certain loan target is rapid and the number of bidders is large, investors will think that it is a "hot" target, and blindly follow the trend of bidding, resulting in herd behavior.There are many reasons behind herding behaviour, one of which is information asymmetry.Generally speaking, information asymmetry means that the quantity and quality of information owned by both parties are not equal, and the party with more and better information often occupies a more favourable position in the transaction. Regarding P2P online lending platforms, information asymmetry is manifested as follows: The information that the lender can obtain about the borrower comes from the information provided by the lender (income, level of assets and liabilities, other loan experience, etc.). In order to obtain lower borrowing costs and faster borrowing, the borrower has the motivation and ability to conceal the unfavourable information (such as the previous loan default record, etc.). The herd behaviour in the P2P lending market is different from the transmission media in the traditional securities market. Unlike the securities market, the P2P lending market does not have sensitive price changes. Investors can only make corresponding decisions by observing the previous investment behaviour. Zhang& Liu (2012) used the Prosper.com platform to verify that herd behaviour is a good indicator for predicting the performance of loan projects, which means that if herd behaviour investment is adopted, it can improve the investment effect of the lender. Shen (2010) also found that P2P investors' investment behaviour exists the phenomenon of following investment and the herd effect is obvious. Based on the above views, this thesis proposes the following hypotheses:

Hypothesis 2: The herd effect of P2P platform will promote the P2P platform to expand the amount of lending.

With the mushrooming of P2P online lending platforms, the speculation performance of P2P online lending platforms is prominent, and online P2P finance has gradually evolved into the distribution centre of online usury. Therefore, it is easier for P2P platforms to take risks and speculate when making lending decisions. The participation of speculators in the market can increase the activity of the market. They bring liquidity to the market through short-term operations and rapid trading. The frequent trading activities of speculators make it easier for buyers and sellers to find counterparties, thus promoting the rapid flow of funds.At present, many P2P platforms appear to be where investors choose their own projects, but in fact the platform packages the financing projects in layers to facilitate trading.In order to achieve a percentage of transaction volume, the platforms will try to facilitate transactions and transfer risks to investors (Yoon, 2019). Many P2P online lending platforms are willing to lower the risk control threshold or even fabricate false data in order to obtain a huge amount of financing in order to maintain a high volume growth. Therefore, when high-quality projects are scarce, P2P platforms often fall into the dilemma of having to accept high-risk projects, which is similar to the research results of China's shadow banking system (Allen, 2019).Therefore, this thesis proposes the following hypothesis for the serious problems of moral hazard and adverse selection faced by P2P online lending platforms in China:

Hypothesis 3: The speculative effect of P2P platforms will prompt P2P platforms to expand the amount of lending.

3.4 Data

The data on P2P platforms used in the empirical analysis of this thesis is taken from China P2P lending dataset compiled by the *Home of online lending (Wangdaizhijia)*[5]. The data, reports, and opinions published by *Wangdaizhijia* are often regarded as most influential in the Chinese online lending industry. Apart from information on P2P platforms, macro-and industrial-level data are taken from the *WIND* database, which is produced by China's leading financial data service provider WIND[6].

We chose 2015-2019[7] as the sample period because this is the period when China's P2P lending industry was officially regulated. Before 2011, the P2P lending industry developed relatively slowly, and then began to see explosive growth in the following three years. With the brutal growth and rapid iteration, the business model of P2P

[5]Wangdaizhijia was established in October 2011 as China's first authoritative P2P online lending portal. It contains original data of all P2P platforms in China.

[6]WIND database is internationally recognized, and it has been widely used in academic research on China.

[7]In 2020, China's P2P platforms have realized zero clearance, so by the end of 2020, only the information of borrowers can be obtained, but the data of the lending platform cannot be obtained.

online lending industry was basically clear in the second half of 2014. Before the end of 2015, there were no clear regulations on P2P platforms in China (Huang, 2018)[8]. After 2015, the development of P2P online lending industry began to gradually stabilize. Therefore, the P2P online lending platform in this period is closer to the peers of micro, small and medium-sized enterprises, and more in line with the future development of China's P2P online lending industry. In order to avoid data interference caused by explosive growth, we selected 1041 P2P platforms in the sample period from 2015 to 2019. In order to ensure data uniformity, we eliminated platforms with abnormal operations, zero turnover platforms and platforms with incomplete information disclosure, and finally got 918 P2P platforms where we have monthly information for the period 2015-2019, which forms an unbalanced panel data set.The data analysis software used in this thesis is STATA[9].

3.5 Empirical models

We use the following fixed effect panel data model to explain total lending volume of P2P platforms during the sample period.

$$volume_{i,t} = \beta_0 + \beta_1 size_{i,t-1} + \beta_2 age_{i,t-1} + \beta_3 investor_{i,t-1} + \beta_4 borrower_{i,t-1} + \beta_5 duration_{i,t-1} + \beta_6 interest_{i,t-1} + \beta_7 growth_{i,t-1} + \beta_8 credit_{i,t-1} + \beta_9 internet_{i,t-1} + \beta_{10} volatility_{\ i,t-1} + \beta_{11} behaviour_{i,t-1} + f_i + \mathrm{f}_t + \varepsilon_{i,t} \quad (3.1)$$

In model (3.1) the dependent variable is P2P lending (**volume)** which is measured by

[8]Huang, R.H. (2018) Online P2P Lending and Regulatory Responses in China: Opportunities and Challenges, European Business Organization Law Review,19(1), 63-92.

[9]Stata is a complete and integrated statistical software that provides its users with data analysis, data management, and professional charting. It has many features, including linear blending model, balanced repetition, and polynomial Ploby mode, to efficiently process panel data.

the natural logarithm of the total monthly lending volume of the P2P firm. P2P lending is related to profitability of the P2P platform since the firm's revenue is proportional to its lending. Our key independent variable in model (3.1) is 'behaviour'. It stands for three behavioural aspects of P2P lending, i.e. lending sentiments, herding, and speculation, respectively. We explain how to construct the proxy for these behavioural aspects ('behaviour') in the next paragraph. In model (3.1), f_i and f_t are firm effects and time effects, respectively. β_i represents regression coefficients, *i* represents P2P platforms, *t* represents time (months), and ε is the residual.

We are interested in three aspects of P2P lenders' behaviour. Firstly, lending sentiments **(news1)**. It captures P2P lenders' overall perception of the P2P industry in response to positive P2P news release in the media,the reason why proxy variables can reflect investor sentiment can be explained when proxy variables are selected.. Media attention refers to the degree of media attention given to a certain object, and is published or reprinted every day with the name of the platform as the keyword of the amount of news. Generally, there are two methods of measuring media attention. One is to examine the influence of media on P2P platform through specific media time, and the other is to test the influence of media on the volume of P2P platform through an event study ,using the number of media releases as the proxy variable of media attention.We manuallycollect news titles published in the news column of the website of *Home of Online Lending (Wangdaizhijia).* We define positive news as either the news title explicitly containing positive words about P2P or the title's tone is positive about P2P; we then count the number of pieces of positive news within a month. We denote this measure as **'news1'**. This measure of positive news can be justified by the literature. For example, Garcia (2013) [10]constructs investor sentiment from media contents by counting the number of positive and negative words from two financial columns published in the New York Times. At present, the collection and identification of positive and negative information are mainly conducted through the comparison of negative and positive vocabulary, and the information is divided into positive, neutral and negative. Usually, the positive information involves steady operation, accumulated transaction amount, registered users, positive guidance, openness and transparency, positive image, authoritative release, industry forefront, etc. The negative information involves the fictitious background of the platform, such as fake state-owned assets, fake venture capital, fake bank deposit, fake listing background, fake resume of the executive team, etc. Negative news of platform shareholders, such as the investment shareholder is a deadweight, the equity of the investment enterprise is pledged, the lawsuit is tied up, the listed shareholder has been shorted recently, and the senior management team has a history of fraud; Senior personnel changes and equity changes; Gossip, such as slow withdrawals, late payments, thunderstorms, etc. Negative public opinion on the asset side, involving false labels, self-financing, non-compliance (such as over-limit) products, poor information disclosure, and high risk of poor borrower qualifications; Explosive news, such as restrictions on cash withdrawal or cash withdrawal difficulties, lost contact, criminal investigation and other vicious negative news. Netloan home has a special public opinion analysis database for third parties to download and use, you can directly match the data through the public opinion analysis system.The author finds that positive words embodied in the news help predict stock returns. We stress that the news column of *Home of Online*

[10]Garcia, D. (2013). Sentiment during Recessions, Journal of Finance, 68(3), 1267-1300.

*Lending(Wangdaizhijia)*is specific on the P2P industry and they mostly report on recent events in this industry both locally and nationwide. Given server information asymmetry and high uncertainty in China's P2P lending industry, we believe that P2P lenders would be very sensitive to the related news.

The second behavioural aspect we examine in the thesis concerns herding behaviour of P2P platforms (lenders). Although herding behaviour has been associated with P2P lenders outside China (e.g.Herzenstein, et al., 2010),[11] we are not aware of any evidence of herding in Chinese P2P online lending. In this thesis, herding refers to the situation in which P2P platforms mimic lending decisions of their peers. We define peers of a P2P platform as other P2P platforms in the same province in which the P2P platform operates. If a P2P platform herds, then we should observe that this P2P firm's lending will be driven by the lending decisions of its peers. If this is the case, then the lending volume of this P2P platform can be explained by the average lending volume of its peers. Therefore, we use the natural logarithm of the monthly average lending volume of other P2P firms in the same province (excluding the P2P firm of concern) as a proxy for herding (**herd1)**.

The third behavioural aspect we examine in this thesis is the speculative element of China's P2P lending. More specifically, we use the price inflation of the provincial commercial property market as a proxy for speculation (**speculation1**). Given that China's real estate market is perhaps the most representative industry that reflects bubbles in the Chinese economy, if P2P lenders are speculative, then we would expect P2P lending to be associated with the price inflation of commercial properties

[11] Herzenstein, M., U. M. Dholakia and R. L. Andrews (2010) Strategic Herding Behavior in Peer-to-Peer Loan Auctions, Journal of Interactive Marketing, 25(1), 27-36.

in the province in which the P2P platform operates. Therefore, from the *WIND* database we collect monthly information on total sales and the total sold area of commercial properties in the province. We then compute the ex post monthly unit selling price, which we calculate based on the monthly growth rate of the selling price of commercial properties in the province (**speculation1**).

In addition to the key independent variables mentioned above, we also control for common factors that affect P2P lending. We classify control variables in model (1) into two groups: characteristics of P2P platforms and macro-level variables. P2P platform-level variables include: (1) P2P size **(size),** which is measured by the natural logarithm of the registration capital of the P2P platform. (2) P2P age **(age)**, which is measured by the natural logarithm of the number of months since the P2P firm started operation in the online lending industry. The longer a P2P platform has been operating in the business, the more likely the firm has established a larger client network. But if P2P firms are speculative, then they do not have strong incentives to invest in risk management mechanisms, and they may only survive for a short-term due to fierce competition. (3) Number of investors (**investor**), which is measured by the natural logarithm of the total number of investors who have made at least one investment via this online lending platform. The total number of investors is relevant because it indicates the supply of funds available for P2P lending. (4) Number of borrowers **(borrower)**, which is measured by the natural logarithm of the total number of borrowers who have borrowed at least once from the P2P platform. The total number of borrowers is an indicator of the demand for P2P lending. (5) Loan duration **(duration)**. We use average loan duration to proxy for the length of outstanding loans. The platform reports its daily average loan duration across loans.

We calculate the average of daily average loan duration over a month. (6) P2P interest rate **(interest)**. It is the average of the P2P lending platform's daily interest rate over a month. The P2P platform reports its daily interest rate which is the weighted average interest rate across loans. The P2P interest rate carries two pieces of information. It is the rate of return for P2P lending, and it is also the cost of borrowing for borrowers. Table 3.1 is the description and interpretation of each variable.

We also consider the following macro-level factors as control variables: (1) Economic growth **(growth**), which is measured by GDP growth rate. Macroeconomic performance should be a fundamental driver for the growth of the P2P lending industry. As there is no monthly data on GDP growth, we use the quarterly growth rate of GDP for the corresponding month; the data is taken from *WIND*. (2) Total new credit **(credit**), which is measured by the ratio of total new credit to GDP in the same period. Total new credit refers to the total amount of new loans issued by banks and financial institutions in a month. Total new credit matters for the scale of P2P lending. This is because liquidity in the financial system affects both the demand for and supply of P2P financing through either the availability of liquidity or the changes in the interest rate in the financial system. Information about total new credit is taken from *WIND*. (3) Internet penetration **(internet)**, which is measured by the ratio of the population that has access to the internet to the total population in the same period. We collect the number of internet users in each month, and then scale it by total population in the corresponding month. The data is taken from *WIND*. The internet is the infrastructure for P2P transactions. (4) Stock market volatility **(volatility)**. We use domestic stock market volatility as a proxy for uncertainty embedded in the Chinese financial system. Participants in the P2P lending market should be responsive to financial market volatilities. More specifically, we first compute the monthly variance of the Shanghai composite index and the Shenzhen composite index, respectively, and then we take the average of monthly variances of the two stock markets. The data is taken from *WIND*.

Table 3.3 shows correlation coefficients. An average P2P platform in our sample has more investors than borrowers. The mean value of the logarithm of the total number of investors is 7.718 (median 7.583), whereas the mean value of the log of the total number of borrowers is 5.372 (median 4.878). The mean of the logarithm of loan duration is 1.329, which indicates that P2P online lending platforms mainly lend money for a short period. On average, over the sample period, the median number of positive news on P2P in a month is 5 (news1) and positive P2P news appeared in over half of the months (53.3%) covered by the sample period.

We use the following fixed effect panel data model[12] to explain the total lending volume of P2P platforms during the sample period.

3.6 Empirical results

Table 3.4 presents the results of estimating the empirical model (1) for the whole sample. Columns (1)-(3) in Table 3.4 refer to the estimation in which a specific measure of behavioural variable is used separately, and Column (4) reports the

[12]We include a few macro-level variables in the empirical model. The monthly observation of these variables is the same for all cross-section units (P2P platforms). This makes the GMM estimation procedure difficult to implement. Therefore, we use a panel data fixed effect model. We use the lagged-one observations of explanatory variables to consider the endogeneity issue.

results when all measures of behavioural variables are included in the estimation.

We first discuss the results regarding the behavioural variables. Overall, the estimated coefficients for indicators of behaviroural variables are all positively significant in Table 3.4, which suggests that China's P2P lending is indeed influenced by behavioural factors related to P2P lending platforms. More specifically, we observe that (a) P2P lending responds positively to positive news about the P2P industry (**news1**). From this result we conclude that P2P lenders show a stronger lending sentiment in response to more positive news on P2P. It is important to mention that this sentiment effect may also be reflected by other participants in the P2P lending market, including investors and borrowers. In P2P online lending, all the information that investors can obtain is the project information provided by the borrower or reported in response to the requirements of the platform and the dynamic publicity of the industry media, which is limited by insufficient information. In this context, although each investor is faced with the same information, the value judgment generated by the information is different. For those investors who lack relevant financial knowledge, they may not be able to accurately estimate the project risk, and they can only grasp it by referring to the media opinion. Just as the research results of Baker et al. (2006) show that investor sentiment is an analysis decision made by investors based on the concepts formed by the market information they have mastered and the expected results for the future. However, since the market is not a perfectly competitive market, it is inconsistent with the reality due to the existence of asymmetric information and other reasons. The real market does not have the above conditions, so the simplification of complex problems will lead to errors and deviations in investors' strategies, and investment concepts formed by existing information will then make decision-making behaviors, that is, investment sentiment will affect P2P lending.However, after controlling for both the supply side (investor) and the demand side (borrower) effects (see the empirical model (1)), we believe that the estimated coefficient regarding the variable '**news1**' should carry lending sentiments of P2P platforms. (b) Lending volume of a specific P2P platform is positively explained by lending volume of its peers. Column (2) of Table 3.4 shows that the estimated coefficient for the average lending volume of other P2P platforms in the same province (excluding the P2P firm of concern) (**herd1**) is highly and positively significant. This result suggests that herding behaviour is an important feature of China's P2P lending. This result is consistent with the literature on herding behaviour in P2P lenders in MMEs (e.g.Herzenstein, et al., 2010). On the P2P lending platform, potential investors can easily observe the bidding status of other investors, and their behavioral decisions are not completely based on their known information, but will make their own decisions according to the behavior of other participants. For example, investors are more inclined to choose to invest with the underlying loan order nearly full. These situations are the performance of limited rationality of investors, there is herd behavior, there may be group bias. From the perspective of individual behavioral decision making, investors will have corresponding behavioral reactions due to the interweaving of emotions, ideas and information in investment decision making. For example, the psychology of loss aversion exceeds the gain of return, which is risk preference. From the perspective of group influence, investors in the P2P lending market tend to form groups due to their similar investment objectives and psychology. The rapid spread of relevant news in the market will stimulate group emotions and pass them on to each other, thus showing similar behavioral rules, such as herd effect. Therefore, the final investment behavior of investors is the comprehensive result of the mutual influence of individual cognition and group cognition (Polk,2006). At the same time, individual risk preference behavior and group herding effect will affect investor sentiment through influencing related factors, such as transaction amount and transaction speed, after being impacted.(c)P2P lending is positively explained by the price inflation of commercial properties in the province (**speculation1**). This suggests that China's P2P lending is likely to be driven by bubbles in the real estate market. This result is consistent with Allen et al. (2019) who claim that more than half of China's non-affiliated entrusted loans, another element of the Chinese shadow banking system, flow into China's real estate industry. According to Allen, et al. (2019), this is because Chinese formal financing channels are restricted from investing in the real estate market; hence some investment in the real estate industry had to be financed by shadow banking activities. In the empirical analysis of this thesis, we consider this financing effect by controlling for total new credit (**credit**) in formal financing channels in the estimation. After controlling for liquidity from formal financing channels, we believe that the estimated coefficient for the price inflation of commercial properties (**speculation1**) can be seen as the evidence of speculation of P2P lending. China's real estate market is the most representative industry that reflects bubbles in the Chinese economy. The qualitative nature of the above-mentioned results remains in column (4) when three different behavioural factors are considered in the same estimation.

Regarding control variables in Table 3.4, we observe that (a) the estimated coefficient for P2P firm size (**size**) is insignificant. (b) the estimated coefficient for P2P firm age (**age**) is negatively significant in explaining P2P lending. This suggests that the longer the P2P firm has been operating in the industry, the less lending the firm makes. This result may be explained by the notion that many P2P platforms that entered into China's P2P lending market at earlier stages were less sustainable, and they have gradually disappeared from the market after late 2015 as the result of the government's clean up of this market. (c) the estimated coefficient for the number of investors (**investor**) is highly and positively significant. More investors imply stronger supply of funds, which supports P2P lending. (d) the estimated coefficient for the number of borrowers (**borrower**) is highly and positively significant, confirming the demand effect. (e) the estimated coefficient for average loan duration (**duration**) is not significant. (f) the estimated coefficient for P2P interest rate (**interest rate**) is positively significant, which suggests that high lending interest rates do not deter demand for P2P lending.

Regarding macro-level factors, the results show that (a) GDP growth (**growth**) positively explains the scale of P2P lending, which is logical. Strong overall economic performance increases the demand for financing from P2P lending on the one hand, and on the other it also increases the supply of capital available for P2P lending. (b) The estimated coefficient for total new credit (**credit**) is positively significant in columns (2)-(4), which suggests that when total new credit is higher in formal financing channels, P2P lending is also higher. This result can be explained by a few possibilities. First, P2P borrowers in China do not have access to formal financing channels to the extent they wish. If they do have sufficient access to formal financing, then when there is more liquidity available in formal financing channels, the demand for P2P financing should be lower. We find the opposite. Second, the overall interest rate may become lower when liquidity in formal financing channels is higher. Lower overall interest rate in the financial system provides downward pressure on interest rates charged by P2P lending, which might attract more borrowers to the P2P market. Third, there may be a liquidity leakage from formal financing channels to P2P lending. This means that when liquidity in formal financing channels is high, some funds will be leaked to informal financing channels, such as P2P lending. For example, some P2P platforms are set up as subordinates of SOEs. These SOEs can obtain cheaper loans from formal financing channels due to their connections with the government; they then use these borrowings to invest in P2P lending to seek higher capital gains.[13] Yao, et al. (2019) claim that there exists a "leakage effect" between SOEs and private equity (PE) investment in China. They argue that when the government controls the interest rate and/or the credit allocation, SOEs obtain funds from banks by the officially controlled interest rate. They then 'relend' their credits to PEs on the 'black' market. (c) The estimated coefficient for the internet accessibility (**internet**) is also highly and positively significant. The internet is the infrastructure for participants to carry out P2P transactions. (d) the estimated coefficient for stock market volatility (**volatility**) is negatively significant. This suggests that uncertainties embedded in the Chinese financial system not only discourage the supply of funds from investors but also reduce demand for P2P lending from borrowers due to weak real economic activities.

We conduct a set of robustness tests based on the whole sample by constructing alternative measures for behavioural aspects of P2P lenders. Firstly, we replace the variable **news1** by **news2.** The variable **news2** is a dummy variable, which takes the value of one if there appears to be positive news on P2P in this month,

[13] Although this is a plausible explanation, it appears to be very difficult to formally test it due to data restrictions.

otherwise it is zero. Similar to the construction of the variable **news1,** we define positive news as either the news title explicitly containing positive words about P2P or the title's tone is positive about P2P. Therefore, the difference between **news1** and **news2** is that **news1** isa count variable, whereas **news2** is a dummy variable. Secondly, we construct an alternative measure of herding. In the main test shown in Table 3.5, when constructing the proxy for herding (**herd1)**, we define peers of a P2P platform as other P2P platforms in the same province in which the P2P platform operates. Here in the robustness test, we define the peers of a P2P platform as other P2P platforms in the P2P industry (nationwide). Considering that we do not have information on the entire population of P2P platforms in the whole industry, we use the available P2P platforms in our sample. More specifically, we use the nature logarithm of the monthly average lending volume of other P2P platforms in our sample (excluding the P2P platform of concern) as the proxy for herding (**herd2**). Thirdly, regarding the proxy for speculation, in the main test shown in Table 3, we use the monthly growth rate of the selling price of commercial properties in the province (**speculation1**). Here in the robustness test we use the monthly growth rate of the total investment in the real estate industry (**speculation2**) as an alternative measure.

Table 3.5 displays the results of estimating empirical model (3.1) by using alternative measures of behavioural variables. As we can see from Table 3.5, the qualitative conclusion regarding these behavioural variables clearly confirms what we obtained in Table 3.4. In addition, the estimated results regarding control variables are also consistent with the results for these variables shown in Table 3.4.

In summary, both Table 3.4 and Table 3.5 provide evidence that P2P lending in China is influenced by different behavioural aspects of P2P platforms, including lending sentiments, herding, and speculation. The results of these behavioural aspects are robust across different ways of constructing proxies for behavioural factors. These results are obtained by controlling for other usual factors discussed in the literature that can explain P2P lending. In the P2P market, when investor sentiment is high, investors will pay attention to the information that is beneficial to investment transactions, and ignore the unfavorable news. As a result, investors will increase their investment intention, and the funds are sufficient or even excess, when faced with a lot of information, it is difficult for a single investor to conduct a comprehensive and in-depth analysis of all the information, and they cannot fully understand the problems they face. Even if the relevant information obtained from multiple channels is limited, it is difficult for individuals to update and respond to new information in a timely and effective manner, and they may ignore the existence of some important information, so there will be herding effect and herd mentality. In the P2P lending market, it is impossible for individuals to collect and analyze information and make a final decision completely in line with the market reaction. Moreover, in many cases, the results of individual behavioral decisions will deviate from rational decisions due to subjective factors, and the investment process will be affected by individual behaviors and groups. From the perspective of individual behavioral decision making, investors will have corresponding behavioral reactions due to the interweaving of emotions, ideas and information in investment decision making. For example, the psychology of loss aversion exceeds the gain of income, resulting in risk preference and speculative effect.

We argue that information asymmetry is severe in China between P2P platforms and borrowers on the one hand, and between P2P platforms and investors on the other. Both types of asymmetric information problem would enhance the likelihood that the lending decisions of P2P platforms are influenced by behavioural factors, such as lending sentiments, herding, and speculation. These behavioural aspects should be more important in explaining P2P lending when the degree of information asymmetry is larger between P2P platforms and investors. In this case, the adverse selection and moral hazard problems of P2P platforms are more severe, which leads to stronger influence of behavioural factors. In this section, we conduct another set of robustness tests by using subsamples. More specifically, we split the sample based on whether the P2P platform has adopted a fund custody mechanism. Since 2015 Chinese P2P regulations have been encouraging P2P platforms to adopt a fund custody mechanism. In response, some P2P platforms have signed agreements with commercial banks that are willing to provide custodian services for investor funds used for P2P lending transactions. Obviously, the adoption of a fund custody mechanism can reduce adverse selection and moral hazard problems between investors and P2P platforms. This is because in a fund custody mechanism commercial banks function as a monitor of P2P platforms on behalf of investors, which reduces the degree of asymmetric information between investors and P2P platforms. Therefore, it disincentivises P2P platforms to take on irresponsible or risky projects. This suggests that lending decisions made by P2P platforms that have a fund custody mechanism in place should be influenced by behavioural factors to a lesser extent as compared to P2P platforms that have not applied a fund custody mechanism. Therefore, we split the whole sample into P2P platforms that have adopted a fund custody mechanism versus P2P platforms that have not. We estimate the empirical model (1) for the two subsamples. The results are reported in Table 3.6 for P2P platforms with a fund custody mechanism and Table 3.7 for P2P platforms without a fund custody mechanism, respectively. For expositional purposes, we report the estimation results by using two alternative measures of behavioural variables in one table for each subsample.

Comparing Table 3.6 with Table 3.7, we observe that the results concerning control variables are very consistent with each other and they are in line with the results of these variables shown in both Table 3 and Table 4. However, differences do exist in the results regarding behavioural variables between Table 3.6 and Table 3.7. More specifically, we observe that (a) the estimated coefficients for both **news1** and **news2** are not significant for P2P firms that have adopted a fund custody mechanism in Table 3.6, whereas they are positively significant for P2P firms that have not in Table 3.7.The effect of investor sentiment on P2P platform is mainly reflected in its impact on the platform's financing efficiency and investment return. The systematic deviation of investors' future expectations will affect investors' decision-making behavior, and thus affect the financing efficiency and investment return of P2P platform. In the absence of fund custody, P2P lending has risks such as insufficient fund security, easy to form a fund pool, and illegal embezzlement of funds, and may become a quasi-financial intermediary. Some P2P platforms even publish false target information, raise funds for their own use, and become illegal fund-raising tools. At this time, P2P investors will pay more attention to external news, thereby reducing information asymmetry. Thus forming systematic investment deviation, resulting in investment increase and decrease; When investors' funds are held in custody, investors will think that the security of funds has been guaranteed to a certain extent, thus reducing the concern and worry about negative information from the outside world. This increased sense of security makes investors consider relatively little external information when making investment decisions. In addition, money custody provides a relatively simple environment for investors to make investment decisions. In the case of funds being managed, investors can focus more on the investment project itself provided by the platform, without paying too much attention to the fund operation and risk control of the platform. This simplification of investment decisions also makes investors less concerned about external information and more focused on the choice of investment projects and income expectations. (b) Although the estimated coefficient for **herd2** is positively significant for both subsamples, the estimated coefficient for **herd1** is not significant for P2P firms that have adopted a fund custody mechanism in Table 3.6, whereas it is positively significant for P2P firms that have not in Table 3.7. (c) Although the estimated coefficient for **speculation2** is positively significant for both subsamples,the estimated coefficient for **speculation1** is not significant for P2P firms that have adopted a fund custody mechanism (Table 3.6), whereas it is positively significant for P2P firms that have not adopted a fund custody mechanism (Table 3.7).

The fund custody mechanism means that the third-party payment platform opens a fund custody account for the P2P online lending platform, so that the funds of platform investors and borrowers can complete the lending process without going through the platform account, so as to avoid the risk of the platform's own capital pool and prevent the platform from running away with funds. When the investor refunds the investment, the funds are first transferred from the investor's bank account to the investor's escrow account of the third-party payment platform. If the loan is successful, the investor's funds are transferred to the borrower's bank account by the third-party payment platform; if the loan fails, the funds are returned to the investor by the third payment platform; When the borrower returns the principal and interest, the funds are first transferred from the borrower's bank account to the borrower's escrow account of the third-party payment platform, and then transferred to the investor by the third-party payment platform, and the P2P online lending platform only charges part of the handling fee. This shows that investor sentiment, herding effect and speculative effect are the analysis decisions and expected results of the future based on the concepts formed by the market information that investors have mastered. However, because the market is not a perfectly competitive market, there are asymmetric information and other reasons that lead to inconsistency with the reality. As far as capital storage is concerned, the government regulates the operation behavior of P2P platforms in the form of laws and regulations, reduces capital risks, attracts investors and promotes the healthy development of P2P platforms through the separation of capital flow and information flow. From another perspective, depositing funds in banks will undoubtedly increase the cost of the P2P platform to fabricate, conceal and fabricate false transaction information, and improve the authenticity of information about P2P platforms in the market. Therefore, P2P investors gradually become rational people and pay more attention to investment returns and investment risks. Instead of intervening in investment behavior through investment sentiment, herding and speculative effects.

The above-mentioned differences regarding results concerning behavioural factors suggest that P2P lending undertaken by P2P platforms that have not adopted a fund custody mechanism are more likely to be influenced by behaviroual factors than their counterparts. This may be explained by the fact that, regarding P2P platforms that have not adopted a fund custody mechanism, investors suffer more from adverse selection and moral hazard problems; consequently, P2P platforms are more likely to be irresponsible and risk-taking.

In summary, the subsample results not only support the results we obtained based on the whole sample regarding how behaviroural factors affect P2P lending, but also suggest that the influence of these behaviroural factors is more profound when information asymmetry between investors and P2P platforms is more severe.

3.7 Conclusion

Before 2015, there was a lack of regulation. In the case of information asymmetry and high uncertainty, the problem of adverse selection and moral hazard will become more serious, which will lead to the increase of risky behaviors of P2P online lending platforms. As a result, their lending decisions will be more likely to be influenced by behavioral factors such as lending sentiment, herding, and speculation. After 2015, along with the gradual establishment of the fund custody mechanism in China's P2P lending industry, the government has successively issued a series of regulatory policies for the P2P industry, with detailed regulations on fund storage, information disclosure, risk management and other aspects, providing clear guidance for the compliance development of the industry. Affected by the policy, the scale of the P2P industry has shrunk, some non-compliant P2P platforms have been closed or rectified, and the overall risk level of the industry has decreased. Compliance costs have increased, and some small P2P platforms have exited the market because they cannot afford the compliance costs.

We present evidence that the P2P lending market in China is significantly influenced by the behavioral factors of P2P platforms, in particular by multiple aspects of lending sentiment, herding, and speculation. In addition, the more serious the problem of information asymmetry between investors and P2P platforms, the more profound the behavioral effect. Specifically, when investors' funds are held in custody, they are less concerned about negative external information and less concerned about external information when making investment decisions. Investors can focus more on the investment projects provided by the platform, the selection of investment projects and income expectations. All these reflect the influence of information asymmetry faced by P2P lending market participants. This can be achieved by establishing a reliable credit evaluation system for borrowers in China, and in the case of P2P platforms, by establishing stricter regulations on risk management mechanisms, such as the mandatory application of fund custody mechanisms. In addition, some measures should be taken to strengthen the corporate governance of P2P platforms, avoid loan default from the perspective of borrowers, improve the governance level of P2P platforms, reduce the risk of loan default of borrowers, and promote the healthy development of P2P online lending industry. These research contents will be reflected in the following chapters.

The research conclusion of this paper has certain practical significance. In the accessible literature, it is proposed for the first time that P2P lenders' behavior is influenced by borrowing sentiment, herding effect and speculative behavior in many aspects. In addition, it further studies the influence of lending sentiment, herding effect and speculative behavior on platform lending under the fund custody mechanism. It provides a good choice for the government departments to introduce relevant policies to strengthen the information disclosure mechanism of lending and reduce the information asymmetry faced by investors. However, this paper also has some defects. For example, due to the limitation of data collection, borrowing sentiment, herding effect and speculative behavior are often measured by a single index, and the diminishing marginal utility of investors and other characteristics of behavioral factors are not further demonstrated, which is also the focus of further research in the future.

Table 3.1 Definitions of variables and data sources

Notation	Variable	Measurement of variables	Data source
volume	P2P lending volume	natural logarithm of total lending volume of the P2P platform	*Home of Online Lending (Wangdaizhijia)*
size	P2P size	natural logarithm of the registration capital of the P2P platform	*Home of Online Lending (Wangdaizhijia)*
age	P2P age	number of months since the P2P firm started operation in the online lending industry	*Home of Online Lending (Wangdaizhijia)*
investor	Number of investors	natural logarithm of total number of investors who have made at least one investment via the P2P platform	*Home of Online Lending (Wangdaizhijia)*
borrower	Number of borrowers	natural logarithm of total number of borrowers who have borrowed at least once from the P2P platform	*Home of Online Lending (Wangdaizhijia)*
duration	Loan duration	average loan duration of the P2P platform	*Home of Online Lending (Wangdaizhijia)*
interest	P2P interest rate	average of daily interest rate over a moth of the P2P firm	*Home of Online Lending (Wangdaizhijia)*
growth	Economic growth	GDP growth rate	*WIND*
credit	Total new credit	ratio of total new credit to GDP in themonth. New credit refers to total amount of new loans issued by banks and financial institutions in a month	*WIND*
internet	Internet penetration	the ratio of population who has access to the internet to total population in the same month	*WIND*
volatility	Stock market volatility	average of the monthly variances of Shanghai composite index and the Shenzhen component index	*WIND*
News1	Number of positive news release on P2P	number of positive news on P2P in a month	*Home of Online Lending (Wangdaizhijia)*
News2	Whether there is positive news on P2P	A dummy variable which takes the value of one if there is a positive news release in the month regarding P2P, otherwise it is zero	*Home of Online Lending (Wangdaizhijia)*
Herd1	Herd on peers in the same province	The natural logarithm of the average lending volume of other P2P firms in the same province (excluding the P2P firm of concern) in the month	*Home of Online Lending (Wangdaizhijia)*
Herd2	Herd on peers in the P2P industry	The nature logarithm of the average lending volume of other P2P firms in our sample (excluding the P2P firm of concern) in the month	*Home of Online Lending (Wangdaizhijia)*
Speculation1	The price inflation of the real estate market	The monthly growth rate of the selling price of the provincial commercial housing	*WIND*
Speculation2	Growth rate of total investment in the real estate industry	The monthly growth rate of total investment in the real estate industry	*WIND*
Fund custody	Whether the P2P uses a fund custody mechanism	A dummy variable which takes the value of one if the P2P platform adopts a fund custody mechanism, otherwise, it is zero.	*Home of Online Lending (Wangdaizhijia)*

Table 3.2 Descriptive Statistics

Variable	Obs.	Mean	Medium	SD	Min	Max
volume	17008	8.349	8.286	1.783	2.950	12.790
size	17008	35.230	34.000	15.490	1.000	143.000
age	17008	8.442	8.517	1.030	4.700	12.660
investor	17008	7.718	7.583	2.014	0.000	15.070

borrower	17008	5.372	4.828	2.345	0.000	15.330
duration	17008	1.329	1.290	0.756	0.000	4.709
interest	17008	0.093	0.092	0.036	0.000	0.727
growth	17008	6.745	6.800	0.180	6.200	6.900
credit	17008	6.961	6.006	3.713	1.833	17.070
internet	17008	10.450	10.500	0.206	9.956	10.710
volatility	17008	5.467	5.420	0.510	4.546	6.965
news1	17008	6.194	5	7.609	0	38
news2	17008	0.533	1.000	0.499	0.000	1.000
herd1	17008	9.764	9.797	0.278	7.709	10.080
herd2	17008	9.426	9.779	1.031	3.839	12.540
speculation1	17008	1.042	0.440	4.570	-29.640	28.910
speculation2	17008	0.195	0.170	0.431	-0.975	2.962

Notes:

Table 3.2 summarises descriptive statistics of the variables used in the empirical analysis.This table presents summary statistics for variables used in the empirical analysis of this thesis. The sample covers 918 P2P platforms in China during 2015-2019. Definitions of variables and their respective data sources are in the Appendix.

Table 3.3 Correlation Analysis

This table presents correlation coefficients for variables used in the empirical analysis of this thesis. The sample covers 918 P2P platforms in China during 2015-2019. Definitions of variables and their respective data sources are in the Appendix.*, **, ***, represent significance at the 10%, 5%, and 1% levels, respectively.

	volume	size	age	investor	borrower	duration	interest	growth	credit	internet	volatility	news1	news2	herd1	herd2	speculation1
volume	1															
size	0.2328***	1														
age	0.3721***	0.0823***	1													
investor	0.8879***	0.2834***	0.3550***	1												
borrower	0.7127***	0.3381***	0.2773***	0.7717***	1											
duration	0.5279***	0.2813***	0.2620***	0.5489***	0.5286***	1										
interest	0.1067***	-0.0555***	-0.0315***	0.2250***	0.1982***	0.1396***	1									
growth	0.0936***	-0.3107***	0.0285***	0.0518***	-0.0510***	-0.015*	0.1597***	1								
credit	0.1443***	-0.0185***	0.0168***	0.0955***	0.0750***	0.0632***	0.0260***	0.5784***	1							
internet	0.1704***	-0.0900***	0.0211***	0.1168***	0.0616***	0.0576***	0.0511***	0.6515***	0.8178***	1						
volatility	-0.0435***	-0.0924***	-0.00110	-0.0165***	-0.0451***	-0.0383***	0.0563***	-0.1613***	-0.3857***	-0.2607***	1					
news1	0.002	0.0743***	0.0013	-0.0049	0.0274***	0.0230***	-0.0192***	0.0610***	0.1342***	-0.0733***	-0.2229***	1				
news2	0.0270***	-0.0893***	0.00630	0.00790	-0.0141	-0.0100	0.0306***	0.1843***	0.3640***	0.1949***	-0.0745***	0.7778***	1			
herd1	0.4362***	0.1033***	0.1012***	0.3684***	0.2966***	0.2651***	0.0153***	0.1730***	0.3849***	0.4754***	-0.0997***	-0.035*	0.0339***	1		
herd2	0.5854***	0.0971***	0.2045***	0.5147***	0.3962***	0.3801***	0.0400***	0.1144***	0.1666***	0.2073***	-0.0413***	0.0019	0.0224***	0.5114***	1	
speculation1	0.0198***	-0.0117	0.00860	0.0224***	0.00230	0.00170	-0.00940	-0.0261***	-0.0711***	-0.0403***	0.0602***	-0.047*	-0.0316***	0.00750	0.0326***	1
speculation2	0.0111	0.00410	0.0180**	0.0113	0.0102	0.0141*	0.0006	0.0254***	0.0531***	0.0989***	0.1033***	0.0435*	0.1845***	0.0553***	0.0096	0.0103

Table 3.4 Impact of behavioural factors on P2P lending: main test on the whole sample

	news1	herd1	speculation1	ALL
	(1)	(2)	（3）	(4)
$size_{t-1}$	0.175	0.187	0.187	0.167
	(1.53)	(1.62)	(1.62)	(1.47)
age_{t-1}	-0.016***	-0.016***	-0.016***	-0.016***
	(-22.52)	(-22.06)	(-22.08)	(-21.42)
$investor_{t-1}$	0.387***	0.362***	0.362***	0.372***
	(46.22)	(43.10)	(43.89)	(44.24)
$borrower_{t-1}$	0.125***	0.114***	0.114***	0.119***
	(19.42)	(17.55)	(17.74)	(18.48)
$duration_{t-1}$	0.012	0.016	0.016	-0.002
	(0.91)	(1.15)	(1.19)	(-0.11)
$interest_{t-1}$	1.740***	0.807***	0.804***	1.764***
	(6.00)	(2.84)	(2.84)	(6.12)
$growth_{t-1}$	0.211***	0.479***	0.476***	0.285***
	(4.06)	(9.54)	(9.59)	(5.60)
$credit_{t-1}$	0.001	0.006**	0.006**	0.005*
	(0.18)	(2.19)	(2.33)	(1.70)
$internet_{t-1}$	0.470***	0.099*	0.103**	0.245***
	(8.66)	(1.90)	(2.13)	(4.56)
$volatility_{t-1}$	-0.066***	-0.109***	-0.110***	-0.054***
	(-5.86)	(-9.82)	(-9.89)	(-4.78)
$news1_{t-1}$	0.003***			0.069***
	(3.55)			(6.12)
	0.001* **			**0.019*** **
$herd1_{t-1}$		0.009***		0.522***
		(3.29)		(12.33)
		0.002* **		**0.081*** **
$speculation1_{t-1}$			0.003***	0.003***
			(2.65)	(2.64)
			0.001* **	**0.001*** **
cons	-2.014*	0.244	0.304	-5.113***
	(-1.81)	(0.22)	(0.27)	(-4.53)
N	15394	15394	15394	15394
R-squared	0.338	0.325	0.326	0.346
Adj-R-squared	0.299	0.285	0.286	0.307
F	665.0	636.9	637.9	583.4

Notes:

This table presents the results of estimating the empirical model (1) based on the whole sample in which P2P lending is explained by measures of behaviour variables (news1, herd1, and speculation1). Other relevant factors are controlled. Definitions of variables and their respective data sources are in the Appendix. *, **, ***, represent significance at the 10%, 5%, and 1% levels, respectively. The standardization coefficients of significant behavioral variables are shown in bold.

Table 3.5 Impact of behavioural factors on P2P lending: robustness test on the whole sample

	news2	herd2	speculation2	ALL
	(1)	(2)	（3）	(4)
$size_{t-1}$	0.174	0.178	0.199*	0.168
	(1.52)	(1.55)	(1.73)	(1.49)
age_{t-1}	-0.016***	-0.016***	-0.016***	-0.016***
	(-21.51)	(-21.44)	(-22.75)	(-22.24)
$investor_{t-1}$	0.387***	0.346***	0.365***	0.368***
	(46.24)	(40.47)	(44.47)	(43.31)
$borrower_{t-1}$	0.125***	0.107***	0.113***	0.117***
	(19.38)	(16.38)	(17.70)	(18.08)
$duration_{t-1}$	0.013	0.003	0.018	-0.012
	(0.96)	(0.19)	(1.31)	(-0.90)
$interest_{t-1}$	1.717***	0.816***	0.714**	1.786***
	(5.93)	(2.86)	(2.53)	(6.19)
$growth_{t-1}$	0.268***	0.488***	0.396***	0.0540
	(5.25)	(9.73)	(7.96)	(1.03)
$credit_{t-1}$	0.002	0.006**	0.004	0.003
	(0.81)	(2.25)	(1.56)	(1.00)
$internet_{t-1}$	0.446***	0.017	0.198***	0.532***
	(8.66)	(0.33)	(4.08)	(9.61)
$volatility_{t-1}$	-0.060***	-0.107***	-0.128***	-0.077***
	(-5.25)	(-9.58)	(-11.49)	(-6.82)
$news2_{t-1}$	0.062***			0.041***
	(5.48)			(3.77)
	0.017***			**0.011*****
$herd2_{t-1}$		0.102***		0.177***
		(7.98)		(13.47)
		0.058***		**0.108*****
$speculation2_{t-1}$			0.153***	0.182***
			(13.03)	(15.45)
			0.390***	**0.464*****
cons	-2.194**	0.404	-0.117	-2.891***
	(-1.98)	(0.36)	(-0.11)	(-2.63)
N	15394	15394	15394	15394
R-squared	0.339	0.326	0.333	0.354

Adj-R-squared	0.299	0.285	0.294	0.315
F	667.4	626.2	659.8	592.6

Notes:

This table presents the results of estimating the empirical model (1) based on the whole sample in which P2P lending is explained by alternative measures of behaviour variables (news2, herd2, and speculation2).Other relevant factors are controlled. Definitions of variables and their respective data sources are in the Appendix. *, **, ***, represent significance at the 10%, 5%, and 1% levels, respectively. The standardization coefficients of significant behavioral variables are shown in bold.

Table 3.6 Impact of behavioural factors on P2P lending: P2P platforms with a fund custody mechanism

	news1	herd1	speculation1	ALL1	news2	herd2	speculation2	ALL2
$size_{t-1}$	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
age_{t-1}	-0.038***	-0.038***	-0.038***	-0.038***	-0.038***	-0.038***	-0.038***	-0.038***
	(-13.63)	(-13.96)	(-13.90)	(-13.64)	(-13.79)	(-13.76)	(-14.15)	(-13.91)
$investor_{t-1}$	0.399***	0.407***	0.399***	0.408***	0.398***	0.386***	0.401***	0.388***
	(13.52)	(13.46)	(13.49)	(13.44)	(13.48)	(12.99)	(13.70)	(13.17)
$borrower_{t-1}$	0.131***	0.132***	0.131***	0.132***	0.131***	0.128***	0.128***	0.124***
	(6.74)	(6.78)	(6.70)	(6.73)	(6.73)	(6.56)	(6.62)	(6.43)
$duration_{t-1}$	0.061*	0.062*	0.059*	0.060*	0.061*	0.0500	0.063*	0.0510
	(1.71)	(1.74)	(1.65)	(1.67)	(1.73)	(1.40)	(1.78)	(1.45)
$interest_{t-1}$	5.586***	5.797***	5.548***	5.786***	5.530***	5.178***	5.425***	5.042***
	(4.29)	(4.42)	(4.26)	(4.40)	(4.24)	(3.97)	(4.20)	(3.89)
$growth_{t-1}$	0.815***	0.740***	0.802***	0.749***	0.821***	0.872***	0.721***	0.781***
	(3.70)	(3.29)	(3.65)	(3.31)	(3.70)	(3.97)	(3.30)	(3.51)
$credit_{t-1}$	0.015	0.017*	0.017	0.016	0.018*	0.016	0.018*	0.016
	(1.41)	(1.65)	(1.62)	(1.50)	(1.69)	(1.52)	(1.72)	(1.46)
$internet_{t-1}$	0.786***	0.954***	0.822***	0.924***	0.834***	0.655***	0.905***	0.731***
	(3.55)	(4.05)	(3.87)	(3.74)	(3.90)	(2.98)	(4.27)	(3.32)
$volatility_{t-1}$	-0.253***	-0.245***	-0.250***	-0.247***	-0.247***	-0.253***	-0.271***	-0.276***
	(-5.82)	(-5.66)	(-5.79)	(-5.66)	(-5.66)	(-5.89)	(-6.28)	(-6.32)
$news1_{t-1}$	0.002			0.001				
	(0.55)			(0.41)				
$herd1_{t-1}$		0.162		0.155				
		(1.30)		(1.24)				
$speculation1_{t-1}$			0.001	0.001				
			(0.37)	(0.33)				
$news2_{t-1}$					0.024			0.011

					(0.53)			(0.24)
herd2$_{t-1}$						0.160***		0.163***
						(2.75)		(2.83)
						0.093***		**0.095*****
speculation2$_{t-1}$							0.181***	0.185***
							(3.76)	(3.79)
							0.044***	**0.045*****
cons	-5.476**	-5.211**	-5.760***	-5.021**	-6.028***	-5.949***	-5.928***	-6.001***
	(-2.53)	(-2.43)	(-2.74)	(-2.29)	(-2.79)	(-2.84)	(-2.84)	(-2.81)
N	876	876	876	876	876	876	876	876
R-squared	0.526	0.527	0.526	0.527	0.526	0.53	0.534	0.538
Adj-R-squared	0.498	0.498	0.497	0.497	0.498	0.502	0.506	0.509
F	91.56	91.85	91.52	76.41	91.55	93.08	94.47	79.97

Notes:

This table presents the results of estimating the empirical model (1) for the subsample of P2P firms that have adopted a fund custody mechanism. P2P lending is explained by measures of behaviour variables after controlling for other relevant factors. Definitions of variables and their respective data sources are in the Appendix. *, **, ***, represent significance at the 10%, 5%, and 1% levels, respectively. The standardization coefficients of significant behavioral variables are shown in bold.

Table 3.7 Impact of behavioural factors on P2P lending: P2P platforms without a fund custody mechanism

	news1	herd1	speculation1	ALL1	news2	herd2	speculation2	ALL2
size$_{t-1}$	0.153	0.153	0.153	0.154	0.154	0.146	0.164	0.157
	(1.33)	(1.33)	(1.33)	(1.34)	(1.34)	(1.27)	(1.44)	(1.38)
age$_{t-1}$	-0.014***	-0.014***	-0.014***	-0.014***	-0.014***	-0.014***	-0.015***	-0.014***
	(-19.05)	(-19.14)	(-19.16)	(-19.07)	(-18.65)	(-18.42)	(-19.80)	(-18.74)
investor$_{t-1}$	0.360***	0.359***	0.360***	0.359***	0.359***	0.347***	0.362***	0.349***
	(42.00)	(41.24)	(42.01)	(41.20)	(41.96)	(39.72)	(42.53)	(40.13)
borrower$_{t-1}$	0.114***	0.113***	0.114***	0.113***	0.113***	0.108***	0.113***	0.107***
	(16.70)	(16.53)	(16.75)	(16.57)	(16.65)	(15.77)	(16.76)	(15.77)
duration$_{t-1}$	0.014	0.014	0.014	0.014	0.014	-0.002	0.016	0.001
	(0.99)	(0.99)	(0.99)	(0.98)	(1.00)	(-0.11)	(1.13)	(0.02)
interest$_{t-1}$	0.400	0.394	0.387	0.379	0.380	0.322	0.306	0.216
	(1.38)	(1.35)	(1.33)	(1.30)	(1.31)	(1.11)	(1.06)	(0.75)
growth$_{t-1}$	0.476***	0.483***	0.478***	0.477***	0.498***	0.483***	0.399***	0.414***
	(9.27)	(9.39)	(9.41)	(9.17)	(9.75)	(9.53)	(7.84)	(8.09)
credit$_{t-1}$	0.006**	0.007**	0.007***	0.007**	0.004	0.007***	0.005*	0.004
	(2.40)	(2.53)	(2.69)	(2.53)	(1.33)	(2.63)	(1.92)	(1.36)
internet$_{t-1}$	0.068	0.053	0.060	0.060	0.082*	-0.004	0.155***	0.098*

	(1.32)	(0.99)	(1.21)	(1.07)	(1.65)	(-0.07)	(3.12)	(1.93)
$volatility_{t-1}$	-0.100***	-0.101***	-0.101***	-0.101***	-0.093***	-0.103***	-0.119***	-0.117***
	(-8.67)	(-8.80)	(-8.87)	(-8.74)	(-7.99)	(-8.99)	(-10.39)	(-10.03)
$news1_{t-1}$	0.001***			0.001***				
	(3.38)			(3.46)				
	0.001* **			**0.001*** **				
$herd1_{t-1}$		0.015***		0.010***				
		(4.46)		(4.34)				
		0.004* **		**0.002*** **				
$speculation1_{t-1}$			0.003***	0.003***				
			(3.04)	(3.05)				
			0.009* **	**0.009*** **				
$news2_{t-1}$					0.040***			0.021*
					(3.42)			(1.80)
					0.011* **			**0.006* **
$herd2_{t-1}$						0.185***		0.186***
						(7.43)		(7.53)
						0.145* **		**0.145*** **
$speculation2_{t-1}$							0.151***	0.149***
							(12.49)	(12.29)
							0.036* **	**0.035*** **
cons	0.800	0.797	0.881	0.790	0.461	0.905	0.452	0.314
	(0.72)	(0.71)	(0.79)	(0.71)	(0.41)	(0.82)	(0.41)	(0.28)
N	14518	14518	14518	14518	14518	14518	14518	14518
R-squared	0.316	0.316	0.316	0.316	0.316	0.319	0.323	0.326
Adj-R-squared	0.275	0.275	0.275	0.275	0.275	0.278	0.283	0.286
F	574.5	574.5	575.7	487.1	576.0	581.8	595.2	510.5

Notes:

This table presents the results of estimating the empirical model (1) for the subsample of P2P firms that have not adopted a fund custody mechanism. P2P lending is explained by measures of behaviour variables after controlling for other relevant factors. Definitions of variables and their respective data sources are in the Appendix. *, **, ***, represent significance at the 10%, 5%, and 1% levels, respectively. The standardization coefficients of significant behavioral variables are shown in bold.

Chapter 4: Influencing factors of P2P loan default

4.1 Introduction

The rapid development of information technology has reduced the necessity of traditional financial intermediaries. As a typical mode of Internet finance, P2P online lending platform has developed rapidly and spread rapidly in China's financial market, and has now become an important part of China's Internet financial market. Since the birth of Zopa in the UK in 2005, P2P online Lending has shown a rapid development momentum, with Prosper, Lending Club and Smava in Germany appearing successively. Since its inception, P2P lending has been welcomed by the vast number of borrowers for its high efficiency, convenience, simple procedures and quick approval. In the P2P lending platform model, members who lend money and members of wealth management exchange information through the online platform, which ultimately leads to unsecured small loans (Linetal, 2009). Hulme (2006) and Meyer (2007) are very optimistic about the future development of online credit models, and the role of the Internet in financial transactions will continue to grow. Compared with developed countries such as the United Kingdom and the United States, online lending in China started relatively late.

However, due to the long-term regulatory vacuum in the initial exploration and savage expansion stage, the platform has gradually deviated from the legal positioning of pure information intermediary, and has begun to implement rigid payment for investors, promising to guarantee the principal and interest. When the borrower fails to repay the loan due to the deadline, the platform will advance the payment in advance, and gradually become the role of credit intermediary, which has also become an important incentive for the large-scale surge of industrial thunder. In the long run, when bad debts exceed expectations and the platform's capital chain breaks, the platform collapses,platformruns away and other vicious events, creating serious industrial chaos, and the comprehensive compliance rectification measures of the regulatory authorities are unable to effectively prevent and control various kinds of accumulated financial risks. An important problem in the P2P lending market is the information asymmetry between the lending platform and the borrower, that is, the lender or platform does not know the credit status of the borrower. This information asymmetry may lead to problems such as moral hazard and adverse selection (Smith 2016). The risks of P2P lending mainly involve three aspects: first, the borrower needs to make adverse selection; Another reason is that borrowers lack experience with new ways of borrowing. Secondly, the comprehensive evaluation of borrower information by P2P lending platforms is inaccurate, leading to the failure of borrowers to repay on time (Freedman et al., 2014). Under the background of the withdrawal of P2P platforms, the amount of credit industry in China's P2P network normal operation platform continues to decline sharply, and behind the rapid development of the P2P industry, there are also a series of problems. Various risks emerge in an endless stream, the lack of supervision is prominent, the problem platform emerges in an endless stream, and the problem of platform operation is widespread. According to the home of net credit website (https://www.wdzj.com/news/), according to the information by the end of December 2019, the normal operation of P2P network platform loan number fell to 343, less than at the end of 2018, 732.The total transaction volume of the P2P online lending industry is 8.99 trillion yuan, and the total loan balance of the normal operating platforms of the P2P online lending industry is 491.591 billion yuan, with a year-on-year decrease of 37.69% at the end of December 2018, a decrease of about 297.4 billion yuan.

By the end of December 2019, the total number of shutdowns and problem platforms in the

P2P lending industry had reached 6,269, and the total number of shutdowns and problem platforms was 6,612 (including suspenations and problems platforms) in the P2P online lending industry. By November 2020, Liu Fushou, chief lawyer of China Banking and Insurance Regulatory Commission, said that the actual operation of P2P online lending institutions in China was completely zero.

At this point, China's P2P industry has experienced a parabolic development of start-up, growth, development, outbreak and closure.Its original intention was to promote social and economic development and realize people's yearning for a better life through the innovation of Internet finance and private lending. However, due to the lack of long-term planning and effective supervision in the development process, the legal positioning of the platform graduallylost, with serious internal unrest in the industry, unfair competition, mechanism mutation, difficulty preventing and controlling risks, and the absolute pursuit of interests. In the end, the entire industry collapsed. How to guide the platform compliance transformation and promote the development of P2P industry according to laws and regulations has become a problem requiring urgent solutions. Therefore, what personal characteristics of borrowers can lead to P2P loan default?

The high risk of online lending platforms mainly comes from two aspects. On the one hand, the government has strengthened the credit supervision, which makes it difficult for many online lending platforms to develop under external pressure. On the other hand, as the online loan is an unsecured loan, the default cost of the borrower is low. If a large number of customers default, the accounts cannot be collected, the platform capital flow stagnates, and the platform cannot withdraw funds normally, which threatens the sustainable and stable operation of the platform. Therefore, personal credit risk has become one of the main risks faced by online lending platforms. In this context, it is particularly important to study the factors affecting the default risk of borrowers on the platform.

Domestic lending platforms attach great importance to their own risk control, and the overdue risk of lending platforms is an important part of risk control. The borrower needs to fully state the basic information of the borrower on the loan platform, such as the borrower's age, monthly income, etc. Through the basic information provided by the borrower, the lender will evaluate the information provided by the borrower, and based on the evaluation, the lender will choose whether to lend.

This paper aims to study the impact of the basic information provided by the borrower on whether the borrower eventually delays, and if so, what factors in the basic information provided by the borrower ultimately affect the borrower's overdue. What are the main influencing factors in the basic information of borrowers, and whether these main influencing factors have a significant impact on the overdue rate is an important research content of this paper.

This paper selects the transaction data of P2P platforms of Renrendai, PPDai and Yirendai for nearly 5 years from 2016 to 2020. The research results show that 11 borrower characteristic information variables, including gender, age, education level, marital status, credit score, credit limit, overdue times, income, working hours, real estate information and automobile information, have a significant impact on loan default. Borrowers' mortgage and auto loan information had no significant impact on loan defaults. Then we selected significant impact indicators to evaluate these three online lending platforms, and the results showed that Renrendai had the highest level of risk control.

It provides help for domestic P2P online lending platforms to improve the level of risk control, which is conducive to domestic investors to better identify risks and effectively safeguard their own interests. The practical significance of this study is to verify the effectiveness of the platform's risk control and find out the main influencing variables of whether the borrowers provide the information on time repayment by studying the influencing factors of overdue loans. On this basis, the paper analyzes the differences of China's online lending platforms in risk control mode and basic architecture, and provides experience for China's P2P online lending platforms to improve their own risk security.

4.2 Literature review

In terms of the demographic characteristics of borrowers,the study of Herzenstein et al. (2008) shows that in terms of the availability of loans, African Americans do not find it easy to obtain loans. However, the borrower's demographic characteristics, such as race and gender, had little effect on the success of the loan. If you want to succeed in obtaining loans, your own financial ability and capital acquisition ability are extremely important. This thesis analyses that financial factors are very important while demographic characteristics are not important at all for the success of borrowing on P2P lending platforms. However, demographic factors will directly affect whether the loan can be successful and whether the loan interest rate is high or low because of their influence on the financial situation to a certain extent. Ravina (2007) also conducted a related study, which showed that when other conditions of two borrowers were basically the same, the attractive borrower would have more advantages. Data showed that the attractive borrower was 1.41% more likely to succeed in borrowing and would also get a lower borrowing interest rate, which would be

0.81% lower. Pope and Sydnor (2008), through data research, concluded that ethnic characteristics would have a certain impact on the evaluation of loan success rate and loan interest rate. Specifically, under the same credit conditions, the probability of successful borrowing for African Americans is 25%-34% lower than that of whites, and the borrowing interest rate is 0.6%-0.8% higher than that of whites. Regarding the expected probability of return, the total loan amount of African Americans is also lower than that of whites, because the higher annual interest rate of African American loans cannot cover a very high default rate. The study also shows that age is a very important factor affecting the probability of borrowing success: the probability of borrowing success is 0.4~0.9% higher for those under 35 years old than for those 35-60 years old, while the probability of borrowing success is 1.1-2.3% lower for those over 60 years old than for those 35-60. In addition, single women obtain lower borrowing rates than similarly qualified men. Barasinska et al. (2009) studied the basic situation of the lender and the choice of the lender in P2P lending platform, and the study showed that, for the lender, gender difference would affect the choice of the borrower under the same conditions. Female lenders tend to choose less risky borrowers with higher interest rates; however, female lenders were more likely to be influenced by irrational and compassionate investment choices, and physically attractive people were more likely to get lower interest rates.

For the detailed analysis of the characteristics of borrowers, the research of Sonenshein et al. (2011) is very representative. The study found that when borrowing, some auxiliary detailed descriptions of the borrowing situation can helpborrowers with low credit ratings to win the trust of investors and obtain success. However, when borrowers describe the purpose of the loan and themselves in too much detail, such borrowers tend to have a high default rate. Therefore, for the borrower, a detailed description of the borrowing situation is conducive to obtaining loans, but for the lender, too much attention is paid to the descriptive information of the borrower, which is not the most rational behaviour for investment, and will bear more risks. Ravina (2007) pointed out that race, gender, weight, appearance, age and other characteristics are important factors for successful access to P2P network lending, but Herzenstein, Andrews, Dholakia and Lyandres (2010) pointed out that characteristics such as race and gender had little effect on the success of obtaining a loan.Gonzalez et al. (2014) studied the impact of personal characteristics of borrowers on online lending decisions, and the research results showed that gender, age and appearance of borrowers affected their success rate of borrowing.

In the borrower's credit characteristics research.In the past years, there have been many studies on the credit riskin the P2P lending market. Klafft (2008) studied the data of borrowers on Prosper platform and showed that the credit rating of borrowers had a great impact on their borrowing interest rate. However, although the ratio of debt to income had a significant impact on the borrowing interest rate, it was not the most important factor. Other information about borrowers, such as the existence of the borrower's bank account and verification of whether the borrower owns property, had little effect on the interest rate of the loan. Another study in this thesis shows that the success of borrowing is closely related to the existence of the borrower's bank account and the borrower's credit rating. Freedman and Jin (2008) analysed the data of Prosper platform and found that after the platform raised the requirements for borrowers, it required users to provide more information related to their own financial situation when submitting applications, and the success rate of the platform's borrowing increased significantly. The empirical research of this platform shows that more financial information provided by borrowers has a very important impact on the success of loans. Lee et al. (2009) found that the credit rating of the borrower issued by the third party was not the only factor affecting the completion of the transaction, and its related explanatory information also played a significant role. To be specific, borrowers have different borrowing rates, which are largely influenced by their own credit rating, but about 28% of the cases cannot be explained by the credit rating of the borrower, but are explained by other relevant information about the borrower. In the actual lending process, investors will distinguish the creditworthiness of borrowers according to other relevant descriptions of borrowers. Puro et al. (2010) used logistic regression models to develop a model that measures the possibility of default of borrowers, so as to help lenders make reasonable borrowing decisions and effectively avoid some risks. In the construction of the model, the independent variables are the borrower's credit rating, borrowing amount, borrowing rate, debt-to-income ratio and current overdue finance, etc.Emekter et al. (2015) studied the impact of credit rating on the credit risk of online lending and found that the credit rating of borrowers is inversely proportional to the incidence of default risk. The higher the credit rating, the lower the default rate, and the lower the credit rating, the higher the default rate.

In the borrower's work characteristics research. Freedman and Jin(2008) believe that the increase in the average borrowing rate on Prosper is due to the addition of more financial information about borrowers on the Prosper platform, such as current income level, job status, and occupation. Riza et al. (2015) measured debt-to-income ratio, FICO score, revolving credit ratio, and the number of credit inquiries in the last 6 months. The annual household income is an important indicator to measure the repayment ability of borrowers, and the income of borrowers is sufficient to indicate the financial affordability of borrowers, and the level of family income directly affects the default probability of borrowers. In most of the past literature on the default risk of other loans, the total household income of borrowers serves as an important indicator of the borrower's ability to repay the mortgage loan.

In the borrower's asset characteristics research.Shen (2009) found that Prosper's credit audit of borrowers requires not only detailed personal information, but also information about loan records and social relationships. The credit records of borrowers provided by third-party credit institutions cooperating with Prosper platform are also examined. Detailed personal information includes age, city of residence, marital status, basic financial information, etc., loan records include lending record, repayment record, FICO score, etc., and social relationships including family and friends, etc. Prosper selects high-quality borrowers through a comprehensive credit review system, strict credit rating, and information review.The asset characteristics of borrowers have a certain impact on the default rate of borrowers (Greiner and Wang, 2009). Borrowers who own real estate and have purchased cars have relatively strong economic strength, relatively stable income, and certain sources of repayment. Chen and Han compared P2P lending practices in China and the United States and found that both ‘soft’ and ‘hard’ credit information had a profound impact on lending outcomes in both countries, but that Chinese lenders relied more on ‘soft’ credit information (Chen and Han 2015). Carlos (2015) made use of the data from the official website of Lending Club and selected variables such as loan purpose, borrower income, current housing status, credit history, debt status,etc.Chen, Zhou, and Wan (2016) discussed the relationship between the social capital of people's groups and their lending results in the P2P lending market.

In addition to the factors related to borrowers themselves, the impact of the management ability of P2P platforms on P2P lending risks is a factor to be considered. Bakos (2008) points out that the loan interest rate of P2P online lending platforms will affect the risk level of projects attracted on P2P platforms, the size of loans and the income of fund providers. A reasonable loan interest rate range should be between the benchmark interest rate and the highest acceptable interest rate of low-risk projects. Bachmann (2011) pointed out that the probability distribution of loan applications is not even. Borrowers with the best credit will not use P2P lending, and the credit rating of the borrowers is medium or below. With the decrease in the credit rating of the borrowers, the probability of initiating a loan application also decreases. Therefore, platform trading volume will also affect platform lending risk. Freedman and Jin (2008) found in their research that P2P platforms directly link the lenders and borrowers together through the website to facilitate the completion of loans. Such a transaction mode has much lower borrowing costs than traditional lending intermediaries. The research of Lee et al. (2012) confirmed that P2P online lending has herding effect. The higher the loan completion ratio of a loan subject is, the more likely it is to attract the attention of more financial investors, which makes investors think the loan is very reliable from a psychological perspective, and eventually they will follow the investment platform.

Based on this, the purpose of this part is to use the loan data of P2P lending platforms in China to evaluate the default risk of borrowers, so as to help lenders and lending platforms make more effective decisions in reducing investment risks. Based on a borrower's demographic characteristics and loan information, a credit risk assessment model is proposed to analyse borrower's credit risk from the perspective of loan default. Specifically, this paper establishes Logit binary regression model based on whether the borrower is overdue and the characteristics of the borrower to study the influencing factors of P2P lending risk, then selects the significant influencing factors of the overdue risk of specific lending platforms, establishes P2P lending risk model through factor analysis, and studies the risk level of different P2P platforms.

4.3 Research hypothesis

In terms of the basic characteristics of borrowers, Lin (2009) divides borrower information into hard information and soft information.The hard information usually refers to the information related to demographic characteristics that can be accurately verified, such as age, gender, income, marriage, region, etc., and also includes the evaluation factors used by traditional commercial banks in the implementation of risk assessment before lending, such as credit file information, debt-wage income ratio, public credit records, etc.It is generally believed that the older the borrower is, the longer he or she has been working, the more economic foundation he or she will have, the stronger repayment ability he or she will not easily violate the contract, which will reduce the risk of loan default.Arminger et al. (1997) believe that younger borrowers are relatively immature and less responsible than older borrowers, and the older borrowers are more risk averse and less likely to default.In addition, different from male borrowers, female borrowers are more prudent in their behavior and rarely try risky lending activities.Therefore, female borrowers will repay the principal and interest in time and have a lower probability of default.In terms of marital status, married people's families usually have two salaries, so the risk of default is lower than that of unmarried people with only one salary, so the default rate is lower.In addition, the overall quality of borrowers with higher education is correspondingly higher (Gather,2012), and borrowers with higher education level have a higher repayment rate. Some behavioral characteristics of borrowers are affected by their education level, and these behavioral characteristics are binding on borrowers to some extent, making it easier for them to comply with the repayment agreement on time. Because they are more educated than less educated borrowers, these borrowers are very concerned about their credit scores, and they are very concerned about the consequences of defaulting. The results of Pope&Sydnor

(2008) and Lin (2013) also proved the above conclusion.

Hypothesis 1: Female borrowers have a lower probability of default.

Hypothesis 2: Older borrowers have a lower probability of default.

Hypothesis 3: Borrowers with higher education have a lower probability of default.

Hypothesis 4: Married borrowers have a lower probability of default.

The borrower's credit characteristics can directly feed back the likelihood that the lender will default. Carlos (2015) first used the Logistic linear regression model to study the relationship between the borrower's own credit rating and the loan default rate, and then used the proportional risk regression model to study the internal relationship between duration and credit rating. It is found that there is a reverse change between the credit qualification level and the incidence of overdue time, and the lower the credit rating, the greater the default risk of the borrower. Emekter et al. (2015) also reached the same conclusion in their study on this project. Iyer et al. (2009) believes that in P2P online lending, investors can identify the credit qualification of borrowers by relying on the basic information filled in by borrowers in the loan application, so as to choose whether to bid or not. Specifically, the lender can determine the possible default rate of the borrower according to the total number of missed payments disclosed by the borrower, the ratio of debt to wage income, recent loan information and the credit rating obtained by the credit rating company according to the standardized indicators. The default rate has the same direction as the number of defaults and debt-to-income ratio, while it is negatively correlated with the credit rating. DuarteJ (2012) believes that loan applications of loan applicants with good historical credit characteristics are more likely to be favored, and they are less likely to fail to repay on time.A higher number of delinquencies indicates that borrowers may be less concerned about their creditworthiness, and online lending participants have a "Matthew effect," which means that borrowers with less creditworthiness are more likely to default again.

Hypothesis 5: The higher the borrower's credit score and the higher the borrower's credit limit, the lower the loan default rate.
Hypothesis 6: The more times the borrower is overdue, the higher the default rate of the loan.

Borrowers have a demand for funds, and their income range will affect their repayment ability.The longer they work, the more work and social experience they accumulate, the more resilient they are to today's competitive society, and the more likely they are to amass more personal wealth over time.Borrowers with low income level are not favored by platforms and investors, because their economic foundation is not strong and they do not have sufficient cash flow, so there may be a high risk of default, resulting in a high probability of failure of lending transactions on the platform. And the working years and working hours of borrowers are directly and positively correlated with their income level. Generally speaking, the longer the working time and working years of borrowers, the higher the corresponding income, the stronger the repayment ability and the lower the default risk (Alexander&Daniel,2011).

Hypothesis 7: The higher the borrower's income, the longer the working time and the longer the working years, the lower the default rate of the loan.

The characteristics of the borrower's assets reflect the repayment ability of the borrower

(Klafft, 2008). The borrowers with real estate and car property represent stronger economic strength. The fixed assets guarantee the repayment ability with less risk and lower default risk. And borrowers with mortgages and car loans, who already have debt, are more likely to default than borrowers who don't.In the case that the borrower has the RV, the borrower's own borrowing ability will be enhanced, at this time, investors need to analyze whether the borrower's RV loan has been paid off, whether it has been mortgaged. In general, borrowers with RV properties are less likely to fall behind.

Hypothesis 8:The borrower owns cars and real estate, the default risk rate is low.

Hypothesis 9:The borrower has car loan and mortgage loan, the default risk rate is relatively high.

4.4 Data and descriptive statistics

In this section, we will describe and summarise the descriptive statistics of the data used in our research, including loan status and characteristic information of loan applicants. This article uses three P2P lending platforms, Renrendai, Paipaidai[14], and Yirendai[15] as the research objects, and selects the transaction data of the P2P platform for nearly 5 years from 2016 to 2020[16]. The reason why we choose Renrendai, PPDai and Yirendai as P2P lending platforms for analysis is mainly based on the following reasons, besides that Steelmann

[14]Ppdai (NYSE:PPDF) is a financial technology company founded in Shanghai in 2007 and successfully listed on the New York Stock Exchange on November 10, 2017

[15]Yirendai（NYSE: YRD）is a Chinese online financial service platform launched by CreditEase in 2012. In 2015, it was successfully listed on the New York Stock Exchange, becoming the first overseas listing of Chinese Internet finance.

[16]The reason why the data of the three online lending platforms after 2016 is that these three platforms are the most standardised among the online lending platforms. Since 2015, the state has issued relevant policies to regulate the online lending industry, so the information after 2015 can better represent the risk level

(2006) and Caglayan (2019) et al have demonstrated the above platforms: As one of the early online lending information intermediary service platforms established in China, Renrendai has a high visibility and influence in the industry. Its steady development and good reputation make it the first choice of many investors and borrowers. As the first P2P lending platform in China, PPDai has a pioneering position in the industry. Its years of operating experience and large user base make it of great value when analyzing the P2P lending market. As a member of the P2P lending market, Yirendai may stand out in terms of its unique business model, risk control or technological innovation, providing diversified perspectives for analysis. In summary, the selection of Renrendai, PPDai and Yirendai P2P lending platforms for analysis can comprehensively understand the industry status quo, business model, market performance and user feedback of the P2P lending market. Data comes from Webloan.com (https://www.wdzj.com/). We use web crawler tools to collect data. Preprocess the data to delete invalid data with excessive missing values, outliers or duplicates to ensure the accuracy of the data; After our data cleaning, Yirendai has more than 2,000 data in 2016. In order to ensure the unity of data volume of each platform, the top 2,000 data pieces of each lending platform are selected each year, and the three P2P lending platforms have a total of 30,000 data pieces in 5 years. The analysis software used in this paper is STATA14.0 and SPSS21.0.[17].

4.5 Empirical models

The main methods of credit risk assessment include Logit regression model, BP neural network, decision tree, hierarchical analysis and so on. Bekhet et al. (2014) used Logit

[17]SPSS (Statistical Product and Service Solutions) is a software for statistical analysis operations, data mining, predictive analysis, and decision support tasks. This thesis uses SPSS21.0 mainly for the final factor analysis.

regression model and radial basis function model respectively to construct credit scoring models, and the results showed that the Logistic regression model was more accurate than the radial basis function model, but the radial basis function model could identify potential defaulters more accurately. Therefore,this thesis uses the Logit model to measure and evaluate borrowers' credit default. The credit default of the borrower is caused by a variety of factors, and the results of credit activities can be divided into performance behaviour and default behaviour, so the Logit binary choice regression model is finally adopted to analyse the default probability of the borrower through the past information and data and provide explanations.

Before formally constructing Logit regression, we first need to construct the default probability model. As mentioned above, when the borrower defaults, it is 1, so we expect to get the probability of default of a borrower, that is, the probability of the dependent variable to take the value of 1. Therefore, the result of regression model has intuitive significance. Possible events represented by dependent variables occur in binary logistic regression; In this case, it corresponds to the event of default. We're going to assume that z is a continuous number that's not observed, it represents the probability a default. Therefore, a higher value of z indicates a higher probability of default. To convert this continuous number to a number from 0 to 1, we use the following conversion:

$$P = \frac{1}{1 + e^{-z}} \quad (5.1)$$

Where p is the probability of default. It can be further assumed that in binary Logit regression, X explanatory variables are linearly correlated with Z, so this model can be transformed into:

$$\text{Logit(P)} = \ln\left[\frac{P}{1-P}\right] = \beta_0 + \sum_{i=1}^{k} \beta_{it}\,X_{it} + \varepsilon \quad (5.2)$$

In particular：

$$\text{Logit(P)} = \beta_0 + \beta_1 \text{Sex}_{it} + \beta_2 \text{Age}_{it} + \beta_3 \text{Education}_{it} + \beta_4 MaritalStatus_{it} + \beta_5 CreditScore_{it} + \beta_6 Credits_{it} + \beta_7 DefaultTimes_{it} + \beta_8 Income_{it} + \beta_9 WorkingHour_{it} + \beta_{10} HasHouse_{it} + \beta_{11} HouseLoan_{it} + \beta_{12} HasCar_{it} + \beta_{13} CarLoan_{it} + \beta_{14} Size_{it} + \beta_{15} Interest_{it} + \beta_{16} Investor_{it} + \varepsilon \quad (5.3)$$

Wher $\beta_i$represents regression coefficients,X represents the characteristic information of the borrower, which will be explained one by one below. *i* represents P2P platforms borrower, *t* represents time (years), and ε is the residual. The dependent variable is the default. This variable is measured by dummy variable. Failure to make full repayment in accordance with the agreed time is considered overdue, which is recorded as 1, otherwise, it is 0. Therefore, the explained variable should choose the **Default.**

In model (5.3), our key independent variables are divided into four aspects. The first aspect is ‘the borrower’s characteristics’, including the borrower's gender, borrower’s age, borrower's education, and borrower's marital status. Among them, the gender of the borrower **(Sex)** believes that the success rate of loans on the platform of females is higher than that of males, because male borrowers may have family pressure, so they prefer high risk and high yield, so there will be the risk that they cannot repay the loan principal on time. Female borrowers are different from male borrowers. Female borrowers are more cautious and seldom try risky lending activities, so female borrowers will repay the principal and interest in a timely manner. This thesis defines male borrowers as 1 and female borrowers as 0. Borrower’s Age **(Age)**, refers to the age when borrowers register borrowing; in general, a person's risk propensity and economic condition will change with age. To a certain extent, the increase in age may lead to the improvement of economic conditions, increasing the borrower's ability to repay and the corresponding reduction of loan default risk. Older borrowers are thought to default less. The borrower’s Education (**Education**) is generally divided into high school and below, junior college, undergraduate, master's degree and above. Among them, high school and below is 1, junior college is 2, undergraduate is 3, master and above is 4. In today's society, the level of education has become an important indicator to measure a person's working ability. Generally speaking, people with a high level of education are more skilled in their work and have relatively high income. At the same time, people with a higher level of education have been influenced by a higher degree of knowledge for a long time, and their outlook on life and values are generally higher than those with a lower level of education, so the probability of default risk will be reduced. Therefore, rational investors tend to invest in borrowers who are more highly educated as highly educated people are less likely to default. Borrowers’Marital Status **(MaritalStatus),** generally divided into married, unmarried and divorced (widowed). Since marital status is a dummy variable, this thesis defines divorced (widowed) as 1, unmarried as 2 and married as 3. Marital status has a certain impact on a person's income; married borrowers have stable families, a relatively high income which is more stable, and so a strong ability to repay the loan. Therefore, marital status may also have an impact on whether or not a borrower defaults.

The second aspect is ‘borrower’s credit characteristics’, which is divided into the credit score of the borrower, the credit limit of the borrower and the number of times the borrower defaults. CreditScore **(CreditScore)** is obtained after the review of the platform. The credit rating is converted from the CreditScore, and each credit rating has a corresponding CreditScore range. The credit score is a borrower's credit attribute, and it is also one of the most important bases on which the financial planner judges the borrower's default risk. In general, the higher a borrower's credit score, the more likely he or she is to comply with lending rules and the less likely he or she will default. The user's Credit limit(**Credits**), obtained through the Renren auditor's review of the materials provided, are both the maximum amount a borrower can borrow per loan and the maximum amount a borrower can accumulate before paying off. DefaultTimes **(DefaultTimes)** refers to the number of times the borrower fails to make full repayment in accordance with the agreed time and is marked as overdue. The number of overdue times has a significant negative impact on the borrower's credit. If there are many overdue cases, the platform will reduce the borrower's credit rating. The lower the credit rating of a borrower identified by the platform, the more likely he or she is to default, because there is a positive correlation between the number of historical defaults of a borrower and the occurrence of default events.

The third aspect is 'working characteristics of the borrower'. The income of the borrower (**Income**) is the actual monthly income of the borrower, defined below 1000 yuan as 1, 1001-2000 yuan as 2, 2000-5000 yuan as 3, 5000-10000 yuan as 4, 10000-20000 yuan as 5, 20000-50000 yuan as 6, 50000 yuan and above is 7. Generally speaking, the higher the real income, the less likely the default event is. WorkingHour (**WorkingHour**） refers to the length of time and working period of a borrower, defined from 1 year to 3 years as 1, from 3 to 5 years as 2, from 3 to 5 years as 3, above 4 years as 4.

The fourth aspect is 'borrower's asset characteristics'. Among them, the borrower's real estate information (**HasHouse**) is the real estate registered under the borrower's name or actually controlled by the borrower, with the real estate being 1 and without the real estate being 0. Real estate can be an important indicator of a person's financial status. Generally speaking, borrowers who own houses have higher levels of wealth, especially for borrowers who can provide real estate information; the influence of collateral will make the defaulter bear a certain cost, so borrowers with real estate are less likely to default on loans. In this thesis, the value of owning a house with a mortgage and owning a house without a mortgage is 1, and the value of other conditions is 0. HouseLoan (**HouseLoan**) refers to the house mortgage information registered under the name of the borrower, with a mortgage is 1 and no mortgage is 0. Borrower's vehicle production information (**hasCar**) refers to the vehicle that is actually owned or controlled by the borrower. So car ownership is 1 and no car ownership is 0, and car ownership is also a measure of wealth. As a result, borrowers who own cars are less likely to default. The carLoan(**carloan**) refers to the loan granted by the lender to the borrower who applies for the purchase of a car. The loan with a car is 1, the loan without a car is 0.

Transaction volume (**Size**) represents the scale of P2P lending platform. The operating income of P2P online lending platform mainly comes from the intermediary service fee providing information services for both lenders and borrowers, which is proportional to the transaction volume. Therefore, the larger the transaction volume of the platform, the higher the operating income of the platform and the larger the scale of the platform. The platform Interest rate (**Interest**) is an indicator reflecting the profitability of the platform. The platform interest rate used in this thesis refers to the weighted interest rate of the platform, which can be obtained directly from the home page of each platform. Generally speaking, the higher the platform's interest rate, the better its profitability, and the better its survival. Investor（**Investor**）refers to the number of people who have invested at least once on online lending platforms. The total number of investors in a platform depends on many factors, including, but not limited to the underlying rate of return, platform visibility, customer acquisition costs, etc. The more the total number of investors there are, the more, on average, the platform can deal with and match the amount of money, the larger the transaction scale, the faster the transaction speed, and the better the survival status. In order to reduce the impact of data magnitude on the results, this thesis conducted logarithmic processing on the total number of investors.

4.6 Empirical results

Because default or not is a dichotomous variable, the individual characteristics of lenders can be directly classified and analysed through dichotomous variables. Only when there are differences in the characteristics of classified individuals, Logit model analysis can be more accurate. Therefore, before the formal analysis of the impact of default loans, we first conduct parametric tests to explore whether there is a significant difference between the personal characteristics of normal loans and default loans. On this basis, binary logit regression is used to model the default risk of loan applicants.

The results of the parametric test are shown in Table 4.4, which summarises the difference between the borrower characteristic information of normal loans and default loans. A normal loan refers to a loan that is repaid in full according to the agreed time, and a default loan refers to a loan that is overdue and may suffer losses. It can be seen from Table 5.4 that there are significant differences in the characteristics of borrowers between the two groups. According to the T-test statistics of the mean value, we can find that there are statistical differences in age, education, marital status, credit score, credit limit, overdue times, income, working hours, real estate information, mortgage information, vehicle production information and car loan information have statistical differences at the 1% level. Results indicate that the elderly, people with high degrees, married people, people with high credit scores, people with high credit limit, people with high income, those working long hours, those with real estate and car ownership, people with mortgages and car loans are less likely to default, while borrowers with more default factors are more likely to default.

In order to further explore the exact impact of various borrower variables on loan defaults, we adopted a binary logit regression that includes all the characteristic variables of the borrower (Table 5.5). In our research, the explained variables are divided into normal loans and default loans, and the explanatory variables are characteristic variables of the borrower in four aspects and P2P platform information, with a total of 16 pieces of information. Among the 16 variables included in the logit regression model, 12 variables (gender, age, education, marital status, credit score, credit limit, overdue times, income, working hours, real estate information, car product information and platform interest rate) have a significant impact on the loan results. The borrower's mortgage information, borrower's car loan information and the platform transaction volume and the total number of investors in the platform characteristics are not significant. The Wald test indicates that the model can fully explain the results of default loans, with a test value of 175.466 and a significance of 0.000.

In terms of borrower characteristics. Lender gender has a significant impact on loan default. Female lenders have fewer defaults than male lenders. This conclusion was also found in descriptive statistical analyses. The number of female P2P borrowers is lower than the number of male borrowers. Since women are generally more rational than men, they are less likely to borrow online, so there are relatively few defaults among women in online lending, and lenders in P2P lending platforms are more inclined to female borrowers (Barasinska et al.,2009). Same conclusion as hypothesis 1. The older you are, the fewer default events occur. The younger the age, the greater the risk of default (Pope and Sydnor,2008). Combined with the analysis of the working time of borrowers in the previous statistical analysis, borrowers with 1-3 years of graduation have a relatively high risk of default, which means that with the increase of the borrower's age and working years, the borrower's income will also increase relatively. With the increase of debt capacity, the occurrence of default will decrease, which is the same as the conclusion of hypothesis 2. Education level is significantly correlated with default risk. Borrowers with less education have significantly higher default events than those with more education. People with higher education, regardless of social class or performance awareness, have higher knowledge than those with lower education, and borrowers with higher education are more likely to be affected by self-restraint and comply with the agreement to repay on time (Gather,2012), the same conclusion as hypothesis 3. As a result, highly educated borrowers are less likely to default. The age of the borrower has a significant impact on default. The borrower's marital status has a significant impact on default. The default events of divorced and unmarried borrowers are significantly higher than those of married borrowers, indicating that for borrowers, stable family and marital relationships can help ease the pressure of loan repayment (Lin,2009), which is the same conclusion as hypothesis 4. Individual borrowers are under more pressure to repay their loans, and defaults are more common.

In terms of the borrower's credit characteristics, the borrower's credit score and credit limit have a significant impact on default. The higher the credit score, the higher the borrower's credit limit, and therefore the less likely it is that a default event will occur. At this stage, all online lending platforms have their own risk control system. They assess the borrower's basic information, financial information, and other characteristics, and provide the borrower's credit score. Based on the score and repayment history, they will give a credit limit. In general, the higher the credit score and the higher the credit limit (Klafft,2008), the less likely a person is to default, the same conclusion as hypothesis 5. The number of delinquent borrowers has a significant impact on defaults. Borrowers with a history of default will pay less attention to the default of online loans, and the risk of default will increase. Borrowers without a history of default will pay more attention to their credit status, so default events are less likely to occur (Puro et al.,2010), the same conclusion as hypothesis 6.

In terms of borrowers' credit characteristics, borrowers' income and working hours have a significant impact on default. The impact of borrowers' income and working hours on P2P platform defaults. The borrower's income is an important index to evaluate his repayment ability. In general, borrowers with higher incomes are more likely to make their payments on time, reducing the risk of default. Conversely, borrowers with lower incomes may face greater repayment pressure and have a relatively high risk of default. Although working hours do not directly determine the repayment ability of borrowers, they may indirectly reflect the stability of their career and income sources. Long-term job security often means a more reliable source of income, which helps reduce the risk of default. However, the length of time worked is not a decisive factor in itself, and should be combined with other factors such as income and occupation type. The longer the borrower works, the higher the income level, the higher the solvency level, and the stronger the ability to repay online loans (Freedman and Jin,2008), the lower the possibility of default events, which is the same as the conclusion of hypothesis 7.

In terms of borrower asset characteristics, property and car ownership have a significant impact on defaults. Such borrowers are less likely to default. The asset characteristics of borrowers have a certain impact on the default rate of borrowers (Greiner,Wang, 2009). Borrowers who own real estate and have purchased cars have relatively strong economic strength, relatively stable income and certain sources of repayment. They are usually middle class with a certain income. Owning a house and a car acts as collateral for fixed assets in online loans. Generally, borrowers will fully consider the cost of default and will not easily default (Carlos,2015), which is the same conclusion as hypothesis 8. However, auto loan information and mortgage loan information have no significant impact on the default rate of a certain loan, which is contrary to hypothesis 9. This is mainly because people with mortgage and auto loan have fixed assets on the one hand, which proves that they have certain solvency, but on the other hand, mortgage and auto loan information may also lead to excessive repayment pressure. As a result, online loans cannot be repaid on time (Li et al.2016).

Among the characteristic variables of P2P platform, the interest rate of P2P platform has a positive impact on default, indicating that the higher the interest rate of P2P platform, the more likely the borrower is to default. Excessive repayment interest will lead to excessive repayment pressure of the lender and increase the probability of default. However, the volume of platform transactions and the number of investors did not have a significant impact on defaults.

In the above logit analysis, we found that 12 variables, i.e. gender, age, education, marital status, credit score, credit limit, delinquency times, income, working hours, real estate information, car information, P2P interest rate, have a significant impact on loan default. In order to further analyse the risk level of each lending platform, we use factor analysis to carry out Cluster analysis. We will carry out factor analysis on 12 variables, obtain the largest common factor affecting default through multi-index cluster analysis, and then analyse the default risk level of the three platforms. In order to verify whether the selected data is suitable for principal component analysis, Bartlett test and KMO test are performed on the original data. The test results are shown in Table 5.6.

According to Table 5.6, the observed value of the statistic of the Bartlett sphericity test is 41924, and the corresponding P value is close to 0. Under the condition of a given significance level of 0.05, the correlation coefficient matrix is considered to be significantly different from the identity matrix. At the same time, the KMO value is 0.755, indicating that there is a certain correlation between the original data. According to the KMO metric, it is known that the original explanatory variables are suitable for factor analysis.

In order to find out which of the three online lending platforms has the highest risk control level, so as to provide reference experience for other lending platforms, we conducted factor score evaluation on the three platforms. As can be seen from the results in Table 4.7, the risk control level of the three P2P platforms shows that the risk control level of Renrendai, PPDai and Yirendai is 0.0083, that of PPDai is -0.0008, and that of Yirendai is -0.0067. Among the three platform risk control levels, Renrendai has the highest risk control level.

4.7 Conclusion

Based on the systematic study of borrower characteristics, this thesis collects the characteristic information of 30,000 borrowers from three P2P lending platforms of

Renrendai, Paipaidai, and Yirendai, and uses the Logit model to analyse the influencing factors of online lending defaults. Then, analysing results based on the influencing factors, significant influencing factors are selected for factor analysis, and the risk evaluation systems of the three P2P platforms of Renrendai, Paipaidai and Yirendai are evaluated, and the risk control level of the three P2P platforms is determined.

The research results show that 11 borrower characteristic information variables, i.e. gender, age, education, marital status, credit score, credit limit, number of overdues, income, working hours, real estate information, and car information have a significant impact on loan defaults; the borrower's mortgage information and car loan information have no significant impact on the loan default. Among them, borrowers of older age, higher educational background, more stable marital status, higher credit score, higher credit limit, higher income, longer working hours, and possession of real estate information and vehicle production information are less likely to default, while the more times a loan is past due, the more likely it is to default later. This result is consistent with the research results (Xuchen, 2017). As shown in demographic characteristics indicators, gender, age, marital status, education level, working years, default history and other factors have a significant impact on loan default. Specifically, women have a relatively low default rate compared to men, mainly because women are more rational than men and exhibit a characteristic of taking less risks than men (Powell and Ansic, 1997). The occurrence of defaults by highly educated borrowers suggests that increased education will reduce the likelihood of default on loans. People with higher education have stronger cognition, richer imagination, stronger recognition of the market environment, stronger ability toanalyse and deal with problems; longer working hours also means that people with higher education are more aware of reputation. They are more likely to pay their bills on time (Greiner and Wang, 2009). The higher the credit limit and credit score of a borrower, the more likely it is to reduce the occurrence of default. Such people attach more importance to their personal reputation and will not easily sacrifice their credit score to default. In addition, people of high income level, including those who own RV, are mostly people of above middle income. Such people have strong ability to pay debt, so default occurs less, which is high income, high asset and low default (Emekter.2014). In addition, the high interest rate of platform loans will increase the default risk of borrowers.

In addition, a sound credit risk evaluation system can be established by using borrower characteristics information of P2P platforms (Magee, 2011). Therefore, we conducted factor analysis on the above 11 significant borrower characteristics indicators, and evaluated the risk control level of the three P2P platforms of Renrendai, Paipaidai and Yirendai. The empirical results show that Renrendai has stronger risk control ability. On reviewing Renrendai's risk strategy, it is found that Renrendai’s information disclosure is relatively transparent. It will publish quarterly related operational data to predict and avoid risks. Project funds will be deposited by ChinaMinsheng Bank. In the case of P2P lendings particularly, the borrower will obtain 4 basic information inquiries, 5 public information screenings, 8 phone verifications, 35 scoring card data entries, 100% information correlation check, and more than 30% quality inspection coverage. This is to ensure the safety of loaned funds. It also further proves that the acquisition and evaluation of borrower's characteristic information is the best risk control method for online lending platforms.

For the study of loan default on P2P online lending platforms, this paper takes the public information on Internet lending platforms and borrower information as independent variables as the explained variables. The research on the factors affecting loan default in P2P online lending is conducive to the establishment of a more sound credit evaluation system for online lending platforms. By establishing a credit risk evaluation model, the factors affecting the credit risk of borrowers are revealed, so as to improve the accuracy of investors' judgment on the credit qualification of borrowers and obtain reasonable investment returns. However, there are many factors affecting the delinquency rate of P2P online lending platforms, and there are also many data that can be used, such as the information of borrowers' social software and the information of borrowers' interaction with other borrowers on the lending platform. These factors are not taken into account in this article. Only the data that can be collected are empirically analyzed, and the influencing factors of loan default are discussed. In terms of the factors affecting the overdue rate of P2P online lending, further studies can be made on the relationship between the borrower's personal online social information and loan default in P2P online lending platforms. Social information is an important part of the risk control means of P2P online lending.

Table 4.1 Loan distribution by the loan status.

State	Number	Percent	Loan Limit
Current	26898	89.66%	100279.49
Default	3102	10.34%	1704.62
Total	30000	100.00%	101984.11

Year	State	Number	Percent
2016	Current	5395	89.92%
	Default	605	10.08%
2017	Current	5398	89.97%
	Default	602	10.03%
2018	Current	5368	89.47%
	Default	632	10.53%
2019	Current	5393	89.88%
	Default	607	10.12%
2020	Current	5344	89.07%
	Default	656	10.93%
Total		30000	

Notes:
The table is the distribution statistics of borrowers' defaults in this thesis. By analysing the default distribution and credit lines of 30,000 borrowers from three P2P lending platforms, Renrendai, Paipidai and Yirendai, the characteristics of defaults are analysed.

Table 4.2 Descriptive statistics.

	N	Mean	Median	Std.D	Minimum	Maximum	Skewness	Kurtosis
Sex	30000	0.7	1	0.4	0	1	-1.1	-0.8
Age	30000	35.5	34	7.7	18	66	0.8	0.3
Education	30000	2.0	2	0.8	1	4	0.1	-1.2
MaritalStatus	30000	2.5	3	0.6	1	3	-0.7	-0.5
CreditScore	30000	117.4	180	78.6	0	245	-0.5	-1.7
Credits	30000	3.4	0	5.9	0	300	10.1	426.5
DefaultTimes	30000	0.2	0	1.6	0	53	16.3	361.2
Income	30000	4.2	4	1.5	1	7	-0.2	-0.2
WorkingHour	30000	2.3	2	1.1	1	4	0.3	-1.3
HasHouse	30000	0.4	0	0.5	0	1	0.5	-1.8
HouseLoan	30000	0.2	0	0.4	0	1	1.6	0.7
HasCar	30000	0.2	0	0.4	0	1	1.2	-0.5
CarLoan	30000	0.1	0	0.3	0	1	2.8	5.6

Notes:
The table is the summary statistics of the variables used in the empirical analysis of this thesis. The sample covers 30,000 borrowers from three P2P lending platforms, Renrendai, Paipidai and Yirendai, from 2016 to 2020. The definition of the variable source is in the appendix.

Table 4.3 Definitions of variables and data sources

Notation	Variable	Measurement of variables
Default	Default payment	Failure to make full repayment in accordance with the agreed time shall be deemed as overdue, and shall be recorded as 1; otherwise, it shall be deemed as 0
Sex	Borrower's sex	The borrower's gender is 1 for male and 0 for female
Age	Borrower age	The actual age at which a borrower registers for a loan
Education	Borrower's education	The borrower's education is generally divided into high school and below, college, bachelor's degree, master's degree and above. Among them, high school and below is 1, junior college is 2, undergraduate is 3, master and above is 4.
MaritalStatus	Marital status of borrower	The borrower's marital status is generally classified as married, unmarried and divorced (widowed). Among them, divorced (widowed) is 1, unmarried is 2, married is 3.
CreditScore	Borrower credit score	The user's credit score is obtained after the review of Renrendai, and the credit rating is converted from the credit score, and each credit rating has its corresponding credit score range. Credit score is the credit attribute of the borrower, and it is also one of the important basis for financial planner to judge the default risk of the borrower. Generally speaking, the higher the borrower's credit score is, the lower the corresponding cost is and the higher the corresponding loan success rate is.
Credits	Borrower's line of credit	The credit limit of the user is obtained after the review of the materials provided by the Renren loan auditor, which is both the upper limit of the borrower's single loan and the upper limit of the borrower's accumulated outstanding loan.
DefaultTimes	Number of times the borrower is overdue	Refers to the number of times that the borrower fails to make full repayment in accordance with the agreed time and is marked as overdue.
Income	Borrower's income	According to the monthly calculation of the actual income of the person, less than 1000 yuan is 1,1001-2000 yuan is 2,2000-5000 yuan is 3,5000-10000 yuan is 4,10000-20000 yuan is 5,20000-50000 yuan is 6,50000 yuan is more than 7
WorkingHour	Borrower's working hours	The length of time the borrower works and the duration of the work shall be less than 1 year (including), 1-3 years (including), 2 3-5 years (including), 3 years (including), and 4 years (including) over 5 years
HasHouse	Borrower's real estate information	The real estate registered in the name of the borrower or actually controlled by the borrower shall be 1 if there is any real estate and 0 if there is no real estate.
HouseLoan	Mortgage information for borrowers	In the name of the borrower registered housing mortgage loan information, there is a mortgage for 1, no mortgage for 0.
HasCar	The borrower's car production information	A vehicle actually owned or controlled by the borrower. So the ownership is in the borrower, so if you have a car, it's 1, if you don't have a car, it's 0.
CarLoan	Borrower auto loan information	Refers to the loan lent by the lender to the borrower who applies for the purchase of a car, with a car loan of 1 and without a car loan of 0.
Volume	Size	The volume of P2P online lending platform represents the scale of P2P platform.
Platform rates	Interest	Platform interest rate refers to the platform weighted interest rate, which can be queried directly from P2P platforms.
Number of investment	Investor	The total number of investors refers to the number of people who have invested at least once on online lending platforms.

Table 4.4 Parametric test of differences between defaulted loans and current loans.

Variables	Current	Default	T-test
Sex	0.863	0.724	175.411***
Age	35.735	33.693	191.895***
Education	2.036	1.749	11.103***
MaritalStatus	2.482	2.392	124.733***
CreditScore	127.725	27.712	74.554***
Credits	3.728	0.550	18.987***
DefaultTimes	0.146	0.388	-22.165***
Income	4.273	3.414	2.416***
WorkingHour	2.304	2.157	230.948***
HasHouse	0.385	0.343	104.89***
HouseLoan	0.193	0.106	705.62***
HasCar	0.245	0.201	135.723***
CarLoan	0.101	0.047	420.353***

Notes:
The table shows the parameter test results based on the mean values of different characteristics of borrowers with normal loans and borrowers with default loans. Through the parameter test, the differences of characteristics of borrowers with normal loans and borrowers with default loans are summarized. Normal loan refers to the loan which is repaid in full according to the agreed time, overdue loan refers to the loan which may suffer losses when overdue. The definitions of variables and their respective data sources are in the appendix.

Table 4.5. Binary logit regression results.

Variables	Value
Sex	0.175***
	(8.712)
Age	-0.006*
	(-2.913)
Education	-0.037***
	(-4.776)
MaritalStatus	-0.046***
	(-3.216)
CreditScore	-0.021***
	(-15.37)
Credits	-0.013**
	(-6.176)
DefaultTimes	0.053***
	(31.634)
Income	-0.001**
	(-3.005)
WorkingHour	-0.135***
	(-34.583)
HasHouse	-0.072**
	(-2.772)
HouseLoan	-0.055

	(0.537)
HasCar	-0.035***
	(-3.327)
CarLoan	0.057
	(0.296)
Size	-0.045
	(0.865)
Interest	0.002**
	(3.067)
Investor	-0.005
	(0.084)
Constant	-0.197
	(0.09)
Log likelihood	175.446
Cox & Snell R Square	0.149
Nagelkerke R Square	0.306

Notes:
This table presents the estimation results of the Binary logit regression results, Default of P2P loans is represented by Default, which is explained from four aspects, including the characteristics of the borrower, the borrower's credit characteristics, the borrower's job characteristics and the borrower's asset characteristics. Moreover, three platform characteristic variables are added into the independent variables. The definitions of variables and their respective data sources are in the appendix. *, **, ***, represent significance at the 10%, 5%, and 1% levels, respectively. The values in parentheses are t-test statistics.

Table 4.6 KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.755
Bartlett's Test of Sphericity	Approx. Chi-Square	41924
	df	66
	Sig.	0

Notes:

The KMO and Bartlett's Test is a Measure of the degree of data aggregation. The Kaiser-Mayer-Olkin Measure of Sampling Adequacy (KMO) is a measure to compare the simple correlation coefficient and partial correlation coefficient of variables. It's between 0 and 1. When the sum of the square of simple correlation coefficients among all variables is far greater than the sum of the square of partial correlation coefficients, the KMO value is close to 1. The closer the KMO value is to 1, the stronger the correlation between variables is, and the more suitable the original variables are for factor analysis. Generally speaking, when the KMO test value is greater than 0.6, the data is proved to be suitable for factor analysis. Bartlett's Test of Sphericityis used to test whether the variances of the differences between different measurements are equal when repeated measurements are taken. If the probability of the spherical test is greater than or equal to alpha (generally set to 0.05), H0 is accepted; otherwise, H0 is rejected.

Table4.7. Risk control level of P2P platform

Variables	Renrendai	Paipaidai	Yirendai
Risk control level	0.0083	-0.0008	-0.0067

Notes:

The tables shows the risk control levels of different P2P platforms, which are calculated using standardised indicators through factor score coefficients. The specific calculation process is to multiply each indicator by the indicator score coefficient to obtain each factor score, and each factor score is multiplied by the factor variance contribution rates and added to get the total factor score. Before standardisation, we normalise all indicators, that is, all indicators represent the default risk control level of the P2P platform. Therefore, the greater the value in the final result, the higher the level of the P2P platform default risk control.

Chapter 5: Influencing factors of P2P loanexit

5.1 Introduction

Internet finance started late in China. In 2007, PPDai was established in Shanghai, which became the beginning of China's P2P online lending industry. Since then, China's online lending platforms have been established: Pleasant loan, Renren loan, Red Ridge Venture Capital and a series of platforms have been established. Their establishment has greatly promoted the development of China's online loan industry. The 2014 government Work report proposed to promote the healthy development of Internet finance. With the support of national policies, as an important part of Internet finance, the P2P online lending industry has entered a stage of rapid expansion. At the peak of the online lending platform, the cumulative annual turnover of the industry reached 252.8 billion yuan, and the number of participating lenders and borrowers reached 1.16 million and 630,000, respectively. The high yield of P2P platforms makes investors flock to them, but at the same time, a lot of risks accumulate until they explode. Since June 2018,P2P online lending platform "explosion thunder tide" appeared, June 19 to June 26, 42 P2P platforms in the country have problems, once the four "high rebate" online lending platform - Tang Xiaoxeng, United Bi finance, Qianbao, Yatang finance all "explosion thunder". From June 2018 to mid-July 2018, in just 50 days, more than 150 P2P online lending platforms were in trouble, with an average of more than 3 mines exploding every day. In order to strengthen the supervision of the P2P lending industry, the relevant departments successively issued a number of policy documents in 2018 and 2019, and the nature of the industry and "edge" issues have been clearly defined. On September 28, 2014, the CBRC proposed for the first time the "Ten principles" for the supervision of P2P online lending industry, which clearly stated that P2P online lending platforms are information intermediaries and should analyse and select borrowers' credit information and provide reference credit evaluation. On December 8, 2017, the Office of the Leading Group for the Special rectification of P2P network lending Risks issued the Notice on the Acceptance of the special rectification and rectification of P2P network lending Risks, which made the P2P network lending industry enter a severe rectification and filing state, and the P2P industry faced a "filing crisis". On January 21, 2019, the Office of the Leading Group for the Special Rectification of Internet Financial Risks and the Office of the Leading Group for the special rectification of P2P online loan Risks jointly issued the Opinions on doing a good job in the classification Disposal and risk Prevention of online loan Institutions, which clearly pointed out that it is necessary to "adhere to the withdrawal of institutions as the main direction of work. In addition to some strictly compliant institutions in the camp, the rest of the institutions can retreat, should be closed, and increase the intensity and speed of rectification work." This means P2P online lending platforms,in order to comply with the legal long-term development, must make their own credit risk control, in order to achieve long-term development purposes.

In addition to the concentrated thunder caused by the financial crisis and the national macro-rectification of P2P platforms around 2018, the failure or fraud of P2P online lending platforms has frequently erupted before, and the number of problem platforms in China reached 275 in 2014, an increase of more than 2 times compared with the number of problem platforms in 2013. The reasons for the failure of online lending platforms mainly include: non-standard management, credit tightening, robbing Peter to pay Paul, increased pressure on filing delays, loopholes in the system or lax supervision, tight liquidity resulting in intensive explosion, lack of credit or credit discount, deliberate fraud, bosses rolling money and running away. Why have so many platforms gone wrong since 2013? Is it bad management or something else? What are the characteristics of the defunct P2P platforms? Clarifying these issues will help to rationally view the current situation and future development trend of the P2P industry.

In the context of the P2P online lending industry, the industry has experienced a start-up period, rapid expansion, and has now reached a stage dominated by transformation and exit. However, due to the large number of P2P platforms and the huge number of investors involved, problems such as financial risks and social risks caused by withdrawal are relatively serious. The P2P lending industry has developed up to now, so what are the characteristics of the problematic platform? Is there a certain relationship between the final exit mode of different problem platforms and their backgrounds? Is there a relationship with the region where the P2P platform is located? Are there other factors involved? It is believed that the industry participants are more concerned about the problem?

In addition, the risks of China's P2P online lending platforms are mostly studied based on platform investors, lenders, platforms' risk control models for lenders and industry supervision, etc., while the studies based on the withdrawal of problematic platforms are relatively rare, and they all use a small amount of data for analysis and research. In addition, the current studies do not consider the nodes where important events occur in the P2P industry, but blindly analyse relevant influencing factors after obtaining sample data, which will inevitably produce certain deviations to the whole result, and the analysis of the reasons for the withdrawal of the platform is not in-depth. In the first topic, we have studied from the perspective of the lending platform, considered the factors affecting the lending volume of the lending platform from the risk direction of the lending platform, andstudied in depthwhether the lending volume of the lending platform itself is affected by lending sentiment, herd effect and speculation. In the second topic, we take borrower credit risk as the starting point and analyse the influence between borrower characteristics and loan default rate. Therefore, on the basis of considering the availability of data, this paper studies the election specific problem platform data from the perspective of risk platform by combing the relevant data of problem platform from 2008 to 2017. From the factors of registered capital, platform background, repayment guarantee, creditor's rights transfer, regional competition, platform survival time, ICP operating licence, bank deposit, whether there is a regulatory background and other factors, the impact of each factor on the withdrawal of P2P online lending platform is analysed through a number of Logit models. This is in order to promote the healthy development of P2P and other Internet finance models. The research results show that in addition to registered capital, whether it is private background, repayment guarantee, creditor's rights transfer, platform survival time, ICP operating license, bank deposits, etc., compared with the results of general problems, the occurrence of such problems can be effectively reduced. The research in this paper can identify, predict and manage the factors affecting the default risk of P2P online lending platforms, determine the quantitative indicators to measure the default risk factors of P2P online lending platforms according to the selection rules of risk indicators, build the risk isolation barrier between platforms in the P2P online lending industry, and standardize the development of P2P online lending platforms. Make its development more safe and efficient.

5.2 Literature review

As for the research on the risk sources of P2P online lending platforms, Gurley Shaw (1960) proposed very early that there was a significant positive correlation between the number of financial intermediaries and the degree of innovation of the entire financial industry. With the development of social economy, the number of financial intermediaries keeps increasing, and financial institutions correspondingly carry out a series of innovative behaviors, which intensifies the competition in the industry. The P2P lending enterprises that emerged earlier have natural competitive advantages and are more likely to gain the recognition and trust of investors, thus achieving higher performance. Miley (2005) argued that in an incomplete market system, we can observe the actual risk factors of online lending by observing the characteristic data related to borrowers. McCrann (2006) believes that in order to reduce risks, P2P online lending platforms may reduce loan interest rates, but the main source of income for online lending platforms is the handling fees of both lenders and borrowers, and low loan interest rates mean low returns. The platform must strengthen capital prevention, otherwise it is difficult to maintain daily management and operating costs. Matthew (2007) compared the overdue rate of lending platform with the risk monitoring measures and found that if the online lending platform can establish an effective risk control and supervision system, its overdue rate or default rate can be controlled within a certain range, which is basically consistent with the overdue rate or default rate of traditional financial institutions. Klafft (2007) studied the profitability data of the Prosper platform in the United States and found that following some simple investment rules could improve portfolio profitability and effectively eliminate some high-risk credit rating issues. Freedman (2008) studied the historical data of Prosper and believed that the risks of P2P online lending mainly came from three aspects. First, investors can only obtain borrower information through the platform and cannot effectively identify risks. Second, due to lack of experience and other reasons, borrowers make mistakes in choosing investment projects. Third, higher interest rates attract lower-quality borrowers. High-quality borrowers have more access to financing and are reluctant to use high interest rates. Klafft (2008) conducted an empirical analysis on Prosper platform and confirmed that the interest rate of P2P lending platform is mainly determined by credit rating and debt-to-income ratio. P2P lending is not much different from the traditional banking system in this respect, and a high debt-to-income ratio may affect the normal operation of the platform. Herrero (2009) believes that due to the lack of experience in obtaining loans in the network environment, compared with loans provided by traditional commercial banks, borrowers using P2P online lending will have a higher probability of default. Shen et al. (2010) found by analyzing the data of Prosper platform that investors of P2P online lending platform are more inclined to high-risk targets, and there is an obvious bandwagon effect, which increases the overall risk of P2P platform. Rocholl et al. (2010) believes that when loan originators seek higher management fee income, default risk will increase correspondingly, because loan risk is placed in a secondary position at this time. Britain, the United States and other countries have relatively complete credit systems and securities trading systems. Verstein (2011) and Chaffee&Rapp (2012) compared the business models and risk control mechanisms of Prosper and LendingClub, two major P2P platforms in the United States, against the background of financial crisis and credit crunch. Technological and financial innovations offer new ways to connect investors and borrowers. Chaffee (2012) compared the business models and risk control mechanisms of Prosper and LendingClub, two major P2P platforms in the United States. In the context of the financial crisis and credit crunch, technological and financial innovations have enabled investors and borrowers to establish new ways of connecting. Lin, Prabhala and Viswanathan (2013) believe that the biggest problem of P2P online lending platforms is risk control, and put forward solutions from a technical perspective. At the same time, they predict that the solution of the problem of information asymmetry will have a revolutionary impact on the P2P online lending industry. Kerjan et al. (2013) made statistics on the transaction volume, loan interest rate and other data of P2P online lending platforms, and came to the conclusion that although investors prefer high profit margins, they are not willing to bear risks. Platforms often set higher loan interest rates in order to improve the rate of return, but the risk control link of the platform is relatively weak, which is the main reason for the high risk of the platform. In Performance Evaluation of P2P Control Systems, Emekter, Riza and Jirasakuldech (2015) jointly proposed the establishment of an interconnected homemade System to strengthen inter-industry communication. Establishing a common assessment system and learning from each other is conducive to reducing unnecessary networks.

There are also many researches on the information asymmetry theory of P2P network lending. According to the rational expectations model of Diamond and Verrecchia (1981), investors are divided into two categories: passive investors and active investors, who generally strive to obtain valid information about their investments. These investors can often earn higher returns. According to Freedman (2008), P2P lending platforms differ from traditional lending markets in two aspects: First, although P2P fund providers face certain credit risks, they have no incentive to investigate borrowers like banks before granting loans; Secondly, P2P lending platforms can use social networks to estimate borrowers' credit and default probability, emphasize the importance of information, and use borrowers' social networks to achieve good risk control. Based on the existing research, Collier and Hampshire (2010) further discussed the impact of multi-level personal reputation system on the information asymmetry in the online lending market, which is also the biggest impact risk in the online lending market. Gleisner and Fabian (2010) took Prosper, the first and largest P2P lending platform in the United States, as the research object and selected 9000 transactions for analysis. They concluded that P2P lending platforms are intermediary in nature and have the advantages of financial, Internet and social platforms. It can enrich the research database of credit evaluation, provide more data support for future transactions, and effectively reduce the wrong influence of loan information asymmetry on loan and other evaluation behaviors. Bachmann (2011) believes that P2P online lending platforms only need to provide information on loan demand, and investors need to identify the relevant information of lenders, but the platforms do not provide loan guarantees. Thus, information asymmetry between investors and lenders is inevitable. Herzenstein (2011) found that in the context of information asymmetry, the P2P online lending industry has an obvious herding effect. Investors' choice of lending will be influenced by both previous investors and investors, and they are more inclined to choose enterprises with a long operating history rather than new enterprises. Lee E and Lee B (2012) studied the largest P2P online lending platform in South Korea, revealing the herding effect in P2P online lending platform, and found that the marginal effect of herding effect decreases with the deepening of the bidding process of the platform. Anonymous (2012) pointed out that P2P lending platforms, as emerging financial institutions, have a much faster liquidity and fund matching speed than traditional financial institutions, but their operating principles are basically the same. Taking banks as an example, the comparison between the two shows that P2P should also rely on reducing the uncertainty of loans, screening investment projects, and choosing more stable investment objects to prevent platform risks.

In the P2P network lending platform default factors. According to the research and analysis of Freedman and Jin (2014), the risks of P2P online lending mainly come from three aspects: first, adverse selection of borrowers; second, borrowers lack experience in facing new lending methods; third, the interest rate provided by P2P online lending platforms is high, but the risks are also great. The borrower may not be able to repay, resulting in a serious loss of interest to the lender. Intermediaries, information, credit intermediaries, and enterprises' own performance in loans are also important factors affecting P2P online lending platforms. The risk of online lending platform has a certain relationship with the registered capital and time. Peng (2003) found that in the early stage of institutional entrepreneurship, the legitimacy and network relationship of P2P online lending enterprises are closely related to the operation time. Terry (2006) believes that the loan interest rate of online lending platforms is too low, and the platforms simply rely on commission as working capital, which is difficult to cover the operation and management costs. P2P platforms should strengthen capital prevention. Yum (2012) found that the higher the registered capital, the more abundant the cash flow, the stronger the strength of the platform, the better the final result of the platform, that is, the lower the probability of problems. Studies by Smith (2016) and Li (2019) show that P2P online lending platforms are affected by many factors such as operation time, platform registered capital, platform type and guarantee conditions during operation. In terms of the qualification and background of P2P online lending platforms, Jiang (2019) found that the private sector has the largest number of platforms with the weakest background support, while P2P online lending platforms with other backgrounds have relatively high strength, high financial strength, good credit endorsement, strong viability, and less possibility of problems. Peng (2003) believes that only obtaining the ICP business license can show that the platform has the necessary venues, facilities and technical solutions, and has the reputation or ability to provide long-term services to users. He believes that the legitimacy and network relationship of P2P online lending enterprises are closely related to the operation time, and the survival time of the platform can represent the operation ability of the P2P platform itself to a certain extent. In terms of the guarantee of online lending platforms, according to national regulations, the cooperative banks of P2P network platforms must require participation in the business. Several articles mention the need for banks to be involved, but mainly to facilitate the lending process. Matthew (2007) found that some platforms directly connect lenders and debits, while others connect through third parties (usually banks). Information intermediary platforms can effectively avoid various risks. But excluding intermediaries increases risk and leads to panic. Prescott and Diamond (2013) believe that the default rate can be reduced by establishing co-guaranteed loan methods and promoting communication between borrowers and lenders. Self-discipline organizations are also very effective in regulating and preventing risks in the P2P market. According to the research of Emekter (2015), adding third-party guarantees to Internet financial platforms can effectively reduce the risk of default. Smith (2016) believes that experienced P2P online lending platforms will pay attention to communication in the risk response of P2P online lending platforms, and repayment guarantee is a powerful measure for risk response. In terms of the supervision of online lending platforms, Schenone (2004) believes that P2P platforms are under the supervision system of SEC, which is conducive to improving their security and financing transparency, and further improving lending efficiency. Arena et al. (2005) confirmed that macroeconomic and institutional environment can affect the probability and time of bank failure. Matthew (2007) believed that due to the lack of responsibility of P2P online lending platforms, the operational effectiveness of the online lending market declined, leading to the accumulation of risks. Puro et al. (2010) proposed that the default risk could be effectively reduced by improving financial laws and regulations and local credit mechanisms. Kevin E Davis(2010) raised the issue of regulatory continuity and proposed reform. Prosper and LendingClub have formed the P2P online lending market in the United States, and its regulatory environment is relatively clear. Lenz &Rainer (2016) put forward the difference between P2P and bank supervision from the regulatory level, and suggested the establishment of special supervision methods.

By combing relevant literature, scholars have conductedmature studies on the characteristics of P2P online lending platforms, the causes of risks and countermeasures of P2P online lending platforms, but there are still some deficiencies. Most of the existing literature is based on theoretical research, and much of it studies the legal or credit risks faced by the platform, without conducting specific research on the problem platform of P2P online lending. This paper makes an in-depth analysis of the risk generation of specific online lending platforms, and puts forward relevant prevention suggestions according to the characteristics and causes of the platforms, which is a relatively mature method for online lending platforms.

5.3 Research hypothesis

This paper will analyse the different outcomes affecting P2P online lending platforms from registered capital, platform background, repayment guarantee, creditor's rights transfer, regional competition, platform survival time, ICP operating licence, bank deposit, whether there is a regulatory background and other factors. Smith (2016) and Li (2019) showed through their research that P2P online lending platforms are affected by many factors such as operation time, platform registered capital, platform type and guarantee conditions during operation. In e-commerce trust and influencing factors, it is mentioned that P2P online lending platforms have strong similarities with e-commerce in terms of transactions. Therefore, in evaluating the factors of P2P online lending platform trust, we can refer to the influencing factors of e-commerce trust, such as registered capital, platform background, ICP certification, etc. Similarly, according to the theory of information asymmetry, there will be serious problems in the integrity and authenticity of information between P2P online lending platforms and relevant stakeholders, such as platform background and third-party qualification certification, which will affect investors' choice of platforms. In the P2P online lending industry, investors cannot observe the behaviour of the platform after the completion of lending, such as whether the depository or custody of the access bank can effectively prohibit the platform from misappropriating funds and prevent the platform from moral hazard. All these provide a theoretical basis for the hypothesis proposed in this paper.

As an important aspect of enterprise assets, registered capital reflects the ability of enterprises to obtain resources and has a positive impact on enterprise performance. Due to the low entry threshold of the P2P industry and the large market development scale, registered capital can be used to measure the financial strength of the platform, especially the newly established platform itself. On the one hand, the higher registered capital can increase the risk cost of platform default, and the closed platform can improve its own strength. On the other hand, the network security risks caused by the purchase of ready-made cheap templates can be reduced to a certain extent. To a certain extent, the registered capital of the platform can reflect the financial strength of the platform itself. The more registered capital, the longer the online lending platform can continue to operate, that is to say, the less likely it is to close down, because the online lending platform with strong capital strength can use part of its own capital to repay investors' losses in the event of default risk, so as to avoid adverse impact on the platform's reputation, resulting in delayed payment difficulties or cash withdrawal difficulties. The higher the registered capital, the more abundant the cash flow, the stronger the strength of the platform, and the better the final result of the platform, that is, the lower the probability of problems (Yum, 2012).

Hypothesis 1: The higher the registered capital of the platform, the lower the exit probability of the P2P online lending platform.

Platform background refers to the faction of the platform, which is generally divided into private, bank, listed, state-owned and venture capital systems. The P2P platform has a good background, which makes the platform obtain an important base for its production development under the development trend of intensifying competition in the lending industry and survival of the fittest. On the one hand, the strong background of P2P platform is equivalent to obtaining a certain credit endorsement, which can attract more new investment in online lending; On the other hand, an online lending platform with a strong background can obtain superior resources such as good reputation, strong financial support, and mature experience in risk control and management brought by a background institution with strong financial strength, which is conducive to the P2P platform to obtain a good brand reputation, improve platform security and reliability, and improve the level of operation. The private sector has the largest number of platforms and the weakest background support, while P2P online lending platforms with other backgrounds have relatively high strength, high financial strength, good credit endorsement, strong viability, and less possibility of problems (Li, 2019), (Jiang, 2019).

Hypothesis 2: The exit probability of state-owned P2P online lending platform is low.

Third party guarantee is a system that P2P platform introduces third party institutions to provide guarantee for creditor's rights in the network lending relationship. The guarantee of small loan company, financing guarantee company and non-financing guarantee company belong to the third party guarantee. Through the introduction of third-party guarantee, P2P online lending platforms can obtain more customer resources and enhance the ability of risk protection, so as to improve the credibility of the platform, attract more investors and expand the scale of operation. Whether it is the third-party financial guarantee company guarantee provided by the P2P platform, the organizational mortgage of real estate and vehicles, or the risk reserve mode, it effectively increases the platform's ability to deal with risks and reduces the probability of platform problems. Establish co-guaranteed loans and facilitate communication between borrowers and lenders to reduce default rates (Prescott, 2013). The addition of third-party guarantees enables Internet financial platforms to effectively reduce the risk of default (Emekter, 2015).

Hypothesis 3: P2P online lending platform with creditor's rights transfer has a low exit probability.

Creditor's rights transfer means that investors can trade the underlying creditor's rights within the platform through operation after completing the bid. Creditor's rights trading can obtain greater liquidity and attract more investors through creditor's rights transfer when investors are short of funds, and creditor's rights transfer is also another form of recognition of the platform. The creditor's rights transfer function allows the lending user to transfer the lent funds to others after a period of time, and investors can convert the funds into balance cash in advance when they are in urgent need of funds, which can effectively enhance the confidence of investors. Following a few simple investment rules can improve the profitability of a portfolio (Klafft, 2007).

Hypothesis 4: The transfer of claims will increase the exit probability of P2P online lending platform.

In general, the regional distribution of P2P online lending platforms in China is relatively extensive, but the regional concentration of the industry is very strong, and the registration and operation of P2P online lending platforms are mostly in Guangdong, Beijing, Shanghai, Zhejiang and these economically developed areas. On the one hand, residents in these areas have strong demand for investment and financing, relatively developed financial activities, and relatively active private lending activities. P2P online lending platforms can make use of local economic and financial resources and advantages, which is conducive to expansion and development. Shaw (1960) pointed out that with the increasing number of financial intermediaries, financial institutions would carry out a series of innovative behaviors accordingly, and industry competition would intensify. The degree of competition in the region where the P2P network lending platform is located also tests the operational strength of the platform itself. P2P online lending platforms have herd effect (Lee, 2012) and (Shen, 2010). If a platform's operating ability is poor, then it is less likely to survive in the online loan market, and in the field of fierce competition, the more likely the platform's problems will be exposed.

Hypothesis 5: Regional competition will increase the exit probability of problematic P2P lending platforms.

The online time of the P2P platform is the normal operation time of the platform from the beginning of its establishment to the present. Generally speaking, the longer the P2P platform is online, the stronger the operation capability of the platform to a certain extent, and compared with the platform with a shorter online time, it has great advantages in terms of operation management experience, system security, risk control ability, brand building, platform visibility and customer group attraction. Thus, it can better cope with the fierce industry competition and sudden various conditions, and then smoothly carry out the platform intermediary services and lending business, and reduce the possibility of P2P platform default. The legitimacy and network relationship of P2P online lending enterprises are closely related to the operation time (Peng, 2003). To a certain extent, the survival time of the platform can represent the operational capacity of the P2P platform itself. The longer the operation time, the more operational experience, which helps to reduce the probability of platform problems (Herzenstein, 2011).

Hypothesis 6: Platform survival time can significantly reduce the exit probability of P2P online lending platform.

ICP business license (telecom operators providing Internet information services and value-added services) is a certificate that must be handled by operational websites in the Internet industry, but only by obtaining this certificate can it be shown that the platform has the necessary venues, facilities and technical solutions, and has the reputation or ability to provide long-term services for users (Peng, 2003). ICP operating license is a symbol of the legitimate operation and strength of the platform. The platform holding this certificate is more reputable in the minds of investors and can attract more investors, thus reducing the exit risk caused by lack of trust. Therefore, the platform with this certificate has more advantages than other platforms, and the possibility of a problematic platform is very small.

Hypothesis 7: ICP operating license can significantly reduce the probability of P2P lending platform withdrawal.

Access bank deposit refers to the transformation of the funds of the platform from the original users (investors, lenders) in the third-party payment system to the corresponding company account, to the virtual account opened by each user, including the platform, in the access bank. Funds are not transferred through the platform system account, but directly into the user's bank account. It ensures the safety of user funds and can effectively prevent the behavior of the platform to set up its own capital pool. When P2P platforms implement the user fund custody system, independent banks or third-party payment institutions can effectively separate their own funds from borrowed funds by opening fund storage accounts for all borrowing users and investment users, thus avoiding the moral hazard of misappropriating funds on the platform. The platform that is connected with the bank depository system has better risk control ability, and the possibility of problem platform is lower (Matthew, 2007).

Hypothesis 8: Bank depository can significantly reduce the exit probability of P2P online lending platforms.

Market supervision is an important topic in P2P lending industry. Only in the context of reasonable supervision can a perfect market develop better, reduce the occurrence of moral hazard and reduce the irregular behavior of the platform (Matthew, 2007). Schenone (2004) also believes that P2P platforms are under the regulatory system of SEC, which is conducive to improving their security and financing transparency, and further improving the efficiency of lending. Whether the platform has joined the regulatory association is also an important indicator to measure whether the platform is in compliance. The platform joining the China Internet Finance Association needs to improve its own information disclosure mechanism and synchronize the released loan information and contract element information to the platform of the China Internet Finance Association, which undoubtedly increases the transparency of the real situation of the platform and enhances the credit endorsement of the platform.

Hypothesis 9: Market regulation can significantly reduce the exit probability of problematic P2P lending platforms.

5.4 Data and descriptive statistics

The data sources and collection methods of this part are as follows: first, by crawling the relevant data of the P2P platform of "Netloan Home", because the centralised outbreak of problem platforms in 2018 has the "herding effect" of national macro control and the closure of P2P platforms, which does not provide a reference for objective research on the risk characteristics of problem platforms. This paper mainly studies the factors affecting the withdrawal of P2P problem platforms, so the choice is all problem platforms.Based on this, we collected a total of 550 P2P online lending platforms that had run away, closed down or had difficulty withdrawing cash before 2017. Then, through the platform's establishment time, registered capital, survival time, distribution region, creditor's rights transfer, repayment protection dimension and ICP operating licence and other variables to match, remove the sample information incomplete platform, the actual number of problematic P2P online lending platform samples is 521. While GDP data from China's statistics bureau website (http://www.stats.gov.cn/sj/). This paper sorts out and summarises the collected information of the problematic P2P platform, and then uses Excel and stata14.0 to describe and analyse the relevant data.

Table 5.1 shows the statistical characteristics of the final outcome data of the platform for the explained variable problem. As can be seen from the table, 252 platforms have generally withdrawn, accounting for 48.4%, and 88 platforms with serious problems, 97 platforms with major problems and 84 platforms with major problems, totalling 269. Accounting for 16.9%, 18.6% and 16.1% respectively, accounting for 51.6% of the total, indicating that the final exit of the entire P2P online lending market is not optimistic, basically half of the normal exit, half of the problem exit. Among them, the number of major problem platforms and huge problem platforms accounted for 67.3%, indicating that the entire P2P online lending market is in a mix, the quality of platforms is uneven, and there are serious violations of law.

Based on the analysis of the registered capital of P2P platforms in Table 5.2, it can be seen that compared with general exit platforms, except for platforms with serious problems, the proportion of platforms with other problems has increased compared with platforms with more than 50 million registered capital of general exit platforms. In particular, the proportion of platforms with major problems is as high as 47.6%. First of all, the registered capital of P2P online lending platforms is increased to more than 50 million in order to meet some specific criteria, but it is not necessarily paid-in capital; in addition, there are many platforms to Qigao registered capital as a gimmick, publicity, to attract investors. It may also indicate that the registered capital is large, and the platform operators choose to hide the actual information and operate the platform for a long time to solve the problem in the follow-up operation; even in the case of violations and laws, the costs and responsibilities after exposing the problem are large. However, with the deepening of regulatory policies, the platform problems will eventually be exposed. Further analysis, from the collected 521 P2P problem platform registered capital, the registered capital is at least 1 million yuan, the maximum is 100 million yuan, and the average registered capital is 22,627,900 yuan. As shown in Figure 5.2, platforms between 2001 and 50 million are the largest, accounting for 52.21%; 5.01 million to 20 million platforms followed, accounting for 27.64%; platforms with less than 5 million accounted for 19.77%, and platforms with more than 50 million were the least, at only 0.38%. It can be seen that the registered capital of the problem P2P platform is generally not high, and the registered capital of most platforms is below 50 million yuan. Strong capital has long been considered a prerequisite for working in related areas of the financial industry, so is capital the key factor causing problems for these platforms? Further empirical analysis is needed. At the same time, as a derivative of micro-finance, is it necessary to stipulate the registered capital threshold for P2P online lending platforms? These are questions to be studied.

Based on the independent variable platform background analysis in Table 5.2, it can be seen that among all types of platforms, there are a large number of private platforms in the platform background, and all exit types account for more than 80%. However, it can be seen from the table that non-private platforms account for the highest proportion of 16.4% in major problems. The private sector performed the worst on major issues, accounting for

99.25% of all major issues.

In terms of repayment protection, the platform that provides repayment protection for the general exit platform accounts for the highest proportion, 69.05%, and the platform that provides repayment protection for the major problem platform accounts for the lowest proportion of 28.57%. However, the proportion of serious and major problem platforms that provide repayment protection is more than 45%.

In terms of the transfer of claims, the majority of all withdrawal platforms do not offer the transfer of claims. The proportion of non-transferable functions in the platform with major problems is much higher than that of other platforms, reaching 85.7135.12%.

In terms of obtaining ICP qualification, the proportion of platforms with serious problems and major problems that have not obtained ICP certification is much higher than that of general exit platforms, but the proportion of platforms with major problems that have not obtained ICP certification is much lower than that of general exit platforms, which implies that many platforms use ICP certification as a cover for illegal acts of platforms, using cognitive bias. It causes the problem of information asymmetry.

In the docking of depositary and management systems, the proportional difference between platforms is not large. The proportion of general exit platform, serious problem platform and major problem platform is 19.05%, 20.45% and 18.56%, respectively, of which the proportion of major problem platform is the lowest. The lowest proportion of major problems is 22.62%. This implies that bank deposit control can effectively prevent the occurrence of runaway problems, but it does not play a large role in preventing illegal platforms.

In terms of whether there is a regulatory background, except for major problem platforms, the proportion of problem platforms with regulatory background is lower than that of general exit platforms. This means that the existence of a regulatory environment is important.

The regional distribution characteristics of the problem platform are analysed. As shown in Figure 5.3, in terms of the geographical distribution of problematic P2P platforms, the number of them in Guangdong, Beijing and Shanghai is among the top in China. Among them, the number of problematic P2P platforms in Guangdong, Beijing and Shanghai accounted for 23.99%, 19.39% and 12.86% of the total number of problematic P2P platforms in China, respectively, and the number of problematic P2P platforms in these three provinces accounted for more than half of the country. The proportion of problem platforms in Zhejiang Province is also higher, reaching 12.67%. In Shandong, Anhui and Jiangsu, which are also in the eastern region, the proportion of problem P2P platforms is only 4.03%, 2.69% and 2.5%. Problematic P2P platforms are also not evenly distributed in the central region. Among them, Sichuan and Hubei have the highest proportion, 4.8% and 4.22% respectively, followed by Hunan and Henan, and Shaanxi the least. In the western region, except for Jiangxi, the proportion is 0.96%, and the proportion of other regions is relatively low. It can also be seen from Table 5.2 that the regional competition of the problematic platform is much higher than that of other classified platforms, which implies that the fiercer the competition, the more likely it is to produce a mixed environment, leading to the occurrence of illegal behaviours.

Judging from the geographical distribution characteristics of the above problem platforms, the number of P2P platforms with problems in the economically developed eastern region is generally higher than that in the central and western regions. The reasons are as follows: first, the number of P2P online lending platforms in these regions is much more than that in other regions. Second, the eastern coastal region is not only the most active area of China's private economy, but also the most dynamic area of private lending. In 2013, the "620 money shortage" led to problems in the capital chain of many small and medium-sized enterprises, and eventually led to the "collapse" of P2P online lending platforms.

According to Figure 5.4, only 7.71% of the platforms were established before 2012, 13.41% were established in 2013, 41.81% were established in 2014, and the remaining 37.04% were established after 2015. This reflects that 2014 was the peak year for the establishment of P2P online lending platforms. A large number of P2P online lending platforms have undoubtedly increased the intensity of competition in the online lending industry. In terms of the time of the problem of the platform, 2014 is also the peak of the establishment of the problem platform. There are many reasons why a large number of P2P online lending platforms had problems during this period. First, a large number of P2P online lending platforms were established during this period, which intensified the market competition in this industry, resulting in the closure of some platforms; The second is the period of bank tightening, resulting in the market "money shortage"; third, P2P online lending platform risk control ability is weak, resulting in a "closing tide"; fourth, P2P online lending platform experience was insufficient; fifth, P2P online lending platform capital was not strong enough. Which reason is the most convincing? Follow-up studies and analyses are still needed.

Regarding the survival time of these problem P2P platforms, the average survival time is only 40 months. Among them, some P2P platforms (such as Fu Xiaobao, etc.) were established for only 2 months before being closed down or fleeing with their money, while the platform with the longest survival time lasted 119 months. In general, according to the descriptive statistics of the survival time of problematic P2P platforms in Table 5.3, platforms with a survival time of less than 12 months account for 2.5% of all problematic platforms; platforms with a survival time of 12-24 months account for 15.74%; those with a survival time of 24-48 months account for 51.06%, and those with a survival time of more than 48 months account for 30.71%. This shows that the problematic P2P online lending platforms in China generally have a short survival time, which may be caused by the following reasons: first, the operation motive caused by insufficient supervision is not pure; second, a lack of business experience. What are the main factors?

5.5 Empirical models

The explained variables and explanatory variables in the econometric model are usually assumed to be continuous variables, but in practice, the explained variables usually have some selection problems, which can be expressed by discrete data, such as P2P problem platform time can be divided into several types, respectively using 1, 2, 3... In this case, it is necessary to establish a discrete choice model. The explanatory variables of the discrete choice model are nonlinear, so it is necessary to transform them into utility models for estimation. According to the two probability distribution forms of random utility terms in utility model, it can be divided into Probite model and Logit model, among which Logit model is the most widely used.Carman (2006) studied several deformation methods of Logistic regression analysis and believed that the classification accuracy of boundary logistic regression model was higher. Therefore, Logistic model is widely used in credit risk evaluation model because of its high classification accuracy. According to the research in Chapter 3, we use the Logit model to measure the platform lending risk. In this chapter, we will draw lessons from the ideas in Chapter 3 to further distinguish the problem platforms and divide the final severity of the problem platforms in the P2P online lending industry into: there are four cases: general exit platform, serious problem platform, major problem platform and very high problem platform. The explained variables involve four class variables. Therefore, the multinomial Logit model (MNLM) is used in this paper.

In fact, the multinomial Logit model can be regarded as an extension of the binary Logit model, and can be regarded as a combination of multiple binary Logit models formed by pairing the results of various categories in the severity of the final situation of the explained variable platform.

The MNLM model is set as follows

$$\mathrm{Ln}\left(\frac{\pi_{ij}}{\pi_{ib}}\right) = \ln\left(\frac{P(y_i=j|x)}{P(y_i=b|x)}\right) = x_i'\beta_j \ \ for\ j = 1,2 \dots, J \qquad (5.1)$$

Where, b is used as the base group, and J is set as the total number of categories included in the category variable (the severity of the final situation of the platform). The classification data of the research object in this paper is 4, that is, the maximum value of J is 4. When j=b, the left side of the equation is ln1=0, thenβ_b=0. That is, the log-odds of a certain category relative to itself is always 0, the coefficient of any explanatory variable corresponding to the group must also be 0. By solving J equations, the prediction probability of each type can be obtained.

$$\pi_{ij} = P(y_i = j|x) = \frac{\exp(x_i'\beta_j)}{\sum_{m=1}^{J}\exp(x_i'\beta_{mj})} \quad for\ j = 1,2,3,4 \qquad (5.2)$$

In this paper, the severity of the final situation of the platform problem, taking the general exit platform as the base group, is

$$Pr(y = 1|x) = \frac{1}{1+\sum_{m=2}^{4}\exp(x'\beta_m)} \qquad (5.3)$$

$$Pr(y = 2|x) = \frac{\exp(x'\beta_{21})}{1+\sum_{m=2}^{4}\exp(x'\beta_m)} \qquad (5.4)$$

$$Pr(y = 3|x) = \frac{\exp(x'\beta_{31})}{1+\sum_{m=2}^{4}\exp(x'\beta_m)} \qquad (5.5)$$

$$Pr(y = 4|x) = \frac{\exp(x'\beta_{41})}{1+\sum_{m=2}^{4}\exp(x'\beta_m)} \qquad (5.6)$$

The parameter estimation of the multinomial Logit model is solved by the maximum likelihood estimation method for βj. To construct the likelihood function corresponding to a multinobial Logit model, and to label the group to which each observation belongs, we need to construct J dummy variables (denoted d1,d2,……,dj). If the severity of the final condition of platform i is j, then d_{ij}=1, otherwised_{ij}=0. The log-likelihood function of the MNLM model is the general form of the binary Logit model:

$$\ln L(\beta) = \sum_{i=1}^{n}\sum_{j=1}^{j} d_{ij} \ln Pr(y_i = j|X) \qquad (5.7)$$

Where $\beta=[\beta_1,\beta_2,\ldots,\beta_i]$ is the column vector of (J−1) × (K), where K is the number of parameters in the model containing constant terms. The first-order deflection is:

$$\frac{\partial \ln L}{\partial \beta_j} = \sum_{i=1}^{n} X_i[d_{ij} - \pi_{ij}] \ for\ j = 2,3,\ldots,J \qquad (5.8)$$

Among them,$\pi_{ij} = Pr(y_i = j|X)$

The second order deflection formula is as follows:

$$\frac{\partial^2 \ln L}{\partial \beta_j \partial \beta_j} = -\sum_{i=1}^{n} \pi_{ij}(1-\pi_{ij})\mathrm{X}_i X_i' \qquad (5.9)$$

$$\frac{\partial^2 \ln L}{\partial \beta_j \partial \beta_j} = -\sum_{i=1}^{n} \pi_{ij}(1-\pi_{im})\mathrm{X}_i X_i' (\text{for j} \neq \text{m}) \qquad (5.10)$$

According to the above two formulas, the Hessian matrix $\mathrm{H}(\hat{\beta})$ is obtained, and thus the variance-covariance matrix is obtained:

$$\mathrm{H}(\hat{\beta}) = -\mathrm{H}^{-1}(\hat{\beta}) \qquad (5.11)$$

In particular：

$$\text{Logit(Result)} = \beta_0 + \beta_1 Capital_i + \beta_2 \text{Background}_i + \beta_3 \text{Guarantee}_i + \beta_4 Creditor_i + \beta_5 Competition_i + \beta_6 Lifetime_i + \beta_7 ICP_i + \beta_8 Deposit_i + \beta_9 Regulatory_i + \beta_{10} LnGDP_i + \varepsilon \text{（5.12）}$$

Wher $\beta_i$represents regression coefficients,X represents the characteristic information of the P2P lending platform, which will be explained in detail below. *i* represents P2P platforms, and ε is the residual.

Platform final outcome type **(Result)**, According to the severity of social impact, the final outcome of the P2P online lending industry platform is divided into: general exit platform, serious problem platform, major problem platform, and major problem platform. Normal closure, suspension of bid issuance and transformation of online lending platforms generally will not have a negative impact on investors, so the three types of exit platforms in this paper are considered as general exit platforms. The withdrawal difficulty and delayed payment may be caused by the borrower's failure to repay in time or the rupture of the capital chain, which disrupts the original repayment plan, affects the planned returns of investors, and also causes investors' funds to be in a state of uncertainty for a long time, bringing great uncertainty risk to investors. Therefore, the platform of withdrawal difficulty and delayed payment is merged into a serious problem platform. Suspected fraud, economic investigation intervention and running havea more serious impact on the interests of investors, and even belong to escape responsibility or suspected criminal behaviour. However, the influencing factors of the two outcomes may be different, so this paper regards running as a major problem platform, and suspected fraud and economic investigation intervention as a major problem platform. In this paper, categorical variables will be used to analyse the final withdrawal of P2P online lending platforms. The set value of general withdrawal platforms is 0, the value of serious problem platforms is 1, the value of major problem platforms is 2, and the value of major problem platforms is 3.

Referring to the above theoretical basis and current situation analysis of P2P online lending platform exit, and considering the availability of data, in this paper, factors such as registered capital, platform background, creditor's rights transfer, regional competition, platform survival time, ICP operating licence, bank deposit, and whether there is regulatory background are used as explanatory variables, and the provincial GDP pairs are added as control variables to analyse the different exit situations affecting P2P online lending platforms.

The registered Capital of the platform **(Capital)** can reflect the financial strength of the platform to a certain extent. In this paper, the registered capital of 50 million is taken as the cut-off point, and the platform with registered capital less than 50 million is set as 0, and the platform with registered capital higher than (or equal to) 50 million is set as 1.

Platform Background (**Background**) refers to the faction of the platform, which is generally divided into private system, banking system, listed system, state-owned capital system and venture capital system. The above classification has been marked on the net loan home and the net loan Tianyan, and this paper mainly uses the data of the net loan home as the classification standard. The platform background is divided into non-private system and private system. The non-private system is 0, and the private background value is 1.

Repayment Guarantee (**Guarantee**) means that no matter whether the P2P platform provides a guarantee by a third-party financing guarantee company, mortgage of real estate and vehicles, or adopts a risk reserve model, it effectively increases the platform's ability to deal with risks and reduces the probability of problems on the platform. This variable is a two-valued variable, 0 without repayment protection and 1 with repayment protection.

Creditor (**Creditor**) allows loan users to transfer the lent funds to others after lending for a period of time, so that investors can turn the funds into balance cash in advance when they are in urgent need of funds and withdraw them, which can effectively enhance investors' confidence. However, for the platform, it undoubtedly increases the cash flow requirements of P2P platforms, especially when there is a run or negative news, a large number of claims transfer makes the platform worse. This variable is a binary variable, with non-transferable claims being 0 and transferable claims being 1.

The level of Competition (**Competition**) in the region where the P2P online lending platform is located also tests the operational strength of the platform itself. In all the data captured, Guangdong, Beijing, Shanghai and Zhejiang successively account for the highest proportion of the total number of platforms in the country, all of which are above 10%. Therefore, these four regions are regarded as having intense regional competition, and the value is 1, while the other regions are not highly competitive, and the value is 0.

The Lifetime of the platform (**Lifetime**) can represent the operation capability of the P2P platform to some extent. The longer the operation time, the richer the operation experience. The median survival time of the platforms in the sample is 17, so this is the cut-off point. The value of survival time exceeding 40 months is 1, and the value of survival time less than 40 months is 0.

ICP Business licence (**ICP**) refers to the telecommunications operators that provide Internet information business and value-added services, and is a basic certificate that must be handled by an operational website in the Internet industry, but only by obtaining the certificate can the platform have the necessary venues, facilities and technical solutions, and have the reputation or ability to provide long-term services for users. The variable is set as follows: the platform without ICP certification is 0, and the platform with ICP certification is 1.

Bank Deposit (**Deposit**) means that the funds of the platform have changed from the original unified collection of the funds of users (investors and lenders) into the corresponding company account in the third-party payment system to the virtual account opened by each user, including the platform, in the access bank. The funds are not transferred through the platform system account, but are directly transferred into the user's bank account. It ensures the safety of user funds and can effectively prevent the behaviour of the platform to set up its own capital pool. The number of platforms that are not connected to the bank depository is 0, and the number of platforms that are connected to the bank depository is 1.

Regulatory background (**Regulatory**) is an important topic in P2P online lending industry. Only in the context of reasonable supervision can a perfect market develop better, reduce the emergence of moral hazard and reduce the irregular behaviour of platforms. The establishment of the China Internet Finance Association on March 25, 2016 is an important sign that the Internet finance industry has entered the era of self-regulation. It means that the P2P online lending industry is more standardised, the information is more transparent, and the disciplinary mechanism is clearer. This paper argues that platforms that withdrew from the P2P market before March 25, 2016, have no regulatory background, while newly established platforms with no problems after March 25, 2016 are considered to have regulatory background. 0 for non-existent regulatory background and 1 for existing regulatory background.

Regional GDP (**LnGDP**) is an important indicator to measure the economic situation of each region, and the level of GDP means the economic status of the region where the P2P platform is located. Regions with high GDP should have relatively sufficient funds, and the possibility of P2P platform withdrawal is small. This paper takes the logarithm of regional GDP as the control variable to analyse the influence of regional GDP on the final outcome of P2P.

5.6 Empirical results

In the analysis of the exit severity of P2P network lending platforms, many people have analysed the situation of P2P platforms through the discrete choice model, and reached some conclusions. However, few studies have been done to verify the applicable conditions of the discrete selection model. Therefore, before selecting a multinomial Logit model, this paper first verifies the applicable conditions of its model. Using a multinomial Logit model first satisfies the Irrelevant Alternatives Assumption (abbreviated IIA). Regarding the IIA hypothesis, the test method adopted in this paper is the Hausmann test, whose basic idea is that if the IIA hypothesis is true, the removal of one of the schemes will not affect the consistent estimation of the parameters of the other schemes. The data test results of this paper are shown in Table 4.4. It can be seen from the table that the data used satisfies the IIA assumptions of multiple Logit models. Multiple Logit models can be applied to the model construction of the final exit data of P2P lending platforms.

On the premise that the collected data on the withdrawal of P2P online lending platform meet a number of Logit model assumptions, taking the final severity of P2P online lending platform as the benchmark, this paper uses STATA14 software to evaluate the data parameters with the general withdrawal platform as the benchmark group. The results are shown in Table 4.5. The following analysis is an illustration with other variables held constant.

The existence of registered capital, P2P platform background, repayment guarantee, and creditor's rights transfer has significant effects on the independent variable $p<0.1$ of the non-general exit platform, among which the P2P platform background and repayment guarantee have the highest significance. Among the platforms with registered capital of more than 50 million explanatory variables, the probability ratio of the platforms with serious problems,major issues, and big problemwill increase compared with the platforms with normal exit (transformation or closure, etc.). As a result, the registered capital does not match Hypothesis 1. At present, the business registration is a subscription system, and the amount of registered capital is filled in by the applicant independently, and the actual payment is not required, but the information is highly asymmetric, resulting in market entities unable to identify and assess transaction risks, and bringing great hidden dangers to transaction security. Blindly believe that the higher the registered capital, the stronger the platform strength, there may be cognitive bias. In order to meet certain regulatory conditions for entering the P2P lending industry, many platforms will deliberately increase the registered capital, but they may not actually pay, and even some platforms will deliberately exaggerate the registered capital in order to attract investors or capital investment. This shows that the registered capital does not represent the strength of the company (Yum, 2012). If the platform is eventually operating in a non-compliant and illegal manner, the termination of the operation will expose its problems with greater legal risks and silent costs. However, as the funds roll larger and larger, the cost becomes higher and higher, and its illegal behaviours are eventually exposed, making the platform with problems more risky than the general withdrawal from the platform.

In terms of platform background, the performance of the private sector is not poor in all problem platforms. According to multiple Logit model estimation results, the performance of the private sector in the platform with serious problems and huge problems decreases with each unit increase compared with the general exit platform. That is to say, the proportion of private platforms with the same problems in cash withdrawal difficulties or delayed payment and economic investigation intervention is smaller than that of non-private platforms. Hypothesis 2 also needs to specifically subdivide the impact of the private sector on the withdrawal of the problem platform. Compared with general exit platforms, the probability of major problem platforms will increase, which should be platforms with good capital strength background, tend to expand their own business, increase the collection of creditor assets, and more likely to misappropriate funds and irrational investment, which makes the management of capital assets complicated, and the relative uncontrollable risk will increase. On the other hand, the private sector is relatively short of funds, careful in operating costs, simple in capital assets, and relatively controllable in the possibility of risks (Li, 2019), (Jiang, 2019). Although the private platform started earlier and has a larger number in the market, it is limited by its own nature, resulting in this kind of platform that does not have a strong ability to resist risks, lacks sufficient competitiveness in the market, and has difficulty forming a scale in the market.

A platform without repayment guarantee cannot effectively control the high risk of bad debts, and the repayment guarantee conclusion is consistent with Hypothesis 3. The platform without repayment guarantee has a low credit degree, so a serious problem platform can easily be formed. (Terry, 2006). The platform with repayment guarantee, whether it is guaranteed by a third-party financing guarantee company, or the mortgage of real estate and vehicles, or the platform using the risk reserve model, its operating risk is relatively small, and the bad debts after the loan can be timely turnover, should not be a platform with serious consequences. Mekter (2015) also concluded that the inclusion of third-party guarantees in Internet financial platforms can effectively reduce the risk of default.

Under the condition of $p<0.01$, allowing the transfer of creditor's rights has a significant impact on the problem platform, and the odds ratio will be reduced compared with the general exit platform. The empirical results of allowing the transfer of claims are inconsistent with Hypothesis 4. It may be that allowing the transfer of claims can enable investors to transfer the funds already lent to a third party under certain conditions, so as to meet the investors' own demand for funds withdrawal in emergency situations, increase the user experience, and help attract more investors and lend funds. However, because it also increases the capital flow requirements of the platform itself, the platform will be able to obtain more funds. The operation of the platform itself is more cautious, risk control measures are strengthened, capital asset planning is relatively more reasonable, and violations are relatively reduced. Emma (2016) also found in the study that Zopa strictly audited user data to reduce risks, indicating that strict platform risk control can indeed reduce the risks of P2P platforms.

In terms of the intensity of regional competition, the more intense the regional competition, consistent with hypothesis 5.the greater the impact on the platform of major problems compared with the general exit platform; the estimated coefficient increased by 0.322. This implies that the fiercer the regional competition, the greater the relative number of platforms, and the more prone to the phenomenon of fishing in troubled waters, the more competitive it is in terms of seizing investor funds and seizing high-quality assets, with high interest as the bait to set up virtual lending information, and the higher the risk of violations. Domestic P2P online lending problem platforms are mainly concentrated in economically developed provinces; the more economically developed the regions are, the more likely P2P online lending problem platforms appear. In addition, there are more and financial enterprises and technology in developed regions, and investors of P2P online lending platforms are more inclined to high-risk targets, and there is an obvious bandwagon effect, which increases the overall risk of P2P platforms (Shen, 2010).

The survival time of the platform with serious problems and the platform with major problems is consistent with Hypothesis 6, and compared with the general exit platform, the survival time is very significant under the condition $p<0.1$. It can be seen that the longer the survival time of the platform, the richer the operation and the lower the willingness to withdraw from the market, the better it can reduce its own risks. This is because the legitimacy and network relationship of P2P online lending enterprises are closely related to the operation time (Peng, 2003). The longer the survival time, the more it proves that the platform's business idea is correct, the borrower's review conditions are standardized, and the borrower's repayment ability is strong. The Matthew effect formed by this will be widely spread among the borrowers, and investors will continue to increase investment and bring more investors.To a certain extent, the survival time of the platform can represent the operational capability of the P2P platform itself. The longer the operation time, the richer the operational experience, which will help reduce the probability of platform problems (Herzenstein, 2011).

As for Hypothesis 7, from the empirical analysis, it can be seen that the final outcome of the platform for which the variable obtains the ICP operating licence is the major problem and the big problem will decrease by 0.265 and increase by 0.731 compared with the general problem, respectively. The platform that obtains the ICP operating licence has the reputation or ability to provide long-term services for users (Peng, 2003). Most of the platforms involved by economic investigation are operated in accordance with standardised procedures, and the proportion of ICP business licences will be higher; When the running platform opens the platform, it may be in order to reach a certain amount of funds, roll money and run away, and there will be more costs in time, funds and information for the ICP operating licence, resulting in the inability to handle the ICP operating licence. Since 2018, the domestic P2P online lending platform has become more complicated in terms of problem types, with a large number of problems such as delayed payment and platform closure, among which the main reason for the closure of the platform is that it does not have the ICP operating licence and cannot pass the acceptance, leading to the emergence of the problem platform.

Regarding Hypothesis 8, whether access to bank deposit has a non-significant impact on the results of the platform, for the general withdrawal platform of the benchmark group, the increase or decrease of its odds ratio is inconsistent. Among them, the success probability of the major problem platform to the general problem has decreased, and the success probability of the big problem has increased compared with the general problem. This indicates that the platform connected to the bank depository system has more risk control ability and is less likely to have problems (Matthew, 2007). Access to the bank depository helps to forcibly isolate the customer's funds at the bank side, and the account balance is stored in the user's depository bank account, which can be withdrawn in time, effectively reducing the occurrence of withdrawal difficulties. The access storage also increases the cost of the platform's own capital pool, increasing the difficulty of malicious money running away, thereby reducing the platform's major problems, i.e., reducing the risk of running away. In the case of major problems, the ratio of P2P violation increases, which indicates that although P2P platforms can enter depository banks and have no way to directly use user funds, there are still ways to collect investors' funds and set up capital pools outside the system, such as platform self-financing or financing related projects, or even fraud.The amount involved is often large, and if the relevant project cannot be repaid in time, it will expose its violations.

As can be seen from the table, the empirical analysis results are inconsistent with Hypothesis

9. The existence of P2P online lending market under the background of supervision has no significant impact on the outcome of serious problems, major problems and huge problems. Schenone (2004) came to the same conclusion that P2P platforms are under the regulatory system of SEC, which is conducive to improving their security and financing transparency. In order to prove the above conclusion, the research results of this paper are mainly based on the fact that the implementation of the regulatory background began in March 2016, while the data selected in this paper is up to 2017, and the regulatory implementation period is relatively short. It is difficult to achieve significant results.

From the empirical results, it can be concluded that the impact of provincial GDP on the P2P industry is not significant. This may be that the provincial GDP is relatively macro, and can significantly affect the withdrawal of P2P online lending platforms.

To sum up, explanatory variables such as registered capital, whether it is a private background, repayment guarantee, or creditor's rights transfer all have an impact on all other problem platforms that are relatively general exit platforms. Explanatory variables such as registered capital, whether it is a private background, repayment guarantee, creditor's rights transfer, platform survival time, or access bank deposit have significant effects on the outcome of a P2P online lending platform with serious problems. Among the factors that have a significant impact on the outcome of major problems, in addition to registered capital, whether it is private background, repayment guarantee, creditor's rights transfer, platform survival time, ICP operating licence, or bank deposit all have a positive constraint effect on the outcome compared with the outcome of general problems, which can effectively reduce the occurrence of such problems. Compared with general problems, explanatory variables such as registered capital, private system, repayment guarantee, creditor's rights transfer, regional competition, ICP operating licence and bank deposit are all very significant under $p<0.01$ conditions.

Among all explanatory variables, the increase or decrease of the model coefficients of each problem group is inconsistent with that of the general problem group, indicating that the P2P online lending platform has serious information asymmetry, or it may not play the symmetrical role of information.

In order to further verify the accuracy of the above conclusions, numerical indicators such as registered capital, regional competition degree and platform survival time were selected to conduct further ANOVA and other tests, and the robustness results were tested as follows:

This part takes the registered capital of P2P online lending platform as the proxy variable of its capital strength, and divides the problem platforms according to the registered capital, which can be divided into four groups: 5 million and below, 5.01 million to 20 million, 2001 million to 50 million, and more than 50 million. Then, variance analysis is used to compare whether the average survival time of each platform is equal, so as to judge whether the registered capital affects the survival time of the platform. The Homogeneity of Variances test results for the survival time of platforms with different levels of capital are shown in Table 5.7. The Levene statistic is 8.01, and its corresponding minimum significance level is 0.

This indicates that there are significant differences in the variance of the survival time of the four groups of platforms, which does not meet the prerequisite of ANOVA. Therefore, a robust mean test can be used. In Table 5.8, Welch and Brown-Forsythe statistics were 2.31 and 2.65, respectively, which could not reject the null hypothesis at the 5% significance level. This shows that there is no significant difference in the average survival time of the four groups of problematic P2P platforms with registered capital of 5 million and below, 5.01 million to 20 million, 20.1 million to 50 million, and more than 50 million. This result implies that registered capital is not a key factor affecting the survival time of problematic P2P online lending platforms. The reason why the registered capital has no significant impact on the survival time of the platform may lie in the fact that there is a capital correlation between some problematic platforms, oreven multiple platforms owned by the same boss.Therefore, the registered capital of the platform cannot accurately reflect whether the platform capital is strong.

It can be obtained by analysing the influence of the platform operating experience and the problem platform survival time: At present, China has zero threshold for the entry of P2P online lending platforms, so investors who do not have experience and qualifications in the financial industry have been involved in P2P online lending platforms. In fact, the normal operation of P2P online lending platform on the one hand is to attract investors to invest and on the other hand there is the need to introduce high-quality borrowers and projects to investors. Among them, most P2P platforms can break through geographical restrictions to attract investors, which is its advantage, and the lack of high-quality borrowers and projects is also the shortcoming of most platforms. Generally speaking, the longer the P2P online lending platform has been in business, the more likely it is to form an established customer base, and the more conducive it is to resist external risks and shocks. In this paper, the establishment time of P2P online lending platform is taken as the proxy variable of its operating experience. The earlier the platform is established, the richer its operating experience is. According to the establishment time, problem platforms are grouped and can be divided into four groups: before 2012, 2013, 2014 and 2015, the level of operating experience of these four groups declined in turn. Then, by comparing whether the average level of the platform survival time of different operating experience is equal, we can judge whether the platform operating experience affects the platform survival time. The Homogeneity of Variances test results of the survival time of platforms with different levels of operating experience are shown in Table 5.7. The Levene statistic is 9.66, and its corresponding minimum significance level is 0. It also shows that there are significant differences in the variance of the survival time of the four groups of platforms, which does not meet the prerequisite of ANOVA and requires a robust mean test. The robust mean test results in Table 5.8 show that Welch and Brown-Forsythe statistics are 65.82 and 68.74 respectively, both of which significantly reject the null hypothesis at the 5% significance level. This indicates that the average survival time of the four groups of problematic P2P platforms established before 2012, 2013, 2014 and after 2015 are not exactly the same. In addition, according to the multiple comparison test results of the survival time of the four groups of platforms in Table 5.9, the three test methods of Tamhane, DunnettT3 and Games-Howell all show that the mean level of survival time of platforms established in different time periods is significantly different at the significance level of 5%. Among them, the survival time of the platform established before 2012 was significantly higher than that of the other groups, and the survival time of the platform established in 2013 was significantly higher than that of the two groups of platforms established after 2014 and 2015, and the average survival time of the platform established after 2015 was the shortest. This indicates that the operating experience of P2P platform is one of the key factors affecting the survival time, and the richer the experience, the longer the survival time. The operating experience of the platform has a significant impact on the survival time of the platform, and the reason may be that customer relationship plays an important role in the development of P2P platforms and the development of financial markets. At present, there is no stable high-quality loan customers, which is the dilemma faced by most platforms.

Analysis of industry competition and problem platform survival can be obtained: the competition degree of the online lending industry in a region is measured by the number of P2P online lending platforms in each region. The greater the number of platforms in a region, the fiercer the competition in the P2P online lending industry in the region is. According to the number of P2P platforms less than 10, the number of platforms 11-20, the number of platforms 21-30 and the number of platforms more than 30, the regions are divided into four groups, and the intensity of industry competition in these four groups increases in turn. Then, by comparing whether the survival time of the problem platforms in the four groups of regions with different levels of competition is equal, we can judge whether the industry competition affects the survival of the platforms. The Homogeneity of Variances test results of problem platform survival time in regions with different industry competition degrees are shown in Table 5.7. The Levene statistic is 20.97, and its corresponding minimum significance level is 0, indicating that there are significant differences in the variance of problem platform survival time in the four groups of regions. The precondition of ANOVA is not satisfied, so a robust mean test is needed. The robust mean test results in Table 5.8 show that Welch and Brown-Forsythe statistics are 901.73 and 826.99 respectively, both of which significantly reject the null hypothesis at the 5% significance level. This indicates that the average survival time of problematic P2P platforms in regions with different levels of competition is not exactly the same. In addition, according to the multiple comparative test results of the number of problem platforms in each group in Table 5.10, the three test methods of Tamhane, DunnettT3 and Games-Howell all show that the survival time of problem platforms in regions with very fierce competition in P2P online lending industry (Guangdong, Beijing and Shanghai) is significantly higher than that in other regions. In addition, the mean test shows that there is no significant difference in the survival time of three problem platforms: no competition, average competition and intense competition. This indicates that there is a positive correlation between the intensity of competition in the P2P industry and the average survival time of problematic platforms in a certain region. The reason may be that fierce industry competition is conducive to financial innovation, making the platform more viable.

5.7 Conclusion

In this part, we mainly study the specific problem platform data in terms of risk platforms, systematically study the main characteristics of problem platforms and the main factors affecting the failure of problem platforms, and divide P2P online lending platforms into general exit platform, serious problem platform, major problem platform and major problem platform through various outcomes. Then, the econometrics method of multiple Logit model is used to study the various influencing factors of each category.

The main conclusions are as follows: first, the registered capital is in all the problem platforms; The platform background is in the platform of serious and large problems; ICP operating licences and bank deposits in the big problem platform exist in the phenomenon of "pulling the banner as a tiger skin", registered capital and other factors cannot represent the background strength level of the platform, the relevant information does not play its role. Second, in terms of risk control, certain repayment guarantees (third-party guarantee, real estate and vehicle mortgage, risk reserve fund, etc.) is conducive to the P2P online lending platform to control the risk of high bad debts, improve the credit degree, truly enhance the risk control strength of the platform, and help reduce the occurrence of problem platforms. Third, the transfer of creditor's rights is conducive to the turnover of investors' lending funds, which increases the platform's requirements for liquidity, but also improves the platform's control of risks from the side and reduces the proportion of platform problems. Fourth, the response of serious problem platform and major problem platform to regional competition is not significant, but the response of major problem platform to regional competition is significant. In other words, the lower the level of competition in the region where the platform is located, the less likely there is to be a large problem platform. Fifth, the earlier the platform goes online, the longer the survival time, the richer the business experience, and the less likely it is to have problems exiting the platform. Sixth, the access of bank deposits can effectively reduce the occurrence of serious problems and major problems, but it cannot reduce the occurrence of irregularities and illegal platforms.

Current studies mostly focus on the default behavior of P2P lenders, and discuss the causes, influencing factors and consequences of default, resulting in relatively little research on P2P lending platforms themselves. Therefore, this paper studies platform default behavior from the perspective of P2P platforms with certain practical significance. This paper comprehensively analyzes the main factors that affect the default behavior of P2P online lending platforms, so that the regulatory authorities, self-regulatory organizations, lenders and borrowers and the platforms themselves can recognize the problems in the development of online lending, and provide references for the formulation of rules and policies in the future normative development process of the P2P lending industry. In addition, it can provide early warning for China's P2P online lending platform, strengthen the risk prevention and supervision of online lending platform itself, and improve the transaction success rate and platform operation capacity of online lending platform.

This paper mainly uses binary regression analysis and qualitative and quantitative analysis method to sort out the literature through these two methods, and summarizes the corresponding theoretical basic knowledge and risk types. In the process of quantitative analysis, variable indicators that can cover various risk types are selected as far as possible, but the selection of variable indicators still has certain subjective characteristics. This will have a limited impact on the universality of predictive model expressions

Table 5.1 Statistical characteristics of problem platform data

Result	Frequency	Percent	Cumulative Percent

General exit platform	252	48.4	48.4
Serious problem platform	88	16.9	65.3
Major issues platform	97	18.6	83.9
Big problem platform	84	16.1	100
Total	521	100	

Note: The above table shows the number, proportion and cumulative proportion of general exit platforms, serious problem platforms, major problem platforms and major problem platforms. The differences in the number of various problem platforms can be intuitively seen from the above table.

Table 5.2 Descriptive analysis of independent variables:

Variables	General exit platform		Serious problem platform		Major issues platform		Big problem platform	
	Frequency	Percent	Frequency	Percent	Frequency	Percent	Frequency	Percent
Registered capital ≤50 million	220	87.30%	74	84.09%	52	53.61%	44	52.38%
Registered capital > 50 million	32	12.70%	14	15.91%	45	46.39%	40	47.62%
Non-private system	39	15.48%	13	14.77%	15	15.46%	14	16.67%
Private sector	213	84.52%	75	85.23%	82	84.54%	70	83.33%
No repayment protection	78	30.95%	45	51.14%	53	54.64%	60	71.43%
Guaranteed repayment	174	69.05%	43	48.86%	44	45.36%	24	28.57%
unassignable	116	46.03%	47	53.41%	48	49.48%	12	14.29%
Assignable claim	136	53.97%	41	46.59%	49	50.52%	72	85.71%
Regional competition is not fierce	61	24.21%	29	32.95%	41	42.27%	31	36.90%
Fierce regional competition	191	75.79%	59	67.05%	56	57.73%	53	63.10%
Survival time <40 months	126	50.00%	41	46.59%	45	46.39%	45	53.57%
Survival time ≥40 months	126	50.00%	47	53.41%	52	53.61%	39	46.43%
Has not obtained ICP certification	173	68.65%	61	69.32%	77	79.38%	56	66.67%
Obtain ICP certification	79	31.35%	27	30.68%	20	20.62%	28	33.33%
Not deposited with the bank	204	80.95%	70	79.55%	82	84.54%	68	80.95%
Docking bank deposit	48	19.05%	18	20.45%	15	15.46%	16	19.05%
No regulatory background	228	90.48%	80	90.91%	84	86.60%	77	91.67%
Existing regulatory background	24	9.52%	8	9.09%	13	13.40%	7	8.33%

Note: The above table shows the number and proportion of platforms classified and counted under different characteristic variables for general exit platforms, serious problem platforms, major problem platforms and major problem platforms. The differences in the number of different problem platforms can be intuitively seen from the above table.

Table 5.3 Descriptive statistics of the lifetime of the problematic P2P platforms

Survival time	N	Proportion	Min	Max	Total	Mean	Standard deviation
≤12 months	13	2.50%	2	12	112	8.62	3.10
12-24 months	82	15.74%	13	24	1576	19.22	3.18
24-48 months	266	51.06%	25	48	9875	37.12	6.63
＞48 months	160	30.71%	49	119	9821	61.38	12.56

Notes:

The table above describes the basic characteristics of the lifetime of the problematic P2P platform, including descriptive statistical indicators such as quantity, proportion, minimum value, maximum value, mean value and standard difference.

Table 5.4 Variables and assignments that affect the final outcome of P2P lending platforms

Notation	Variable	Measurement of variables
Platform end result	Result	Generally, the exit platform is 0, the serious problem platform is 1, the major problem platform is 2, and the major problem platform is 3.
Registered capital	Capital	Registered capital less than or equal to 50 million is 0, registered capital greater than 50 million is 1
Platform background	Background	The non-private system value is 0, and the private system value is 1
Repayment protection or not	Guarantee	Zero for no repayment protection and one for repayment protection
Assignment of claim	Creditor	Non-transferable claims are 0 and transferable claims are 1.
Regional competition	Competition	The regional competition is 0, and the regional competition is 1.
Platform lifetime	Lifetime	Survival time <17 months is 0, survival time ≥17 months is 1
ICP business licence	ICP	The number of platforms that have not obtained ICP certification is 0, and the number of platforms that have obtained ICP certification is 1
Bank deposit	Deposit	The number of platforms that are not connected to the bank depository is 0, and the number of platforms that are connected to the bank depository is 1.
Regulatory background	Regulatory	0 for non-existent regulatory background and 1 for existing regulatory background
Regional GDP	LnGDP	Take the ln value of the GDP of the province where P2P is located

Note: The above table shows each index of the analysis of influencing factors for the exit of P2P online lending platform, in which the explained variable is Result. Explanatory variables are Capital, Background, Guarantee, Creditor, Competition, Lifetime, ICP, Deposit, Regulatory, and LnGDP are control variables

Table 5.5 Hausman test for the independent hypothesis

Variable	Chi2	P value	Verify
Serious problem platform	5.26	0.99	Satisfy H0
Major issues platform	9.03	0.99	Satisfy H0
Big problem platform	17.42	0.64	Satisfy H0

Note: The above table shows the results of the Hausman test for the independent hypothesis, Chi2 is the Hausman test statistic, and the corresponding significance level is P value. When P value is less than 5%, it is considered that the 5% significance level test has been passed, and the null hypothesis H0 is rejected (problem severity i and problem severity j are independent).

Table 5.6 Estimates of multiple Logit models

Result	Serious problem platform	Major issues platform	Big problem platform
Capital	1.528***	1.32***	0.71***
	(20.181)	(10.937)	(9.048)
Background	-1.642***	-1.72***	-0.308***
	(24.272)	(18.818)	(9.104)
Guarantee	-2.648***	-0.377***	-0.11***
	(59.224)	(4.207)	(6.117)
Creditor	-1.499***	-1.828***	-1.759***
	(16.15)	(21.247)	(21.673)
Competition	-0.675	-0.121	0.322**
	(0.859)	(0.102)	(3.835)
Lifetime	-0.492*	-0.592*	-0.324
	(2.878)	(2.951)	(1.023)
ICP	0.096	-0.265**	0.731***
	(0.084)	(3.521)	(4.083)
Deposit	-0.005	-0.185***	0.122***
	(0.01)	(5.184)	(6.085)
Regulatory	0.241	0.294	-0.52
	(0.201)	(0.241)	(0.977)
LnGDP	0.277	-0.144	0.075
	(0.164)	(0.037)	(0.012)

Note: The above table shows the estimation results of Model 5.12 based on the whole sample, showing the multinomic Logit estimation results of Serious problem platform, Major issues platform, Big problem platform based on general problem groups. The risk of P2P lending is explained by the end Result type of the platform. The variables are defined in Table 5.1. *, * *, * *, represent significance at the 10%, 5%, and 1% levels, respectively.

Table 5.7 Test of variance homogeneity of survival time of each platform

Grouping variable	Levene Statistic	df1	df2	Sig.
Registered capital	8.01	3	517	0.00
Registered time	9.66	3	517	0.00
Competition degree	20.97	3	517	0.00

Note: The above table describes the variance homogeneity test of the survival time of each group. When the Levene Statistic is large, the corresponding sig is less than 0.05, which indicates that there is a significant difference in the variance of the survival time of the platforms, and the prerequisite for ANOVA is not met. Similarly, if the Levene Statistic is small and the corresponding sig is greater than 0.05, it is considered that there is no significant difference in the variance of the platform survival time, so the prerequisite for ANOVA is met.

Table 5.8 Robustness test of mean survival time of each group of platforms

Grouping variable	Statistical variable	Statistic	df1	df2	Sig.
Registered capital	Welch	2.31	3	4.96	0.20
	Brown-Forsythe	2.65	3	2.06	0.28
Registered time	Welch	65.82	3	129.32	0.00
	Brown-Forsythe	68.74	3	117.09	0.00
Competition degree	Welch	901.73	3	62.13	0.00
	Brown-Forsythe	826.99	3	259.93	0.00

Note: The table above describes the robustness test of the mean survival time of each group of platforms. When the variance homogeneity test fails, the robustness test of the mean is required. The test principle is that when Welch and Brown-Forsythe statistics are small and the corresponding Sig is greater than 0.05, it is considered that there is no significant difference in the mean value. On the contrary, there is a significant difference.

Table 5.9 Results of multiple comparison tests of problem platform survival time for each group

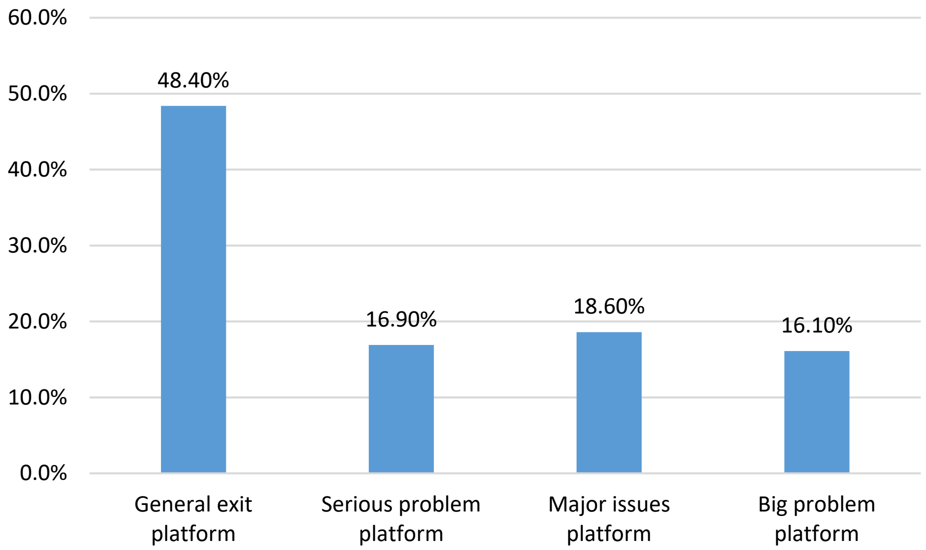
(I)Registered time	(J)Registered time	Mean Difference	Std	Tamhane		Dunnett T3		Games-Howell	
				Floor	Upper	Floor	Upper	Floor	Upper
Before 2012	2013	18.17143*	3.925	7.475	28.868	7.494	28.849	7.785	28.558
	2014	29.67431*	3.659	19.600	39.749	19.624	39.724	19.909	39.440
	After 2015	38.05699*	3.649	28.005	48.109	28.029	48.085	28.314	47.800
2013	Before 2012	-18.17143*	3.925	-28.868	-7.475	-28.849	-7.494	-28.558	-7.785
	2014	11.50288*	1.931	6.332	16.674	6.336	16.670	6.468	16.538
	After 2015	19.88557*	1.912	14.761	25.010	14.765	25.006	14.896	24.875
2014	Before 2012	-29.67431*	3.659	-39.749	-19.600	-39.724	-19.624	-39.440	-19.909
	2013	-11.50288*	1.931	-16.674	-6.332	-16.670	-6.336	-16.538	-6.468
	After 2015	8.38268*	1.280	4.999	11.766	5.000	11.766	5.081	11.684
After 2015	Before 2012	-38.05699*	3.649	-48.109	-28.005	-48.085	-28.029	-47.800	-28.314
	2013	-19.88557*	1.912	-25.010	-14.761	-25.006	-14.765	-24.875	-14.896
	2014	-8.38268*	1.280	-11.766	-4.999	-11.766	-5.000	-11.684	-5.081

Note: The above table describes the results of multiple comparison tests for the survival time of each group of problem platforms, where * of Mean Difference statistic means that it passes the significance level test of 5%. When the significance level test is passed, the mean is considered to be significantly different. Three test statistics, Tamhane, Dunnett T3 and Games-Howell, showed the upper and lower limits of the 5% significance level test, and passed the 5% significance level test when the Mean Difference was in the middle of the upper and lower limits of the statistic

Table 5.10 Results of multiple comparison tests on the survival time of each problem platform

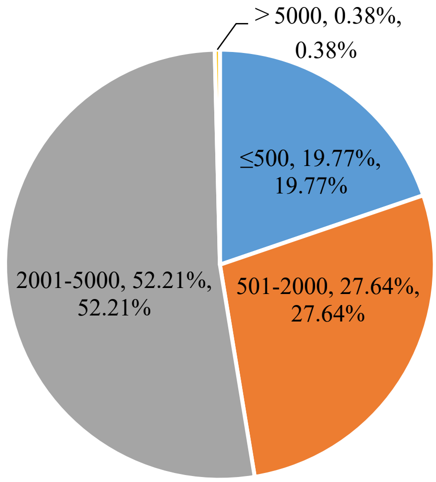
(I)Platforms Number	(J)Platforms Number	Mean Difference	Std	Tamhane		Dunnett T3		Games-Howell	
				Floor	Upper	Floor	Upper	Floor	Upper
Less than 10	11-20	-12.739*	3.551	-11.363	7.885	-11.349	7.872	-11.093	7.615
	20-30	-8.901*	2.927	-8.730	6.928	-8.724	6.922	-8.527	6.724
	More than 31	-13.493*	2.179	-9.366	2.380	-9.359	2.373	-9.206	2.220
11-20	Less than 10	1.739	3.551	-7.885	11.363	-7.872	11.349	-7.615	11.093
	20-30	0.837	3.669	-9.077	10.752	-9.064	10.739	-8.803	10.478
	More than 31	-1.754	3.105	-10.300	6.792	-10.280	6.772	-10.039	6.531
20-30	Less than 10	0.901	2.927	-6.928	8.730	-6.922	8.724	-6.724	8.527
	11-20	-0.837	3.669	-10.752	9.077	-10.739	9.064	-10.478	8.803
	More than 31	-2.592	2.366	-8.951	3.768	-8.945	3.761	-8.781	3.597
More than 31	Less than 10	3.493	2.179	-2.380	9.366	-2.373	9.359	-2.220	9.206
	11-20	1.754	3.105	-6.792	10.300	-6.772	10.280	-6.531	10.039
	20-30	2.592	2.366	-3.768	8.951	-3.761	8.945	-3.597	8.781

Note: The above table describes the results of multiple comparison tests for the survival time of each group of problem platforms, where * of Mean Difference statistic means that it passes the significance level test of 5%. When the significance level test is passed, the mean is considered to be significantly different. Three test statistics, Tamhane, Dunnett T3 and Games-Howell, showed the upper and lower limits of the 5% significance level test, and passed the 5% significance level test when the Mean Difference was in the middle of the upper and lower limits of the statistic



Note: The figure above shows the proportion of general exit platform, serious problem platform, major problem platform and huge problem platform. The differences in the number of various problem platforms can be seen intuitively from the figure above.

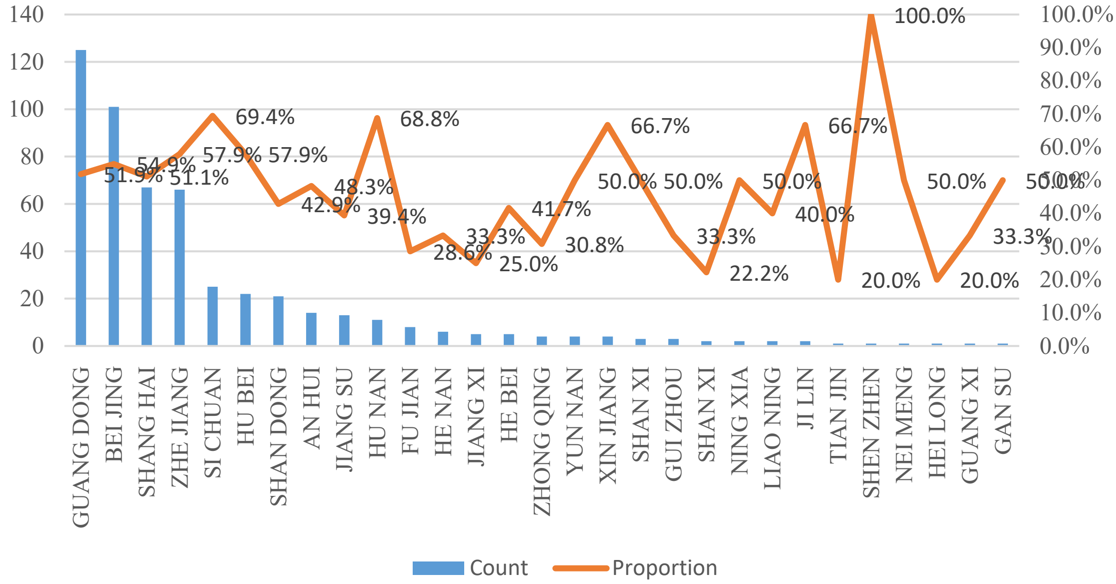
Figure 5.1 Proportion of P2P platform exit solution categories



Notes:

The figure above shows the proportion of registered capital of P2P platforms with different problems. Through this figure, the distribution of P2P problem platforms with different registration scales can be clearly found.

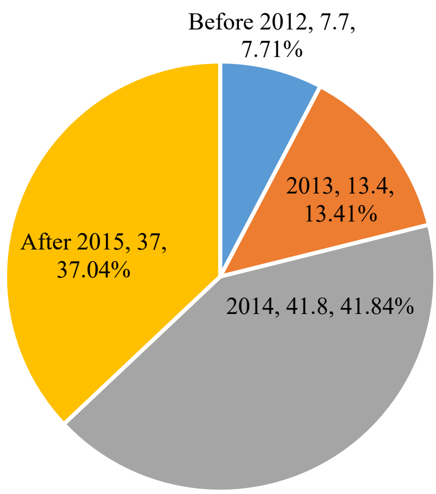
Figure 5.2 Proportion of registered capital of problematic P2P platforms



Notes:

The above figure uses excel bar chart and line chart to compare and analyse the number and proportion of P2P platforms with problems in different provinces and cities in China.

Figure 5.3 Number and proportion of P2P platforms with problems in each region



Notes:
The figure above shows the establishment time analysis of P2P platforms with different problems, through which the distribution of P2P platforms with different establishment times can be clearly seen.

Figure 5.4 Analysis of the establishment time of the problematic P2P platform

Chapter 6: Summary of the thesis

6.1 Summary of results

In order to study the risk of P2P platforms, we conduct in-depth research around three sub-topics. (1) The behavioural characteristics of P2P lending in China (2) Risk assessment of P2P lending in China (3)Risk characteristics of China's P2P lending platform.

The first sub-topic is mainly studied from the perspective of lending platforms. From the perspective of the lending platform, it considers the influencing factors of the lending volume of platform, and conducts an in-depth study on whether the lending volume of the lending platform itself is affected by lending sentiment, herding effect and speculation. Specifically, P2P lenders respond positively to lending sentiment (positive news) in the P2P industry. We interpret this result as P2P lenders showing stronger lending sentiment in the wake of more positive news about P2P. On the other hand, the influence of herd effect on P2P is also significant and effective. Specifically, when the total amount of lending on other P2P platforms increases, P2P platforms will have a follow-on effect and expand their own lending volume. This result shows that herd behaviour is an important feature of P2P lending in China. The research and analysis of speculative behaviour found that the rising prices of commercial real estate in the province positively explained the P2P lending volume (speculative behaviour). This suggests that P2P lending in China is likely to be driven by a bubble in the real estate market, as formal financing channels in China are restricted from investing in the real estate market, so some investments in the real estate sector have to be financed through shadow banking activities, of which P2P online lending is the best embodiment in the Internet sector.

In the second subtopic, we select three representative companies in the industry, Renrendai, PPDai and Yirendai, and use large samples to establish the Logit model for analysis. Through the analysis of the impact of four characteristics, namely, basic characteristics of borrowers, credit characteristics of borrowers, working characteristics of borrowers, and asset characteristics of borrowers on the default rate of loans, the study found that under the background of increasingly strict supervision, 11 borrower characteristic information variables, such as gender, age, education background, marital status, credit score, credit limit, overdue times, income, working hours, real estate information and car information, have a significant impact on loan default, while borrower mortgage information and car loan information have no significant impact on loan default. Among them, borrowers who are older, have a higher level of education, a more stable the marital status, a higher credit score, a higher credit limit, a higher income, work longer hours, and are able to produce real estate information and vehicle production information are less likely to default, while those who have more past offences are more likely to default. In addition, in the second sub-topic, we evaluate the risks of borrowers through the historical data of P2P platforms, and establish a credit risk assessment body by using the characteristics of borrowers on P2P platforms. Factor analysis is made on the above 11 borrower characteristic indexes, and the risk control level of the three P2P platforms of Renrendai, PPDai and Yirendai is evaluated. It is found that Renrendai has a strong risk control ability. Through actual investigation and research, it is found that the information disclosure of Renrendai is relatively transparent. It will publish quarterly operational data to predict and avoid risks. The project funds were deposited by China Minsheng Bank. Especially for P2P loans, borrowers will receive 4 basic information inquiries, 5 public information screenings, 8 telephone verifications, 35 scorecard data entries, 100% information correlation checks, and over 30% quality inspection coverage to ensure the safety of loan funds. This further proves that the acquisition and evaluation of borrowers' characteristic information is the best risk control method for online lending platforms. It is also hoped that the Renrendai risk evaluation model in this thesis's P2P platform risk study can provide reference for the transformation of other P2P platforms.

In the third part, based on the analysis in the first two chapters, we analysed the relevant factors affecting the withdrawal of problem platforms from the perspective of P2P lending platforms, selected 521 specific problem platform data, and used a Logit model to systematically study the main characteristics of problem platforms and the main factors affecting the failure of problem platforms. The results of P2P online lending platform are divided into general exit platform, serious problem platform, major problem platform and big problem platform. Then, using the econometrics method of multiple Logit models, various influencing factors of each category are studied. The main conclusions are as follows: first, registered capital is in all problem platforms; the background of platform is a serious and big problem. Factors such as ICP operating licences and bank deposits, which have major problems in the registered capital of the platform, cannot represent the background strength level of the platform, and relevant information does not play its due role. Second, in terms of risk control, certain repayment guarantees (third-party guarantees, real estate and vehicle mortgages, risk reserves, etc.) help P2P online lending platforms control the risk of high bad debts, improve credit, truly enhance the risk control strength of the platform, and help reduce the occurrence of problem platforms. Third, the transfer of creditor's rights is conducive to the turnover of investors' loan funds, increasing the platform's liquidity requirements, improving the platform's risk control from the side, and reducing the proportion of platform problems. Fourth, the response of serious problem platform and major problem platform to regional competition is not significant, but the response of major problem platform to regional competition is significant. Fifth, the earlier the platform is launched, the longer the survival time, the richer the business experience, and the less likely there is to be problems when exiting the platform. Sixth, access to bank deposits can effectively reduce the occurrence of serious problems and major problems, but it cannot reduce the occurrence of violations and illegal platforms.

6.2 Implications

P2P online lending was once in legal limbo, especially before 2015, when the government lacked formal regulatory documents for the Internet finance industry and the whole industry was mixed. The lack of legal supervision also led to the stage of low threshold and high risk for the whole industry to some extent.In 2015, when the state's supervision of Internet finance was not perfect, the online lending industry ushered in explosive growth, and some small loan companies and even individuals easily entered the industry.Many of the P2P platforms that have mushroomed are extremely irregular in both platform operation and company management, thus increasing the internal risks of the platforms. The reason why there is a large number of problem platforms in P2P online lending, which are not easy to be discovered before the incident, is that the business process of P2P online lending platforms is relatively complex and the risks are hidden. In order to gain the trust of investors, operators of P2P online lending platforms will overstate their investment returns and over-package the platforms, resulting in information asymmetry. In addition, the P2P online lending platform is a new product in China, which is still in the stage of exploration and development. The relevant information disclosure, legal supervision and other systems are not perfect, which pushes the problem of the P2P online lending platform walk to the edge of the law. Therefore, due to information asymmetry, unsound laws and other reasons, it is particularly difficult to identify and supervise problems of P2P online lending platforms.

With the promulgations of the Interim Measures for the Management of Business Activities of Online Lending Information Intermediaries and the establishment of the Notice on Strengthening the Construction of Credit Investigation System in the Field of P2P Network Belt and other regulations, the P2P lending industry is also gradually changing in terms of the formation mechanism of interest rates, the range of product forms and other aspects, and the differences between platforms are gradually narrowing.

Especially with the continuous introduction of the policies and documents of the Banking and Insurance Regulatory Commission and the online loan regulation office, the regulation of the online loan industry still takes "liquidation and transformation" as the main tone. Except for a few powerful platforms seeking transformation and development, the vast majority of platforms will leave through active liquidation, business withdrawal or transformation and development, and the special rectification work of online loans may come to a close. It is worth noting that the private financial market is still in strong demand, the potential of long-tail customers is still huge, and private capital is still an indispensable force to serve the real economy. With the continuous improvement of the legal system, the increasing maturity of the credit investigation system and the continuous breakthrough of the financial innovation, the net loan industry may appear in the financial market with a more novel attitude. Therefore, with the continuous development of the P2P online loan industry and the continuous improvement of supervision, industry research must continue. With the development of the industry, the early warning system must be constantly updated. The research conclusion of this thesis is that the risk of the lending platform is affected by borrowing sentiment, herding effect and speculative behaviour, and the borrower is comprehensively affected by the characteristics of the borrower, the credit characteristics of the borrower, the working characteristics of the borrower and the asset characteristics of the borrower. In addition, by summarising the risk prevention of the Renrendai platform, it is proved that the acquisition and evaluation of the borrower's characteristic information is the best risk control method for the online lending platform.

Therefore, in order to provide a basis for the strategic transformation of other P2P platforms and support the orderly and healthy development of China's online lending industry, the next step for the risk research of P2P platforms is to build a risk evaluation system for P2P online lending platforms. By establishing the risk evaluation index system of P2P online lending platform, the risk evaluation of P2P online lending platform is carried out, and the default risk of borrowers is effectively assessed. It provides a simple and feasible evaluation method for investors to identify problem platforms, provides model data support for lending platforms, and provides relevant suggestions for regulators' supervision activities.

6.3 Limitations of the study

Starting from the development history of P2P platform, this thesis frstly introduces the P2P platform, discusses the development of the P2P platform, the establishment of the P2P platform rules and regulations, and the theory of P2P risk. It combines the characteristics of Chinese P2P lending behaviour, and the risk assessment of Chinese P2P online loans, and adopts the progressive research method. After studying the causes of platform risks, the reasons why benchmark-based platform (Renrendai) can effectively avoid risks are discussed in detail. Some problem platforms are selected to systematically study the characteristic variables of the problem platform.

However, this thesis still has many shortcomings. First of all, factors affecting herd behaviour have received more attention from scholars, while the influence of herd behaviour on the market, investors and platform in the P2P lending market has just started. The discussion of the influence of herd behaviour in this thesis mainly focuses on the influence of herd effect on the amount of lending on P2P platforms. However, whether P2P platforms have herd effect is proved by literature research. Due to the lack of more data on herd behaviour indicators, there is no demonstration of the investment behaviour of herd effect, which can be studied from this perspective in the future.

Second, due to the poor level of data disclosure of other P2P platforms, this study only selected the data of Renren and other three lending platforms as samples for analysis. Although these platforms are relatively representative of the Chinese industry in terms of scale and platform types, their better risk control actually affects the analysis of borrower defaults. In this aspect, whether the three platforms can represent the whole P2P market in China remains to be demonstrated. Data of different platforms can be collected for research after considering the specifications of other platforms.

Third, some index variables of platform borrowers are collected. However, due to the lack of data on most platforms, only 14 highly representative variables were retained in the end. The research object of this thesis is the P2P platform, but the lender in the P2P market is not included in the research scope, and the dishonest behaviour of the lender will also have an impact on the market. Therefore, after the research on the P2P platform is relatively complete, the research on the main body of the lender can be added to strengthen the healthy operation of the P2P market.

Fourth, due to the late emergence of the P2P online lending industry in China, which has only existed for about 10 years, domestic scholars have conducted few studies on the risks of P2P online lending, while most foreign studies focus on foreign P2P platforms. Therefore, whether the relevant research conclusions of foreign P2P platforms can fully support the research results of this thesis, especially after the liquidation of P2P platforms' social networks in 2020,is still uncertain. There are few studies on the risks of P2P lending platforms in China, and so only a few studies can provide reference for this thesis, which may lead to further improvement of research results.

Fifth, due to the complex and diverse factors affecting P2P online lending platforms and the limited available data and my own knowledge and ability at the present stage, this thesis cannot summarise all the factors required to analyse and study the risk factors affecting P2P platforms completely. Therefore, the selection of the research model may not be the most scientific. Future research in this area can try to add more explanatory variables, such as whether the borrower has certification of other projects, and integrate other models to obtain better empirical results.

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