Essays on the Economics of Peer-to-Peer Lending

by

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Abstract

This thesis presents three empirical studies about the peer-to-peer (P2P) lending market. The first study examines whether the announcement of a government support policy could have an impact on the P2P lending market, using the U.K.'s introduction of a tax-free P2P individual savings account as an example. I find that after the announcement of the new policy, high-risk borrowers were attracted into the market and this resulted in losses to lenders. The second study is a discussion of how a Ponzi scheme affected Chinese P2P lending platforms. I find that after the Ezubao Ponzi scheme, platforms suffered a higher default risk and paid higher premiums to cover lenders' losses, which resulted in negative returns for P2P lending platforms. The third study examines the lifecycle of the development of the P2P lending market in China. Based on the industry lifecycle (ILC) theory, I find that the P2P lending market in China experienced rapid growth and then a significant decline in 13 years. Even though the lifespan of the market is short, the market can still be pictured as having five phases of development. In line with theoretical predictions, the earliest entrants among P2P lending platforms survived the longest in the market.

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Chapter 1

Introduction

FinTech is short for financial technology, which covers three main areas, summarized by Navaretti et al. (2017): transactions, fund and credit management, and insurance. As a new growing industry, FinTech has been connecting financial services with information technology to solve financial problems since the 2008 global financial crisis. In response to the tightening of credit and deleveraging by traditional financial institutions during the crisis, FinTech now not only provides similar services to traditional financial institutions but can also serve those customers who were previously excluded by traditional finance. The FinTech industry has rapidly expanded since 2008, especially in peer-to-peer lending, which is one of the most important applications of FinTech (Arner et al., 2015).

Peer-to-Peer (P2P) lending is a new type of direct financing which connects borrowers and lenders through the internet. The first P2P lending platform was Zopa, which launched in 2005 in the United Kingdom. In 2006, Prosper and Lending Club were established in the United States, which are recognized as the most influential and most famous P2P lending companies in the world. Following them, the Chinese P2P lending market emerged in 2007. According to data from the Cambridge Centre for Alternative Finance, from 2010 to 2019, P2P lending markets developed rapidly around the world, with China, the United States, and the United Kingdom being the three leading P2P lending markets.

There are three main participants in the P2P lending market: borrowers, lenders, and P2P lending companies or platforms. Borrowers are those who lack money and need to borrow. Lenders, also called investors, are those who have funds available to lend and expect to receive returns. Through the internet, P2P lending platforms match borrowers and lenders directly. After registering on the platform, borrowers can apply for a loan with their preferred loan amount and length of borrowing by providing their personal information. When receiving credit applications and collecting borrowers' information, platforms are responsible for differentiating trusted borrowers from high-risk borrowers by analyzing the credit reports of borrowers and qualifying them. Then, the loan applications of qualified borrowers are published on the platform. Depending on the trading rules of different platforms, lenders either invest in fixed fundraising portfolios with fixed return rates or look for and bid on borrowers or loan applications that match their investment expectations. The trading is complete once the requirements of borrowers are matched with the investments by lenders. After receiving funds from lenders, borrowers are responsible for repaying the principal and interest on time, while lenders receive their return. As agents, P2P lending companies not only provide services to match borrowers and lenders but also take responsibility for monitoring loan performance. They charge service fees to borrowers and sometimes charge management fees to lenders.

With the development of the P2P lending market, studies on P2P lending become a focus of academic research. Liao and Zhang (2017) reviewed the previous literature and pointed out that studies mainly focused on two aspects: the identification of borrowers and the behaviour of lenders. To apply for credit, borrowers need to provide their personal information, which creates the same information asymmetry problem as for borrowers in traditional financial markets. As reviewed and summarized by Bachmann et al. (2011), studies on borrowers are mainly focused on how different types of characteristics, such as financial, demographic, or social characteristics, affect the success of loan applications. As for studies on lenders in the P2P lending market, according to Liao and Zhang (2017), those that focus on lenders mostly discuss whether investors behave rationally. Most studies believe that herding behaviour existed in the P2P lending market (Gao, Caglayan, Li and Talavera, 2021; Herzenstein et al., 2011; Zhang and Liu, 2012). Moreover, as one of the key participants, the focus on P2P lending platforms is concentrated on their business model. Zhao et al. (2017)

focused on the working mechanisms of P2P lending platforms. They summarized and reported on different types of platforms and their trading rules by reviewing mainstream P2P lending platforms around the world. However, studies about P2P lending have certain limitations. Basha et al. (2021) reviewed 198 published papers from 2008 to 2020 and pointed out that the majority of these papers concentrate geographically on examining the P2P lending market in the United States and China. They also found that most of the empirical studies focus mostly on the determinants of P2P lending funding success and loan performance but less on macroeconomic determinants.

However, few studies have focused on the external determining factors of P2P lending. The history of P2P lending is still quite short, and there are few studies that describe the development of P2P lending from the perspective of the market. My work discusses the development of the P2P lending market and adopts the standpoint of P2P lending platforms to consider how extraneous factors such as policy changes or unexpected financial scandals affect market participants, particularly borrowers and P2P lending platforms. The main part of this thesis consists of Chapter 2, Chapter 3, and Chapter 4. These chapters are structured as follows:

In Chapter 2, I chose to examine Zopa in the United Kingdom, where the government implemented the new Innovative Finance ISA (IFISA) policy. To assess whether the announcement of government policy would affect the P2P lending market, I collected data from Zopa on newly funded borrowers in the period from May to October 2015. The default rates estimated by the Probit model show a significant increase in the probability of default for new entrant borrowers after the IFISA announcement compared to those before. In addition, the principal loss rate was analyzed by the Tobit model, and the results showed that new borrowers who entered after the IFISA announcement started defaulting earlier. In addition, the increase in the number of potentially defaulting borrowers revealed by the hurdle model suggests that high-risk borrowers started to apply for loans in the P2P lending market. This suggests that the new IFISA announcement led to the entry of higher-risk borrowers and that P2P platforms such as Zopa did not fully anticipate this higher risk and continued to accept their loan applications, leading to losses for lenders.

A Ponzi scheme is a classic financial fraud that destroys the trust of investors in the market. Ezubao was one of the most famous P2P lending platforms in China, which was exposed to a Ponzi scheme causing a highly negative influence not only on investors but also on other P2P lending platforms. Looking from the perspective of platforms, in Chapter 3, I collected data from the top-ranked platform, Renrendai from October 2015 to March 2016 to analyze how the Ezubao scheme affected other platforms in the market. The results showed that after the Ezubao scheme was made public, the Renrendai platform suffered a higher default risk from an increasing number of borrowers who tended to default on more principal and interest. Because of the premium compensation arrangements, the platform had to pay more premiums to cover investor losses, therefore reducing its profits.

In Chapter 4, to give an overview of the development of the P2P lending market in China, I predicted that it would follow the same lifecycle process as other mature industries. I collected two datasets: one containing information from registered P2P lending platforms from 2007 to 2020, the other comprising detailed monthly P2P lending market statistics from 2014 to 2019. Based on the framework of the industry lifecycle theory, I found that P2P lending in China experienced five complete stages in a short lifespan. It was a new market in the beginning when it was introduced to the public, then it entered a significant growth stage, before reaching maturity and finally beginning to decline until its eventual termination. I also found that the earlier entrants among P2P lending platforms survived longer than the later entrants. Finally, Chapter 5 concludes my research.

Chapter 2

Government Policy and Peer-to-Peer Lending: Evidence from the Innovative Finance ISA

Abstract

Policy and regulation are important factors in the development of any market or industry, including the P2P lending market. Government encouragement and support can raise awareness amongst borrowers and lenders and encourage them to enter the P2P lending market. This study examines whether this will increase information asymmetry in the P2P lending market, leading to adverse selection, which entails more high-risk borrowers obtaining loans, in turn leading to greater losses for lenders. In July 2015, HM Treasury in the United Kingdom announced the creation of the Innovative Finance ISA (IFISA), and I use data from the P2P lending platform, Zopa, to examine whether the newly announced IFISA policy impacted the P2P lending market. The findings show a significant increase in the probability of default for new entrant borrowers after the IFISA announcement compared to those before. The loss given default also grew. This suggests that the new IFISA announcement led to the entry of higher-risk borrowers and that P2P lending platforms such as Zopa did not fully anticipate this higher risk and continued to accept their loan applications, leading to losses for lenders.

2.1 Introduction

Peer-to-Peer (P2P) lending has been the fastest growing source of alternative finance in recent years. It matches borrowers with lenders via online platforms on the Internet and is considered a complement to traditional lending, serving subprime borrowers that banks cannot cover (Tang, 2019). As with banks, P2P lending is exposed to credit risk, especially with respect to information asymmetry (Greiner and Wang, 2009).

Previous literature that has addressed P2P lending and information asymmetry has focused on the analysis of individual characteristics of borrowers before they were approved for a loan and their probability of success in being given credit. However, only a limited number of studies have focused on external factors, such as government policy (Chen, Dong, Liu and Sriboonchitta, 2019). Policies and regulations are important factors supporting the further development of the P2P lending market. Government encouragement and support can raise awareness amongst borrowers and lenders and encourage them to enter the P2P lending market.

In July 2015, HM Treasury in the United Kingdom announced the creation of the Innovative Finance ISA (IFISA), an investment utilising P2P lending networks and offering tax advantages. This signal of government support was positive news for the growing P2P lending market. Though the official announcement of the IFISA attracted investors and borrowers who acknowledged this new financial approach, the public had varying views on the policy. Some of the voices expressed worry about potentially huge losses with the rapid growth of P2P lending. These concerns are reasonable. Even though this policy is beneficial for attracting borrowers and lenders, positive public sentiment can still turn negative. Malandri et al. (2018) pointed out that favourable public sentiment has a positive impact on financial markets. However, heightened media publicity may also lead to excessive investment (Zhang and Su, 2015). According to Shaffer (1998), borrowers who were previously rejected by other banks try to apply to new market entrants for a loan, and high default rates may be experienced because of the pool of risky borrowers. As a new entrant to the financial credit market, P2P lending might be followed by the same pattern of exposure to high default risk.

This study seeks to contribute to discussing whether the introduction of P2P lending to a larger number of borrowers and lenders with government support has led to changes in the level of risk in this market. And whether it will increase information asymmetry in the P2P lending market, leading to adverse selection, which entails more high-risk borrowers obtaining loans, in turn leading to greater losses for lenders. To examine whether the newly announced IFISA policy impacted positively or negatively on the P2P lending market, for this chapter I chose as an example the platform called Zopa, which is the first P2P lending platform in the world. The analysis focuses on the period from May to October 2015, which straddles the July 2015 official announcement of the new IFISA instrument by HM Treasury. In this period, the impact of the information component of the new policy on the P2P lending market could be analyzed. To evaluate the impact of the announcement of the IFISA policy, I collected data on 41,693 newly funded loans on Zopa in April 2020. In addition, in this study, I use the concepts of the probability of default, the loss given default, and the potential defaulters to examine the credit risk of borrowers and the losses caused by delinquency (Gao et al., 2017; Moffatt, 2005; Schuermann, 2004).

The data shows a substantial increase in the number of new borrowers granted loans on the Zopa after the announcement of the IFISA policy. The findings show that the announcement of the IFISA policy has a significantly positive impact on the credit risk of borrowers. To be specific, estimating by the Probit model shows a significant increase in the probability of default for new entrant borrowers after the IFISA announcement compared to those before. It is likely to have been driven by an increase in high-risk borrowers. In addition, the loss given default was analyzed by the Tobit model, and the results show that a significant increase in the average percentage of default amount to the principal amount by new borrowers who entered after IFISA was announced. It also indicates that those borrowers started defaulting at an earlier stage. Furthermore, the increase in the number of potentially defaulting borrowers revealed by the Hurdle model suggests that high-risk borrowers started to apply for loans in the P2P lending market. This suggests that the new IFISA announcement led to the entry of higher-risk borrowers and that P2P platforms such as Zopa did not fully anticipate this higher risk and continued to accept their loan applications, leading to losses for lenders.

The rest of this chapter is structured as follows: Section 2.2 reviews related literature about P2P lending. Section 2.3 provides background information about P2P lending in the United Kingdom and the IFISA policy. Details of the empirical tests, descriptions of the data and variables, and hypotheses and models are given in Section 2.4 and Section 2.5, respectively.

2.2 Literature Review

P2P lending, which first emerged in 2005, is regarded as a new financial innovation in the financial market reliant on the development of technology to offer credit. It matches borrowers' financial needs with lenders' investment needs through the Internet. A borrower receives funds and pays a lender principal and interest according to the agreed maturity. However, Everett (2015) pointed out that P2P lending is the latest version of social lending, which has been around for centuries. A private loan transaction between borrowers and lenders without an intermediary is not a new business model. It is a normal activity of lending money between acquaintances, but P2P lending offers a new model that depends on online interaction. In offering credit to borrowers in financial markets, there is not much difference between traditional financing by banks and the new financial instrument of P2P lending.

Therefore, some studies focus on the relationship between P2P lending and traditional financing. Havrylchyk et al. (2017) pointed out that the development of P2P lending, driven by banks, decreased the supply of credit with a lower leverage ratio after the global financial crisis. In addition, de Roure et al. (2019) built a theoretical model finding that P2P lending expands when banks suffer higher exogenous regulation costs. According to a Bank of England report, the development of P2P lending may affect the credit business of traditional banks (Atz et al., 2016). Nonetheless, Tang (2019) pointed out that P2P lending could complement bank activity by providing small loans and offering funds to subprime borrowers who are not funded by banks. In addition, Balyuk (2019) used data from Prosper, which is one of the largest P2P lending platforms in the United States, and found that P2P lending can provide credit access to more borrowers. Similarly, Havrylchyk et al. (2017) pointed out that borrowers in countries underserved by banks may benefit from P2P lending. Not only borrowers but also lenders can benefit from P2P lending. According to Morse (2015), P2P lending could capture value with disintermediation, especially for lenders. Lenders can optimize portfolio sections through P2P lending, and small and medium-sized lenders might achieve a fixed income if they choose P2P lending assets.

However, according to de Roure et al. (2019), P2P lending loans bear a higher risk than bank loans. As with bank loans, risk, especially credit risk, is one of the most important elements that concerns participants in the P2P lending market. Credit risk is the default risk that a borrower might fail to make a payment to a lender, leading to a loss on the part of the lender. In the P2P lending market, information asymmetry is the main cause of credit risk.

Information asymmetry in the P2P lending market has been the focus of much research. Greiner and Wang (2009) claimed that information asymmetry between borrowers and lenders is a fundamental and important challenge for P2P lending companies. Everett (2015) confirmed that this problem does exist in this market. However, Yan et al. (2015) proposed that information asymmetry could be reduced by using big data in the P2P lending market. After collecting information on borrowers and assessing it, P2P lending platforms could evaluate the credit risk of individual borrowers and then decide whose loan application to accept. For example, Morse (2015) argued that relationships and soft information such as borrowers' social connections, local indicators, and social circles could help to weaken moral hazard. Additionally, Greiner and Wang (2009) and Herrero-Lopez (2009) all focused on borrowers' social information and features. Herrero-Lopez (2009) pointed out that social features could affect the possibility of funding in P2P companies. People who have reliable social connections with other trusted people are more likely to get funded. Otherwise, people would need to obtain funding from P2P lending at a higher interest rate. Greiner and Wang (2009) defined social capital as a kind of information offered by borrowers to demonstrate their trust. Social capital is also used in bank loan evaluation systems. However, for P2P lending platforms, borrowers and lenders operate on the Internet, where it is harder to evaluate borrowers' credit risk. Social capital is very important information in the P2P lending market (Xu, Luo, Chen and Zheng, 2015). Borrowers offering evidence of social capital are more likely to get funded at a lower interest rate, but offering such evidence does not guarantee a good borrower, and it cannot help a lender make a better investment decision (Chen et al., 2016; Xu, Luo, Chen and Zheng, 2015). Lenders can learn effectively from actual risk, as Freedman and Jin (2011) showed in their research, and they can reduce risk over time.

However, Iyer et al. (2009) pointed out that lenders can use the information offered by borrowers to judge the quality of their creditworthiness in P2P lending. As with borrowers' credit scores and maximum rates, these can all be treated as credible signals for lenders. There is much research concentrating on information about borrowers and their quality. First, many studies are focused on loan application information. Loan information may affect the success of a borrower's loan application. Analysing data from the Prosper platform, Puro et al. (2010) argued that factors with a higher correlation to successful borrower applications are the loan amount, the interest rate, and the borrower's credit rating. Herzenstein et al. (2011), also using data from Prosper, and Barasinska and Schäfer (2010), studying the German platform Smava, reached similar conclusions: high lending rates increase the success rate of applications, and large loan amounts reduce the success rate. In addition, Caglayan et al. (2020) found through their study of Chinese P2P platforms that borrowers with better credit ratings who are willing to pay higher interest rates are likely to reapply after a failed application. Kgoroeadira et al. (2019) analysed 14,537 small-firm loans to show that borrowers who own their homes and obtain higher credit ratings imply lower risk.

Personal information associated with borrowers is also the subject of research. Herzenstein et al. (2011) pointed out that the profile of borrowers also plays an important role. A trusted or successful identification is associated with an increase in loan funding. Talavera et al. (2018) argued that borrowers who are willing to offer more verifiable information when completing their applications have better credit behaviour. Pope and Sydnor (2011) argue that there are racial differences. Black people from Prosper are 25 to 35 per cent less likely to have access to finance than white people with similar credit profiles. As for gender, Barasinska and Schäfer

(2010) and Ravina (2007) argued that there are no gender differences in P2P lending. However, Chen et al. (2017), using data from Chinese P2P platforms, concluded differently, finding that female borrowers are less likely than male borrowers to apply successfully for a loan, even though female borrowers are a better credit risk. Furthermore, geographical differences (Burtch et al., 2014; Lin and Viswanathan, 2016), the borrower's appearance (Ravina, 2007), and the style of language used in the loan application may also affect the loan application (Chen et al., 2018; Larrimore et al., 2011). Most studies believed that lenders could identify good borrowers by the information provided.

A review of the existing literature demonstrates that previous research on P2P lending and information asymmetry has focused on the analysis of individual characteristics of borrowers before they were approved for a loan and the probability of success in being accepted for credit. Few studies have touched on external factors, such as macroeconomic and country-level determinants (Basha et al., 2021). Foo et al. (2017) argued that macroeconomic factors are negatively correlated with P2P lending. Nigmonov et al. (2022) used Lending Club's data to argue that in the United States, the probability of default in the P2P lending market is increased by a higher interest rate and inflation. And Yoon et al. (2019) found evidence in the Chinese P2P lending market that there is a significant impact of the macro environment on increasing the default rate of platforms.

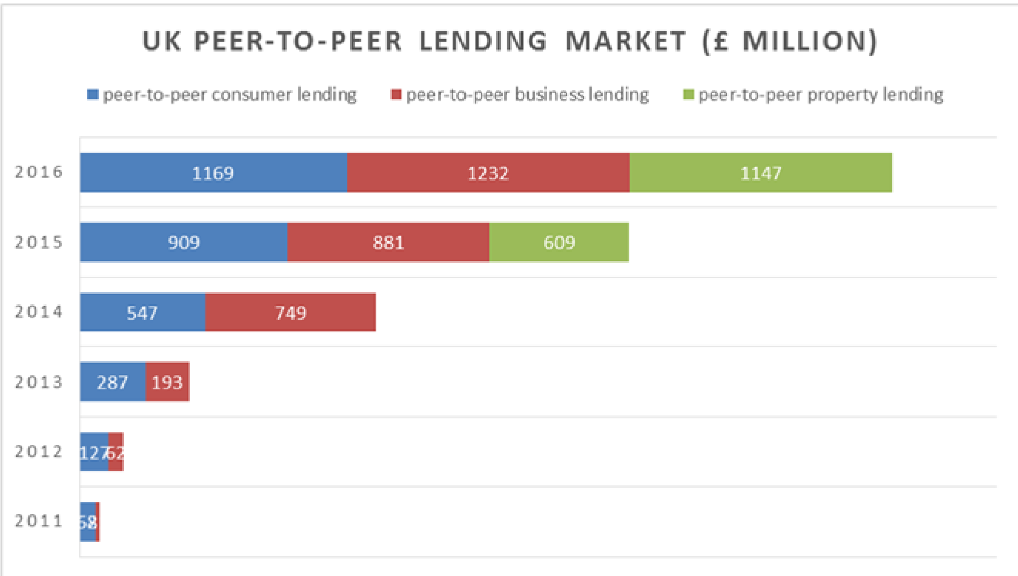
As the P2P lending market expands, especially with government support, it will lead to more borrowers and lenders becoming aware of and entering the P2P lending market. It is still uncertain whether this development will increase information asymmetry in the P2P lending market, leading to adverse selection, which entails more high-risk borrowers obtaining loans, in turn leading to more losses for lenders. The main motivation and objective of this paper is to examine whether the introduction of P2P lending to a larger number of borrowers and lenders with government support has led to changes in the level of risk in this market. I chose to investigate this question by assessing the impact of the event of July 2015, when the UK Treasury announced the creation of the Innovative Finance ISA (IFISA).

2.3 Background

2.3.1 P2P Lending Market in the United Kingdom

The P2P lending market in the United Kingdom is one of the biggest markets in the world. As shown in Figure 2.1, the volume of P2P consumer lending in the United Kingdom increased from £68 million in 2011 to £1,169 million in 2016, according to the fourth United Kingdom alternative finance industry report. To be specific, in 2016 P2P business lending surpassed P2P consumer lending to become the largest sector. It generated £1.23 billion. And the total volume of P2P consumer lending was £1,169 million in 2016, which showed a 29% annual increase. Larger P2P lending companies dominate the market where Zopa, Funding Circle, and RateSetter are three market-leading P2P lending companies. Zopa, for example, has an almost 50 percent market share of P2P consumer lending.

Figure 2.1: P2P lending market volume in the UK



Note: This figure shows the total volume of the P2P lending market from 2011 to 2016 in the United Kingdom. It includes P2P consumer lending, P2P business lending and P2P property lending. Data Source: The fourth UK alternative finance industry report

2.3.2 Innovative Finance ISA

For a long time, investors had to pay 20% tax on income from investments in the P2P lending market. Tax reduces the overall yield of the industry. On 8 July 2015, HM Treasury in the United Kingdom announced that the Innovative Finance ISA (IFISA) would be created for use in the P2P lending market, giving investors tax advantages. The IFISA was implemented on 6 April 2016, allowing investors to invest up to £20,000 a year in the P2P lending market tax-free. The official announcement of the IFISA attracted the interest of potential investors, according to a report on the BBC (Milligan, 2016). The article supposed that the policy of granting tax-free interest on investments in the IFISA would indeed earn investors about £900 a year in interest if they chose a five-year P2P loan portfolio. However, in this article, the former head of the Financial Services Authority, Adair Turner, also warned the public that over the next five to ten years there would be huge losses in P2P lending.

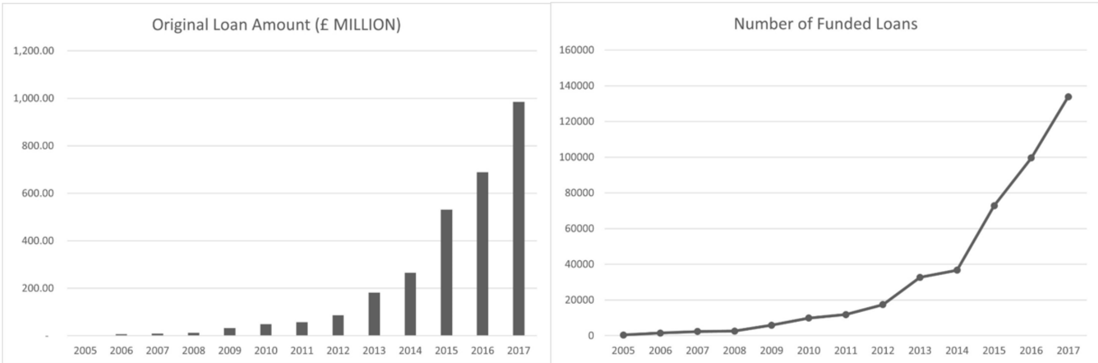
The argument about the new IFISA is related to P2P lending and risk. The spread of the new government support policy from its announcement to its implementation attracted many lenders and borrowers. Based on the P2P lending business model, borrowers could apply for and receive loans without any collateral, repaying the principal and interest according to the agreements entered into. This means that lenders take on all the credit risk. Because IFISAs are unlike Cash ISAs that offer guaranteed returns and unlike the Stocks and Shares ISAs that compensate a certain level of loss through the financial services compensation scheme if firms failed. It implies that lenders who invest in P2P lending are not compensated for any losses, which makes it particularly important to pay attention to the credit risk in the P2P market. In this study, I will discuss how the announcement of the new IFISA policy affected risk in the P2P lending market, taking Zopa as an example.

2.4 Data and Variables

2.4.1 Zopa

The data used in this research is collected from Zopa. Zopa is launched in 2005. As the first P2P lending platform in the world, Zopa focused on personal loans. Borrowers on Zopa could apply for loans for their personal use, such as paying off credit cards, buying a car, home improvements, or planning a wedding. It is the one of most important P2P consumer lending companies in the United Kingdom.

Figure 2.2: P2P lending volume on Zopa



Note: The figure shows the volume of P2P lending on Zopa from 2005 to 2017. It contains the total amount of original loans by year and the total number of loans financed by year. Data Source: Zopa's website

Zopa is the leading P2P lending platform in the United Kingdom. During the last 12 years, the total amount in loans on Zopa grew significantly from £1.4 million in 2005 to £985.1 million in 2017. At the same time, the number of funded loans increased from only 411 in 2005, increasing to around 10,000 in 2010 and to 133,899 in 2017. As shown in Figure 2.2, it is clearly seen that after 2013, both the original loan amounts and the number of successive funded loans grew rapidly. Its loan volume in 2016 is about £689 million, so, compared to the total market volume in the United Kingdom, Zopa had gained almost half of the whole market share at that time. Zopa publishes the loan book on its website. Individual loans are all collected in the loan book, and Zopa follows the routine of updating these loans' performance data monthly. It is easy to trace and analyse for both investors and researchers, and considering the market share and fame of Zopa, it is the best example platform from which to collect and analyse data.

To evaluate the effect of the announcement of the IFISA policy, I collected data on Zopa in April 2020. The data set comprised 41,693 newly funded loans from May to October 2015, covering three months before the policy announcement and three months after. The announcement of the IFISA in July 2015 was the first time the IFISA policy - the initial important government policy related to P2P lending - was officially delivered to the public. It worked as a channel of information that guided the public to understand P2P lending and encouraged borrowers and lenders to get involved in this new market. Therefore, during this period, even if the IFISA was not formally implemented, its impact on the P2P lending market as an information component is worth discovering.

However, the limitation of this data set is that the monthly updating routine stopped in April 2020 and has not recommenced at the time of writing this paper. As a result, my analysis faces the problem that the longest-term loans (60-term loans) were still in the process of repayment. Except for this incompletely updated data set, Zopa is still the most suitable P2P lending platform for this research.

2.4.2 Variable Description

In Zopa's loan book, each individual loan is listed with detailed information that could be treated as variables for all analyses. The basic information of funded loans in Zopa's loan book includes the disbursal date, original loan amount, the principal collected, lending rate, term and latest loan status. The description of selected variables is listed below.

The disbursal date is the date on which a loan is successfully funded. With the disbursal date, in this study, it is possible to ascertain whether the loan was funded before or after the announcement of the new IFISA policy. In addition, by identifying the disbursal date, a new dummy variable, **Announcement**, can be constructed. **Announcement** is the post-announcement dummy variable, based on the initial announcement of IFISA to the public, 8 July 2015. Considering the time to deliver the announcement to the public and that new applications for loans on Zopa normally take three working days to be approved, new borrowers who applied for a loan as a result of the IFISA announcement should be considered if they applied a little after the date of that announcement. Hence, the dummy variable of **Announcement** is defined by 1 meaning that the disbursal date of funded loans is after 15 July 2015. It refers to those borrowers who applied for funding after the IFISA announcement. Otherwise, **Announcement** is defined by 0.

For each individual funded loan, **Term** refers to the maturity of the loan in months; for instance, a 12-term loan refers to the length of borrowing being 12 months. Zopa allows borrowers to apply for a loan over 1 to 5 years with a certain amount and lending rate. There are five types of loans: 12-term, 24-term, 36-term, 48-term, and 60-term. And **Original Loan Amount** is the amount of the funded loan, also called the principal on a loan. Borrowers could apply for different original loan amounts and loan term lengths at the outset, but the lending rate is decided by Zopa. **Lending Rate** is the price of borrowing money, which is borrowers' Annual Percentage Rate (APR) to lenders.

After the agreed repayment date, Zopa will update the loan record based on the borrower's repayment behaviour, which is shown in the **Principal Collected** and the **Loan Status**. **Principal Collected** is the accumulated number of principal that borrowers have repaid. And **Loan Status** describes the performance of repayment records on the snapshot date. There are four types: 'Completed', 'Active', 'Late', and 'Default'. Based on those four types of loan status, Loan Status could be defined as a variable, **Default**.

Default is a binary variable. When **Default**=1, it means that a borrower who pays principal and interest later than the date of repayment is recorded as 'Late', and a borrower who fails to repay the principal and interest is recorded as 'Default'. Both kinds of loan status represent non-performing loans as well as high-risk borrowers. On the other hand, when **Default**=0, 'Completed' and 'Active' indicate good borrowers. It means that a borrower pays principal and interest on time. High-risk borrowers incur losses to lenders. There are two variables describing losses. **Loss** represents the amount of the loan that remains unpaid after the maturity of the loan. In addition, **Loss Rate** represents the percentage of the loan amount remaining unpaid relative to the principal amount after the loan has matured.

2.4.3 Data Description

From May to October 2015, there was a total of 41,693 new funded loans recorded by Zopa. Table 2.1 provides the descriptive statistics of variables for the Zopa platform. The average original loan amount is £7,246.01. The minimum of a funded loan is £1,000 and the maximum is £29,640. In addition, 50% of funded loans are less than £5,300, and 25% of loans are more than £10,090. With a substantial standard deviation, it indicates that borrowers prefer a small amount of money or a large amount. Ranging from 2.45% to 24.75%, the average lending rate on Zopa is 8.87%. Moreover, Table 2.1 shows that borrowers prefer longer repayment periods. As there are only five different term lengths, 75% of borrowers choose to borrow for more than 36 months. The average length of borrowing is 43.83 months. It implies that longer-term loans are more popular with P2P lending borrowers. After the maturity date, most of the principal could be collected, as shown in Table 2.1, the average collected principal is £6750.45 with ranging from £0 to £29,640. It indicates that the worst borrowers had failed to repay any principal, compared with the figures of Original Loan Amount. Moreover, figures show that 8.97% of borrowers fail to pay the principal, and the average loss amount is £408.14. On average, each loan will lose 5.16% of the principal amount.

Table 2.1: Descriptive statistics

Variable	(1) Obs	(2) Mean	(3) Std. Dev.	(4) Min	(5) Max	(6) P25	(7) P50	(8) P75
Original Loan Amount	41,693	7,246.012	5,594.046	1,000	29,640	3,120	5,300	10,090
Lending Rate	41,693	0.088741	0.057205	0.0245	0.2475	0.0445	0.0687	0.1105
Term	41,693	43.82865	15.91515	12	60	36	48	60
Principal Collected	41,693	6,750.445	5,466.98	0	29,640	3,020	5,100	9,160
Default	41,693	0.089727	0.285794	0	1	0	0	0
Loss	41,693	408.1366	1,818.386	0	26,963.5	0	0	0
Loss Rate	41,693	0.051575	0.186602	0	1	0	0	0

Note: This table shows the number of observations (1), mean (2), standard deviation (3), minimum (4), maximum (5), and quartiles (6)-(8) of the following variables. *Original Loan Amount* is the amount of principal. *Lending Rate* is the interest rate of borrowing money. *Term* is the length of borrowing. *Principal Collected* is the principal already paid back by borrowers on the maturity date. *Defualt* equals 1 if borrower defaulted and 0 otherwise. *Loss* is the difference between the principal that should be repaid and the repayment principal. *Loss rate* is the percentage of non-repayment principal to the original amount of principal.

However, in this research, all data was last updated on the day of collection on 1 April 2020. Zopa stopped the quarterly publication of their loan book after this date, but the 60-term funded loans are still in the repayment process while the rest of them have ended. Taking into account these unexpected circumstances, I also categorized and organized data by *Term*, and the statistics show some differences. The detailed outcomes are placed in the Appendix (Shown as Table A.2). As shown in Table A.2, the longer the term, the larger the amount borrowers prefer to borrow and repay. The average loan amount for the 36-term loans is £5,690.69 while the average principal collected is £5,489.18. Meanwhile, for the 60-term loan, the average loan amount is £10,157.2 while the average principal collected is £9,198.85. Furthermore, the longer the term, the larger the percentage of borrowers defaulting, and the higher the rate of loss of principal. In addition, the loss amount is similar. For example, 7.19% of 36-period loan defaults resulted in a loss ratio of 3.93%, while 12.8% of 60-period loan defaults resulted in a loss ratio of 7.70%. And the average loss amount for the 36-term loan is £201.51, compared to £745.78 for the 60-term loan. Borrowers whose loans were funded in longer terms caused more loss to investors. However, the shortest loan period charges the highest lending rate. The average lending rate for 12-term loans is 10.78% and it is about 8.73% for 36-term and 60-term loans. This may explain why borrowers at Zopa prefer long-term rather than short-term borrowing.

Table 2.2: Frequency of Announcement

Variable Announcement	(1) Freq.	(2) Percent	(3) Cum.
0	14,887	35.71	35.71
1	26,806	64.29	100.00
Total	41,693	100.00	

Note: This table shows frequency (1), percentage(%) (2), and cumulative percentage (3) of the variable, *Announcement*. *Announcement* equals 1 if the loan is funded after 15 July 2015 which is the date the IFISA policy was announced. Otherwise, *Announcement* equals 0.

In addition, to examine the impact of the IFISA announcement, the data is classified by a post-announcement dummy variable, *Announcement*. As Table 2.2 shows, there are 14,887 new funded loans being accepted in the three months prior to the IFISA policy announcement. However, in the three months following the announcement, there are almost twice as many new funded loans issued on Zopa, that is, 26,806. The detailed statistics in Table A.3 show that there is not much difference between the pre-announcement and the post-announcement group, only the default, the average loss amount, and the average loss rate increase slightly compared to the pre-announcement. This indicates that there is no significant change in data characteristics between the three months prior to the IFISA policy announcement and the following three months, and it also shows that Zopa's loan characteristics have not revealed any fundamental differences and that the data have a certain stability and consistency that facilitates making comparisons.

2.5 Hypotheses and Methodology

2.5.1 The Probability of Default

New entrants in a credit market are forced to assume a lot of risks in the traditional banking credit market (Shaffer, 1998). The high default rate may be explained by borrowers who were previously rejected by other banks applying to the new entrant for a loan. According to the theoretical methods of Broecker (1990), the new entrants' pool of borrowers is adversely selected because the information used by banks for screening loan applications and monitoring borrowers is generated through long-term relationships between borrowers and lenders. New entrants in credit markets are immature in screening borrowers, which leads those new entrants to be more likely to accept high-risk borrowers initially.

P2P lending can be regarded as a new entrant in the financing market. Although P2P lending is based on the Internet, from the borrower's perspective, the process of acquiring funds is quite similar to that used by other sources of finance: borrowers borrow money from lenders and repay the principal and interest on time. For borrowers, dealing with a new bank branch or lenders from a new P2P financing platform is the same in principle: they are all credit providers (Zhou et al., 2018). Moreover, compared to traditional banks, P2P lending platforms offer unsecured loans, which means that borrowers are not required to provide any collateral, and once borrowers are unable to repay the principal and interest, P2P lending platforms will have no collateral to compensate for the loss. The cost of default behaviour for P2P borrowers is very low, and the assessment of the credit risk of borrowers is important (Mild et al., 2015).

The official government announcement about the new IFISA policy made many people aware of the P2P market. After the IFISA announcement, the prediction was that the market share of P2P lending would expand rapidly. As a new financing approach, borrowers would be keen to apply for a loan on P2P lending platforms, especially the group of borrowers who had been rejected by banks. (Balyuk, 2019; Havrylchyk et al., 2017; Tang, 2019) And according to Emekter et al. (2015), they argued that P2P lending platforms are available to qualified borrowers with low credibility, leading to adverse selection problems. Failure to address credit risk increases the probability of default. Therefore, in this research, the first hypothesis is:

After the IFISA policy was announced, the probability of default increases.

To examine the impact of the IFISA policy announcements on the probability of default, firstly, applying the Pre-Post Comparison Evaluation (Pomeranz, 2017), the data were divided into two groups based on the date of the IFISA policy announcement. They are the pre-announcement group and the post-announcement group. Further, I present the probit model to estimate the probability of default. Many studies have examined the probability of default by adopting the probit model (Gao et al., 2017; Liu et al., 2018; Tao et al., 2017; Yoon et al., 2019; Zhou and Wei, 2020). The model is built as follows:

$$Pr(Default = 1) = \Phi(\alpha + \beta Announcement + \delta \mathbf{Features}_i + \epsilon_i) \tag{2.1}$$

Where the dependent variable, *Default*, represents whether the borrower defaulted at the end of the repayment period. It is a binary variable. When it equals 0, it means that the borrower has paid off all the principal and interest. When it is equal to 1, it means that the borrower failed to pay back the principal and interest on time. Pr(*Default*=1) indicates the probability that the borrower is unable to repay. It may be stated as the probability of this borrower being a high-risk borrower.

The post-announcement dummy estimator, *Announcement*, is the independent variable which is a binary variable as well. *Announcement*=1 stands for a loan funded after the IFISA announcement, which means this loan is in the post-announcement group, otherwise it would be in the pre-announcement group. The coefficient β predicts whether the announcement of the new IFISA policy would affect borrower delinquency behavior. Furthermore, Φ is the cumulative normal distribution. According to Chen, Dong, Liu and Sriboonchitta (2019), they found that some variables, such as term, interest rate, loan type, interest due, and changes in regulation are related to the default risk. Therefore, $\mathbf{Features}_i$ are a set of control variables such as the original amount of the loan, lending rate, and term.

2.5.2 The Loss Given Default

According to the new Basel Capital Accord, credit risk valuation analysis can be conducted in two aspects: the default rate, which reflects the probability of default, and the loss given default, which is an indicator of the severity of losses after default (Schuermann, 2004; Zhou et al., 2018). For P2P lending, it is a direct financing interaction between borrowers and lenders. The loss on default is the amount that the lender loses if the borrower defaults, and the loss given default is the ratio of the loss. As defined by Zhou et al. (2018), the loss given default in this study is given as the variable *Loss Rate*. It is calculated by:

$$Loss\ Rate = 1 - \frac{PrincipalCollected}{OriginalLoanAmount} \tag{2.2}$$

Based on the previous discussions in Section 2.5.1 that new entrants will be exposed to higher risks and more losses (Broecker, 1990; Shaffer, 1998), while the previous studies indicated a positive association between the probability of default and the loss given default (Altman and Kishore, 1996; Jarrow, 2001; Schuermann, 2004), the second hypothesis could be generated:
After the IFISA policy was announced, the loss given default increases.

To further discuss the impact of the IFISA policy announcement, I estimate the loss rate by the following model:

$$Loss\ Rate = \theta + \gamma Announcement + \delta \mathbf{Features}_i + \mu_i \tag{2.3}$$

Where *Loss Rate* is the dependent variable, it represents the percentage of the loan amount remaining unpaid relative to the principal amount after the loan has matured. The post-announcement dummy estimator, *Announcement*, is the independent variable. And the coefficient γ predicts whether the announcement of the new IFISA policy would affect the loss given default. $\mathbf{Features}_i$ are a set of control variables as mentioned previously.

2.5.3 The Potential Defaulters

Previous studies focusing on the default behaviour of borrowers have tried to predict and capture the behaviour of potential defaulters (Byanjankar et al., 2015; Gao, Yen and Liu, 2021; Zhou et al., 2019). In this study, to estimate the impact of the announcement of the IFISA policy on the default risk, in this study I have further examined the losses caused by the potential defaulters. Based on the argument and methodology of Moffatt (2005), he pointed out that there are different types of borrowers. First, there are good borrowers, who will never default at any time, regardless of what happens. In contrast, bad borrowers always default. In between, there are the potential defaulters, who may default as a result of changes in specific factors. When affected by specific factors, potential defaulters are changed into actual defaulters, which makes the default risk increase. Therefore, the hurdle model could be applied. The hurdle model has two processes. The first hurdle is to identify these potential defaulters amongst good borrowers. While the second hurdle is focused on analyzing the loss amount of these defaulters, including potential defaulters and bad borrowers who always default.

Based on previous discussions about new entrants and higher risks (Broecker, 1990; Shaffer, 1998), the third and fourth hypotheses could be generated:
After the IFISA policy was announced, the potential defaulters increases.
and
After the IFISA policy was announced, the loss of defaulters increases.

The model can be written as:

$$H_i = D_i * S_i \tag{2.4}$$

The first hurdle, which is intended to identify potential defaulters, is:

$$D_i = \begin{cases} 1, & \text{if } D_i^* > 0 \\ 0, & \text{if } D_i^* \leq 0 \end{cases} \tag{2.5}$$

where

$$D_i^* = \rho + \tau Announcement + \delta \mathbf{Features}_i + \nu_i \tag{2.6}$$

And the second hurdle is intended to estimate the default amount of defaulted borrowers:

$$S_i = \varphi + \omega Announcement + \delta \mathbf{Features}_i + \varepsilon_i \tag{2.7}$$

S_i is the amount that defaulters fail to repay. In the first hurdle, Equation 2.5 and 2.6, D_i^* is represented as the defaulted amount of an individual funded loan. When D_i^* is larger than 0, it means that a borrower has a positive unpaid remaining amount when the loan matures. It also means the probability of default of borrowers is positive. Or in other words, a borrower is treated as a potential defaulter and D_i equals to 1; otherwise, when D_i equals 0, this signifies a good quality borrower. Equation 2.7 is intended to measure the loss attributable to these defaulted borrowers. And, $\mathbf{Features}_i$ are control variables, as mentioned above.

2.6 Empirical Results

In the following section, it examines the default risk of Zopa after the announcement of the IFISA policy by focusing on the probability of default, loss given default, and potential defaulters respectively. However, it is important to notice that all data was last updated on the day of collection on 1 April 2020. Because Zopa stopped the quarterly publication of their loan book after this date, the 60-term funded loans are still in the repayment process, while the rest of them have ended. Taking into account these unexpected circumstances, different term lengths, and the snapshot date, results regarding the 60-term loan will be discussed independently.

2.6.1 Results on the probability of default

Table 2.3 presents the marginal effects of the post-announcement dummy and loan characteristics estimated based on Model 2.1. First, column (1) of Table 2.3 reports the marginal effect estimation for all newly funded loans approved between May and October 2015. The results show that the coefficient on the post-announcement dummy estimator is positive and statistically significant at the 1% level. It indicates that after the announcement of the IFISA policy, there is an increase in the probability of default for borrowers. It is consistent with the first hypothesis. According to Chen, Dong, Liu and Sriboonchitta (2019), they found that the policy change has the potential to create an increased probability of default. This suggests that borrowers who have been granted loans after the announcement of the new IFISA policy are more likely to be high-risk, poor creditworthy borrowers, leading to an increased probability of default.

Table 2.3: Probit model results

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	Default	Default	Default	Default	Default	Default
Announcement	0.0093***	0.014**	0.0124**	0.0088*	0.0063	0.0083
	(0.0028)	(0.0074)	(0.0054)	(0.0051)	(0.0071)	(0.0051)
ln(Original Loan Amount)	0.0059***	0.0027	-0.0052	0.0069*	0.0055	0.0112***
	(0.0020)	(0.0056)	(0.0042)	(0.0041)	(-0.0463)	(-0.0036)
Lending Rate	1.1605***	0.438***	0.6555***	0.9032***	1.3539***	1.6502***
	(0.0216)	(0.0577)	(0.0367)	(0.0349)	(0.0673)	(0.0437)
Term	0.0026***					
	(0.0001)					
Pseudo R2	0.1223	0.1494	0.1499	0.1571	0.1748	0.1026
Type of Maturity	All	12	24	36	48	60
Observations	41,693	2,556	7,129	9,710	5,155	17,143

Note: This table reports the average marginal effect. Standard errors are in parentheses. Column (1) shows the estimated results for all data. Columns (2) to (6) display the estimated results for sub-datasets which are classified by types of Term. The dependent variable is *Defualt*, equals 1 if a borrower defaulted and 0 otherwise. *Announcement* equals 1 if the loan is funded after 15 July 2015 which is the date the IFISA policy was announced; otherwise, *Announcement* equals 0. *ln(Original Loan Amount)* is the natural logarithm of amount of principal. *Lending Rate* is the interest rate of borrowing money. *Term* is the length of borrowing.And *** $p<0.01$, ** $p<0.05$, * $p<0.10$

In addition, the original loan amount, lending rate, and term have positive and significant effects on the probability of default. More specifically, higher principal amounts, higher interest rates, and longer maturities appear to increase the probability of default of borrowers. The results are consistent with Jin and Zhu (2015) and Hu et al. (2019), whose findings supported that the original loan amount, lending rate, and term are important determinants of increasing the probability of default of borrowers. However, as mentioned above, because of the specificity of 60-term loans, in what follows I estimate independently for five types of term based on Model 2.1, and the results are shown in column (2) to column (6) in Table 2.3.

The positive sign of the post-announcement dummy estimator indicates that there is an increase in the probability of default for borrowers after the announcement of the new IFISA policy, and this effect is significant in columns (2), (3) and (4) (at the 5%, 5% and 10% levels respectively). Focusing on the 12-term loans, after controlling for Original Loan Amount and Lending Rate variables, the result shows that there is a 1.4 percentage point greater probability of default after the IFISA policy announcement. In addition, for the 24-term loans, the probability of default increased by 1.24 percentage points after the IFISA policy announcement. Similarly, it showed an increase of 0.88 percentage points for the 36-term loans. These results suggest that borrowers who enter the market after the announcement will have a higher default risk than previous borrowers, even if they applied for the same amount of loans and were charged the same lending rate.

However, among borrowers who have finished repaying their loans, there is no evidence that the announcement dummy would affect the probability of default in the group of borrowers who were funded by 48-term loans. A similar result is found in the estimation of the 60-term loans. As the borrowers who are in this group are in the process of repaying their loans, there is greater uncertainty about their repayment performance. In terms of the current analysis, however, the credit risk of new borrowers who applied for 48-term loans or 60-term loans probably remains unaffected by the announcement of the new IFISA policy.

An interesting finding through comparing estimations of different terms is that after the announcement of the new IFISA policy, the probability of default for short-term loans is likely to be affected more easily than that for long-term loans. It is possible, in other words, that the credit risk of short-term loans is more vulnerable to external policy change as compared to long-term loans. In the traditional financial market, high-risk and low-credit borrowers can only issue short-term debt (Chatterjee et al., 2009; Diamond, 1991). It might appear that new high-risk borrowers prefer to apply for short-term loans (e.g., 12, 24, or 36 terms) in P2P lending platforms.

In addition, other variables associated with the probability of default have not shown consistently stable and significant relationships. However, the inclusion or exclusion of them does not affect the findings regarding the announcement dummy variables. Specifically, the original loan amount has a positive and significant effect on the probability of default for only 36-term loans and 60-term loans. And the coefficient associated with lending rate is positive and statistically significant at the 1% level in all terms of loans. These are consistent with many studies showing that the higher the lending rate, the higher the probability of default (Chen, Gu, Liu and Tse, 2020; Santoso et al., 2020).

Overall, the probability of borrower default is the determinant factor to measure credit risk. After the IFISA announcement, borrowers who were newly and successfully funded by Zopa were riskier than borrowers who were funded before the announcement, especially for short-term loans. This is mainly because the expansion of the P2P lending market attracted more high-risk borrowers. As with traditional banks in general, high-risk borrowers will apply for and accept loans from new entrant branches in greater numbers (Broecker, 1990; Shaffer, 1998). This suggests that Zopa may have accepted more high-risk borrowers than before as its business expanded, exposing the platform to a greater risk of default.

2.6.2 Results on the Loss Given Default

The above analysis is a discussion of the probability of default behaviours, but the losses caused by these defaults are also a matter of concern. This is mainly because the unsecured nature of P2P lending makes lenders in the P2P lending market bear the risk directly and without the possibility of compensation. Hence, the Loss Given Default is an important indicator to identify and analyse the credit risk of P2P lending (Xia et al., 2021). The following discussion is to estimate the impact of the announcement of the new IFISA policy on the loss given default, based on Model 2.3, the results are displayed in Table 2.4.

The results in column (1) show that the post-announcement dummy has a significant positive impact at the 1% level on the loss given default. Specifically, the loss given default increases by 0.68 percentage points after the announcement of the new IFISA policy. The percentage of unpaid amounts relative to the principal has increased, which implies that more losses have been incurred as a result of delinquent behaviour. It also implies that high-risk borrowers may stop paying back their principal at an earlier stage of the repayment process. If it is experiencing more losses and larger loss amounts, this is evidence that this market is accessing high-risk borrowers who may have entered. It is consistent with the estimated results of the probability of default shown. Moreover, the original loan amount lending rate and term have a positive coefficient for the loss given default (significant at the 1% level). These findings are similar to those of Serrano-Cinca et al. (2015) and Zhou et al. (2018), who pointed out that the loan maturity interest rate and the amount would have a stronger positive impact on the loss given default.

Table 2.4: Tobit model results

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	Loss Rate	Loss Rate	Loss Rate	Loss Rate	Loss Rate	Loss Rate
Announcement	0.0068***	0.0106**	0.0079**	0.0070**	0.0033	0.0065*
	(0.0018)	(0.0051)	(0.0032)	(0.0032)	(0.0045)	(0.0034)
ln(Original Loan Amount)	0.0045***	0.0024	-0.0017	0.0049*	0.0004	0.0078***
	(0.0013)	(0.0035)	(0.0025)	(0.0025)	(0.0035)	(0.0024)
Lending Rate	0.7613***	0.2513***	0.3823***	0.5649***	0.8647***	1.1390***
	(0.0193)	(0.0523)	(0.0309)	(0.0314)	(0.0625)	(0.0476)
Term	0.0018***					
	(0.0001)					
Pseudo R2	0.1385	0.1297	0.1424	0.1487	0.1602	0.0954
Type of Maturity	All	12	24	36	48	60
Observations	41,693	2,556	7,129	9,710	5,155	17,143

Note: This table reports the average marginal effect. Standard errors are in parentheses. Column (1) shows the estimated results for all data. Columns (2) to (6) display the estimated results for sub-datasets which are classified by types of Term. The dependent variable is *Loss Rate* represents the percentage of the loan amount remaining unpaid relative to the principal amount after the loan has matured. *Announcement* equals 1 if the loan is funded after 15 July 2015 which is the date the IFISA policy was announced; otherwise, *Announcement* equals 0. *ln(Original Loan Amount)* is the natural logarithm of amount of principal. *Lending Rate* is the interest rate of borrowing money. *Term* is the length of borrowing.And *** p<0.01, ** p<0.05, * p<0.10

When the post-announcement dummy estimator is estimated separately depending on different terms, it can be observed that consistently take on a positive coefficient. The loss given default increase is affected by the policy announcement. The coefficient of the announcement dummy is significant in three groups, 12-term, 24-term, and 36-term, after controlling for the original loan amount and lending rate. In detail, the announcement dummy estimator had a significantly positive effect on the loss given default in both at a 5% significance level. As for the 60-term borrowers who have not yet completed their repayments, the coefficient of the announcement dummy is significant at a 10% significance level. These results are consistent with the second hypothesis. However, there is no significant effect on the 48-term loans.

Compared to the results for the probability of default in Section 2.5.1, it is noted that the risks for short-term loans have increased after the announcement of the IFISA policy, and those borrowers who are funded for short-term loans such as the 12-term, 24-term, and 36-term loans might lead to lenders losing more of their investment principal. Short-term loans are more likely to be selected by higher-risk borrowers after the new policy was announced, resulting in more risk and increased losses for lenders. What is slightly different between these results from the loss given default estimation and the previous estimation of the probability of default is the 60-term loans. Specifically, there is no evidence that the announcement of the new IFISA policy had a significant impact on the probability of default but did have a significant impact on the loss given default. It is still important to highlight that due to the date of data collection, borrowers from the 60-term loans have not yet completed the full repayment process and there is still some uncertainty in their repayment behaviour. Therefore, the difference between the probability of default and the loss rate shown in the results may indicate in the 60-term loans, higher-risk borrowers are predictable in their default behaviour, but they may commit delinquency at an earlier stage, resulting in more losses for the lender. It should also be aware that the results may differ from the existing ones when the 60-term loan repayment has been completed, for example, the announcement of an IFISA policy may significantly affect the probability of default, alternatively, it is possible that there is no significant impact on the loss given default. This result will still require further analysis and discussion in the future due to the limitations of data collection.

Furthermore, an interesting finding is that only the lending rate has a significant impact on both the probability of default and the loss given default for the 48-term loans. There is no evidence that the announcement dummy estimator is significantly related to the probability of default or the loss given default, whether the control variable of lending rate is included or excluded. Additionally, the original loan amount has a positive and significant effect on the loss given default for only 36-term loans and 60-term loans. And the coefficient associated with lending rate is positive and statistically significant at the 1% level in all terms of loans. These are consistent with many studies showing that the higher the lending rate, the higher the probability of default (Calabrese and Zanin, 2022).

In summary, the examinations of the LGD are generally consistent with the second hypothesis, with an increase in losses after the announcement of the IFISA policy.

As Chen, Dong, Liu and Sriboonchitta (2019) stated the policy change is likely to bring an increase in risk. With the same original loan amount and lending rate, borrowers who entered the market after the IFISA was announced had increased unpaid amounts as a percentage of the principal. Borrowers in the P2P lending market make monthly payments to the lender based on a fixed term, and generally, the percentage of the outstanding amount decreases as the repayment progresses. When the default amount as a percentage of the principal is higher, it represents borrowers who have defaulted at an earlier period, resulting in a higher default amount. The P2P lending market is experiencing a greater number of losses and a larger amount of losses. As with traditional banks, high-risk borrowers are more likely to apply for loans from new entrant branches (Broecker, 1990; Shaffer, 1998). It implies that the P2P lending market is accessing high-risk borrowers who may have entered the market from the beginning as fraudsters. The announcement of the new policy may have created the opportunity for fraudsters to make a profit illegally at the early stage of this new financing market.

2.6.3 Results on the Potential Defaulters

This section provides more information about the default risk of borrowers after the announcement of the IFISA policy. The hurdle model can effectively identify defaulters amongst good borrowers and estimate the default amount only of these bad borrowers. As shown in Table 2.5, it reports the estimations results of the post-announcement and loan characteristics based on Model 2.4.

Firstly, it is observed that borrowers who have been granted loans after the announcement of the IFISA policy are more likely to become potential defaulters. As shown in column (1), in the first hurdle, the post-announcement dummy has a positive coefficient and is significant at 1% level. And secondly, the defaulters among the borrowers who received loans after the announcement of the IFISA policy incurred more losses. The coefficient associated with the post-announcement dummy is positive and statistically significant at 1% level which is shown in the second hurdle. These observations are consistent with the third and fourth hypotheses and also with the previous discussion on the probability of default and the loss given default.

Table 2.5: Hurdle model results

VARIABLES	(1) Loss	(2) Loss	(3) Loss	(4) Loss	(5) Loss	(6) Loss
			First hurdle			
Announcement	0.0695***	0.2868**	0.1310**	0.0964**	0.0408	0.0456*
	(0.0201)	(0.1337)	(0.0593)	(0.0449)	(0.0601)	(0.0273)
ln(Original Loan Amount)	0.0492***	0.0577	-0.0414	0.0676*	0.0065	0.0622***
	(0.0148)	(0.1006)	(0.0466)	(0.0354)	(0.0466)	(0.0193)
Lending Rate	8.3580***	7.0773***	7.1109***	7.8345***	11.3680***	8.7810***
	(0.1572)	(0.8754)	(0.3663)	(0.2899)	(0.5482)	(0.2457)
Term	0.0198***					
	(0.0008)					
			Second hurdle			
Announcement	659.07***	909.67**	520.54**	522.19**	171.61	651.46**
	(170.2585)	(432.1134)	(217.6051)	(244.3788)	(445.7725)	(271.8369)
ln(Original Loan Amount)	1,634.51***	564.88*	388.61**	1,097.29***	1,071.22**	2,199.55***
	(126.7848)	(303.63)	(167.2478)	(194.2912)	(349.9719)	(196.988)
Lending Rate	71,766.95***	22,581.07***	26,231.47***	42,848.15***	85,546.12***	89,790.19***
	(1,589.51)	(3621.795)	(1454.256)	(2000.661)	(5205.188)	(2787.979)
Term	165.00***					
	(7.1195)					
Type of Maturity	All	12	24	36	48	60
Observations	41,693	2,556	7,129	9,710	5,155	17,143

Note: This table reports the average marginal effect. Standard errors are in parentheses. Column (1) shows the estimated results for all data. Columns (2) to (6) display the estimated results for sub-datasets which are classified by types of Term. The dependent variable is *Loss* represents the amount of the loan that remains unpaid after the maturity of the loan. *Announcement* equals 1 if the loan is funded after 15 July 2015 which is the date the IFISA policy was announced; otherwise, *Announcement* equals 0. *ln(Original Loan Amount)* is the natural logarithm of amount of principal. *Lending Rate* is the interest rate of borrowing money. *Term* is the length of borrowing.And *** p<0.01, ** p<0.05, * p<0.10

In addition, focusing on the estimations of the various terms shows that there is a positive coefficient associated with the post-announcement dummy estimator at a 5% significance level on the 12-term, 24-term, and 36-term loans in the first hurdle and at a 10% significance level on the 60-term loans. It implies that there is a higher probability that borrowers become defaulters after the IFISA announcement. More importantly, the defaulters tend to default on more principal and interest. This finding is supported by the positive coefficient on the post-announcement dummy estimator (significant in the second hurdle at 5% level), except for 48-term loans. There is no evidence of a significant impact of the post-announcement dummy estimator for 48-term loans which remains consistent with the previous results.

Using the results of the hurdle model, it can be further found that after the IFISA policy was announced, Zopa attracted new borrowers applying for loans, especially high-risk borrowers, which is consistent with the previous hypothesis. In particular, high-risk borrowers prefer to apply for short-term loans. However, the model also shows no significant relationship between the amount defaulted by the potential defaulters and the policy release. This illustrates that after high-risk borrowers enter the market, they are destined to incur defaults leading to losses for lenders.

To sum up, after the IFISA policy was announced, it attracted a lot of borrowers into the P2P lending market. The volume of business went up with an increased number of borrowers; however, these are higher-risk borrowers. The increase in the default rate and the increase in the percentage of the default amount brought about by these high-risk borrowers will cause an increase in losses for lenders in the P2P lending market. It is therefore critically important for P2P lending platforms to effectively identify whether a borrower is a potential defaulter.

2.6.4 Robustness Tests

In this section, the results of the robustness tests are provided to support the previous discussion. With the growth of the P2P lending market, more borrowers entering the P2P lending market is an observable trend. To confirm that the entry of a large number of high-risk borrowers is a result of the impact of IFISA policy announcements rather than the continued development of the market, I have additionally collected data for the same time period in 2014 to do the same estimations. I collected new borrower data from the same period a year earlier, from May to October 2014. However, the data collected does not include data on the 12-term loans. Because Zopa stopped issuing 12-term loans in the first eight months of 2014, there is insufficient data to support a pre-post comparison. Then I set up a placebo dummy estimator dated 15 July 2014, which had the same function as the post-announcement dummy estimator in the former test for simulating the policy announcement.

Firstly, examining the probability of default and the placebo dummy estimator according to Model 2.1, it is found that the placebo dummy estimator variables have no significant correlation with the probability of default. As shown in Table A.4, the coefficient of the placebo does not take a significant coefficient for all columns, it implies that the risks to new borrowers have not changed significantly after the date I set for the placebo dummy. Secondly, by estimating the loss given default and the placebo dummy estimator according to Model 2.3, it is observed that there is no significant impact on the loss given default in Table A.5. It implies that the losses incurred because of the default have not been significantly affected after the date I set for the placebo dummy. Additionally, as shown in Table A.6, the placebo dummy estimator does not take a significant coefficient for all columns in both the first hurdle and the second hurdle. It notes that the placebo dummy does not affect the probability of becoming a potential defaulter and the loss caused by potential defaulters. It means that there is no evidence of a significant change in the credit risk for newly awarded borrowers before or after the date. There is also no evidence that the losses caused in terms of defaulters would change.

Overall, after the same analysis of the data from May to October 2014, we can argue that the increase in default risk after the announcement of the IFISA policy is not related to the pre-existing trend showing the increase in the scale of business. It is also not related to possible monthly behavioural differences in borrowers. This examination provides evidence to support our previous discussion that after the IFISA announcement, high-risk borrowers entered the P2P lending market and incurred more losses.

2.7 Conclusion

Peer-to-peer lending is considered an innovation to complement bank credit. Even though loans in this market are regarded as subprime credit with a higher risk, P2P lending has seen substantial growth because of many competitive advantages (Basha et al., 2021). According to Shaffer (1998), borrowers who have been rejected by other banks will apply to new market entrants for a loan. A high default rate may then be experienced because of the pool of risky borrowers. P2P lending is treated as a new entrant in the credit market and it may follow the same pattern. The implementation of the new Innovation Finance ISA improved the knowledge of P2P lending amongst the public, attracting investors and borrowers into this market. As a feature of this expanding market, borrowers with weak credit ratings would prefer to borrow from P2P lending platforms.

This study made an attempt to discuss the impact of the introduction of P2P lending with government support on the changes in the level of credit risk in this market. I chose as an example the platform called Zopa, which is the first P2P lending platform in the world. The analysis focuses on the period from May to October 2015, which straddles the July 2015 official announcement of the new IFISA instrument by HM Treasury. After analysing loans funded through Zopa in the announcement period, it is found that the initial policy announcement for the new IFISA contributed to an increase in borrowers, and given the change in the quality of borrowers in this period, also an increase in both the default and loss given default. That is to say, the probability of default amongst borrowers rose and the total percentage of principal loss also grew. High-risk borrowers came into the P2P lending market after the IFISA announcement. In general, the announcement of the new Innovative Finance ISA affected the P2P lending market not only in terms of the volume of lenders and borrowers but also in terms of the default risk. High-risk borrowers were attracted by and accepted in the P2P lending market.

According to Broecker (1990), new entrants in credit markets are immature in screening borrowers. High-risk borrowers are adversely selected in new credit markets. Similarly, after high-risk borrowers entered the P2P lending market, the increasing default rate and loss of principal show that P2P companies such as Zopa did not fully anticipate this higher risk. Their current algorithms for screening loans and analyzing risk may underestimate the risk of new borrowers, resulting in the inability to effectively identify high-risk customers and thus accept loan applications from high-risk customers, which can then lead to an increase in credit risk. P2P lending platforms should strengthen their monitoring of borrower risk and keep their algorithms updated so as to reduce credit risk.

While the previous discussion provides some interesting findings, there are still some limitations regarding data disclosure and availability on platforms. Firstly, as previously mentioned, Zopa data stopped updating resulting in the impossibility of observing the default outcomes for 60-term loans. Secondly, because of data collection limitations, I was not able to collect data from other P2P lending platforms, particularly from P2P lending borrowers focused on business purposes that differ from borrowers from Zopa. In addition, other external factors that may affect the credit risk of P2P lending are also important, such as interest rates on other financing alternatives, which are left for future studies.

Appendix A

Table A.1: Variable description

Variable	Description
Snapshot Date	The date which all data are collected is on 1 April 2020
Disbursal Date	The date of a loan successfully funded
Original Loan Amount	Amount of principal
Lending Rate	The price of borrowing money (APR)
Term	Length of borrowing,such as 12, 24, 36, 48, 60 months
Loan Status	Repayment status on snapshot date.
	Four types:"Completed" "Active" "Late" "Default"
Principal Collected	The principal borrower already paid back
Default	1 if borrower defaulted and 0 otherwise
Loss	Remaining amount (loss principal amount)
Loss Rate	The percentage of loss principal to the principal
Announcement	1 if a loan funded after 15 July 2015 and 0 otherwise

Note: This table lists the description for all variables.

Appendix A

Table A.2: Descriptive statistics by Term

Variable	(1) Term	(2) Obs	(3) Mean	(4) Std. Dev.	(5) Min	(6) Max	(7) P25	(8) P50	(9) P75
Original Loan Amount	12	2,556	2,323.552	2,188.223	1,000	25,370	1,080	1,600	3,010
	24	7,129	3,623.292	2,715.331	1,000	26,170	2,050	3,040	4,300
	36	9,710	5,690.693	3,841.608	1,000	28,030	3,150	5,020	6,940
	48	5,155	7,945.106	4,952.315	1,010	28,590	4,810	6,500	10,120
	60	17,143	10,157.2	6,126.53	1,010	29,640	5,300	9,050	13,640
Lending Rate	12	2,556	0.107804	0.069411	0.0351	0.2425	0.053	0.0679	0.1604
	24	7,129	0.093948	0.065784	0.0245	0.245	0.0453	0.0652	0.1317
	36	9,710	0.087321	0.06222	0.0246	0.2475	0.0422	0.0607	0.1124
	48	5,155	0.07969	0.047195	0.0298	0.1815	0.0403	0.068	0.0998
	60	17,143	0.08726	0.049856	0.0296	0.1839	0.0446	0.0731	0.1076
Principal Collected	12	2,556	2,292.925	2,187.616	0	25,370	1,040	1,600	3,010
	24	7,129	3,538.623	2,722.873	0	26,170	2,030	3,020	4,180
	36	9,710	5,489.182	3,894.041	0	28,030	3,060	4608.16	6705.36
	48	5,155	7,635.857	5,057.896	0	28,590	4,270	6,170	10,070
	60	17,143	9,198.854	6,183.11	0	29,640	4,792.51	7,870	12,300
Default	12	2,556	0.030516	0.172037	0	1	0	0	0
	24	7,129	0.053023	0.224095	0	1	0	0	0
	36	9,710	0.071885	0.25831	0	1	0	0	0
	48	5,155	0.076043	0.265092	0	1	0	0	0
	60	17,143	0.128041	0.334145	0	1	0	0	0
Loss	12	2,556	30.62778	300.8667	0	7,730	0	0	0
	24	7,129	84.66907	524.5859	0	10,400	0	0	0
	36	9,710	201.5114	968.0329	0	15,672.48	0	0	0
	48	5,155	309.0264	1,399.625	0	24,540.93	0	0	0
	60	17,143	745.7762	2,566.791	0	26,963.5	0	0	0
Loss Rate	12	2,556	0.013877	0.101846	0	1	0	0	0
	24	7,129	0.026338	0.132044	0	1	0	0	0
	36	9,710	0.039300	0.163256	0	1	0	0	0
	48	5,155	0.043844	0.171222	0	1	0	0	0
	60	1,7143	0.076968	0.225293	0	1	0	0	0

Note: This table is classified by *Term* (1).And it shows the number of observations (2), mean (3), standard deviation (4), minimum (5), maximum (6), and quartiles (7)-(9) of the following variables. *Original Loan Amount* is the amount of principal. *Lending Rate* is the interest rate of borrowing money. *Principal Collected* is the principal already paid back by borrowers on the maturity date. *Defualt* equals 1 if borrower defaulted and 0 otherwise. *Loss* is the difference between the principal that should be repaid and the repayment principal. *Loss rate* is the percentage of non-repayment principal to the original amount of principal.

Appendix A

Table A.3: Descriptive statistics by Announcement

Announcement	Variable	(1) Obs	(2) Mean	(3) Std. Dev.	(4) Min	(5) Max	(6) P25	(7) P50	(8) P75
0	Original Loan Amount	14,887	7,259.546	5,669.637	1,010	29,640	3,120	5,300	10,100
	Lending Rate	14,887	0.088939	0.057928	0.0245	0.2475	0.0445	0.0683	0.1127
	Term	14,887	43.70283	15.78942	12	60	36	48	60
	Principal Collected	14,887	6,846.303	5,596.465	0	29,640	3,040	5,080	9,260
	Default	14,887	0.083966	0.277346	0	1	0	0	0
	Loss	14,887	362.4567	1,663.213	0	26,950	0	0	0
	Loss Rate	14,887	0.046909	0.178060	0	1	0	0	0
1	Original Loan Amount	26,806	7,238.496	5,551.714	1,000	29,640	3,110	5,340	10,090
	Lending Rate	26,806	0.088631	0.0568	0.0269	0.2475	0.0446	0.0689	0.11
	Term	26,806	43.89853	15.98441	12	60	36	48	60
	Principal Collected	26,806	6,697.21	5,393.096	0	29,640	3,010	5,100	9,126.52
	Default	26,806	0.092927	0.290336	0	1	0	0	0
	Loss	26,806	433.5054	1,898.65	0	26,963.5	0	0	0
	Loss Rate	26,806	0.054166	0.191134	0	1	0	0	0

Note: This table is classified by *Announcement*. *Announcement* equals 1 if the loan is funded after 15 July 2015 which is the date the IFISA policy was announced. Otherwise, *Announcement* equals 0. And it shows the number of observations (1), mean (2), standard deviation (3), minimum (4), maximum (5), and quartiles (6)-(8) of the following variables. *Original Loan Amount* is the amount of principal. *Lending Rate* is the interest rate of borrowing money. *Term* is the length of borrowing. *Principal Collected* is the principal already paid back by borrowers on the maturity date. *Defualt* equals 1 if borrower defaulted and 0 otherwise. *Loss* is the difference between the principal that should be repaid and the repayment principal. *Loss rate* is the percentage of non-repayment principal to the original amount of principal.

Appendix A

Table A.4: Probit model estimation in placebo test

VARIABLES	(1)	(2)	(3)	(4)	(5)
	Default	Default	Default	Default	Default
Placebo	-0.0015	-0.0058	-0.0028	0.0012	0.0003
	(0.0031)	(0.0059)	(0.0048)	(0.0072)	(0.0058)
ln(Original Loan Amount)	0.0009	-0.0009	-0.0050	0.0085	0.0050
	(0.0024)	(0.0055)	(0.0038)	(0.0058)	(0.0045)
Lending Rate	0.9621***	0.4094***	0.7209***	0.8381***	1.4870***
	(0.0404)	(0.0743)	(0.0594)	(0.0960)	(0.0828)
Term	0.0012***				
	(0.0001)				
Pseudo R2	0.1117	0.0679	0.1131	0.0912	0.0968
Type of Maturity	All	24	36	48	60
Observations	41,693	2,556	7,129	9,710	5,155

Note: This table reports the average marginal effect. Standard errors are in parentheses. Column (1) shows the estimated results for all data. Columns (2) to (5) display the estimated results for sub-datasets which are classified by types of Term. The dependent variable is *Defualt*, equals 1 if a borrower defaulted and 0 otherwise. *Placebo* equals 1 if the loan is funded after 15 July 2014; otherwise, *Placebo* equals 0. *ln(Original Loan Amount)* is the natural logarithm of amount of principal. *Lending Rate* is the interest rate of borrowing money. *Term* is the length of borrowing.And *** $p<0.01$, ** $p<0.05$, * $p<0.10$

Appendix A

Table A.5: Tobit model estimation in placebo test

VARIABLES	(1)	(2)	(3)	(4)	(5)
	Loss Rate	Loss Rate	Loss Rate	Loss Rate	Loss Rate
Placebo	-0.0011	-0.0023	-0.0017	-0.00009	0.00000519
	(0.0018)	(0.0026)	(0.0026)	(0.0042)	(0.0036)
ln(Original Loan Amount)	0.0007	-0.0007	-0.0025	0.0061*	0.0033
	(0.0014)	(0.0024)	(0.0021)	(0.0034)	(0.0028)
Lending Rate	0.5432***	0.1647***	0.3635***	0.4779***	0.9148***
	(0.0304)	(0.0398)	(0.0424)	(0.0733)	(0.0658)
Term	0.0007***				
	(0.0001)				
Pseudo R2	0.1028	0.0610	0.0951	0.0850	0.0888
Type of Maturity	All	24	36	48	60
Observations	41,693	2,556	7,129	9,710	5,155

Note: This table reports the average marginal effect. Standard errors are in parentheses. Column (1) shows the estimated results for all data. Columns (2) to (5) display the estimated results for sub-datasets which are classified by types of Term. The dependent variable is *Loss Rate* represents the percentage of the loan amount remaining unpaid relative to the principal amount after the loan has matured. *Placebo* equals 1 if the loan is funded after 15 July 2014; otherwise, *Placebo* equals 0. *ln(Original Loan Amount)* is the natural logarithm of amount of principal. *Lending Rate* is the interest rate of borrowing money. *Term* is the length of borrowing.And *** p<0.01, ** p<0.05, * p<0.10

Appendix A

Table A.6: Hurdle model estimation in placebo test

VARIABLES	(1) Loss	(2) Loss	(3) Loss	(4) Loss	(5) Loss
		First hurdle			
Placebo	-0.0206	-0.1260	-0.0520	0.0068	0.0059
	(0.0355)	(0.1223)	(0.0717)	(0.0952)	(0.0489)
ln(Original Loan Amount)	0.0112	-0.0304	-0.0730	0.1356*	0.0421
	(0.0278)	(0.1147)	(0.0569)	(0.0765)	(0.0381)
Lending Rate	10.7859***	7.8891***	10.2162***	10.8549***	12.5237***
	(0.4301)	(1.3409)	(0.7713)	(1.1351)	(0.6785)
Term	0.0139***				
	(0.0015)				
		Second hurdle			
Placebo	-160.86	-324.95	-194.88	42.93	-6.26
	(327.3266)	(394.7787)	(431.7034)	(837.0603)	(522.4484)
ln(Original Loan Amount)	1031.098***	147.67	158.82	1830.928**	1679.49***
	(259.3695)	(361.8526)	(340.5527)	(693.7334)	(415.9347)
Lending Rate	97304.7***	25468.17***	59696.4***	94901.1***	129388.5***
	(4680.05)	(5090.25)	(5742.89)	(12266.15)	(8238.22)
Term	127.9961***				
	(7.1195)				
Type of Maturity	All	24	36	48	60
Observations	41,693	2,556	7,129	9,710	5,155

Note: This table reports the average marginal effect. Standard errors are in parentheses. Column (1) shows the estimated results for all data. Columns (2) to (5) display the estimated results for sub-datasets which are classified by types of Term. The dependent variable is *Loss* represents the amount of the loan that remains unpaid after the maturity of the loan. *Placebo* equals 1 if the loan is funded after 15 July 2014; otherwise, *Placebo* equals 0. *ln(Original Loan Amount)* is the natural logarithm of amount of principal. *Lending Rate* is the interest rate of borrowing money. *Term* is the length of borrowing.And *** p<0.01, ** p<0.05, * p<0.10

Chapter 3

The Ponzi Premium: Evidence from a Scandal in the Chinese Peer-to-Peer Lending Market

Abstract

In December 2015, the top-ranked Chinese P2P lending platform Ezubao was investigated by the police in relation to a potential Ponzi scheme. Lenders on the platform suffered severe investment losses. The Chinese P2P lending market suffered a trust shock due to the Ezubao Ponzi scheme. I study the effect of this shock. In order to overcome the trust crisis and attract lenders, P2P lending platforms introduced a risk premium to guarantee lenders that the platform will cover the loss of principal. In this chapter, I discuss whether there was any impact on other P2P lending platforms after the Ezubao scheme occurred, whether there was any influence on the credit risk for other platforms, and whether the use of risk premiums by P2P lending platforms as a promise to cover investors' losses had an impact on the platforms themselves. The findings show the probability of default increased significantly, as demonstrated by the fact that defaulters on funded loans increased. Furthermore, the risk premiums that P2P platforms promised increased. Third, the real return on funded loans (for platforms) decreased significantly after the exposure of the Ezubao scheme.

3.1 Introduction

The beginning of the Chinese peer-to-peer (P2P) lending market was in 2007, and following a period of slow development until 2013, the industry showed explosive growth. However, in December 2015, the top-ranked P2P lending platform Ezubao was investigated by the police for a Ponzi scheme. Lenders on the platform suffered severe investment losses.

A Ponzi scheme is a scheme that 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, which leads to more investments. However, because Ponzi schemes involve financial crimes, there is little specific information on the schemes published to the public, so studies on Ponzi schemes are limited. Trust is the core element of a Ponzi scheme, but exposed Ponzi schemes could destroy the trust of investors in the financial market (Deason et al., 2015; Gurun et al., 2018). In the P2P lending market, the trust of lenders plays a very important role since P2P lending is a type of unsecured loan without any collateral. The Chinese P2P lending market suffered a trust shock due to the Ezubao Ponzi scheme. Therefore, in order to overcome the trust crisis and attract lenders, P2P lending platforms have introduced a risk premium to guarantee lenders that the platform will be responsible for using a premium to cover the loss of principal.

In this chapter, I discuss whether there was any impact on other P2P lending platforms after the Ezubao scheme occurred, whether there has been any influence on the credit risk for other platforms, and whether the use of risk premiums by P2P lending platforms as a promise to cover investors' losses will have an impact on the platforms themselves. The amount of premiums that are paid from the risk premium to the P2P lending platforms is the key factor on which to focus. In this study, a leading, trustworthy Chinese platform, Renrendai, was selected as a sample platform that provided premiums to its investors. Data from 54,918 funded loans were collected from October 2015 to March 2016 as well as the published quarterly and annual investment reports of Renrendai's platform from 2015 and 2016. Through the Probit, Tobit, and Hurdle model with a pre-post comparison evaluation, findings show that first, the probability of default increased significantly, referring to the fact that defaulters on funded loans increased. Second, the risk premiums that P2P platforms promised increased. Third, the real return on funded loans decreased significantly after the exposure of the Ezubao scheme.

The rest of this chapter is structured as follows. Section 3.2 discusses the background. Section 3.3 describes the dataset and variables. Section 3.4 introduces the hypothesis and the empirical methodology. Section 3.5 is the empirical test with displayed results and discussion, and Section 3.6 is the conclusion.

3.2 Review of Ponzi Scheme

A Ponzi scheme occurs where a fraudster sets up what appears to be a legitimate investment scheme usually with above average rates of return. The survival of a Ponzi scheme inevitably depends upon bringing new investors into the scheme or else it will ultimately collapse (Button et al., 2009). A Ponzi scheme can be extremely harmful. Once a scheme collapses, it may seriously destroy the belief of investors in investment instruments as well as in the financial market (Wang et al., 2019). As details about Ponzi schemes are rarely published, especially after the collapse of a scheme, available data are difficult to collect for research. Therefore, research on Ponzi schemes is relatively limited, and most studies focus on the trust of investors.

Researchers agree that winning the trust of investors is the most important determinant of success in Ponzi schemes. According to research carried out by Deason et al. (2015), Ponzi schemes target groups of victims who are vulnerable to being cheated, such as the elderly or members of a religion. Rantala (2019) believed that the creation of social networks between people helps Ponzi schemes grow and survive. In agreement with Deason et al. (2015), Rantala (2019) also believed that older people, as well as people with high levels of education and income, are prone to invest more in Ponzi schemes. In addition, based on cases in China, Huang et al. (2021) found that women and older investors are more likely to be introduced to Ponzi schemes. Furthermore, Ji (2019) pointed out that organizers of Ponzi schemes gain the trust of investors by blindsiding them through information asymmetry.

Seeking ways to prevent Ponzi schemes is another topic explored by researchers.

Zhu et al. (2017) note that operators rely on the spread of information in Ponzi schemes to improve the affordability of their interest payments and maintain their fraudulent operations. Moore et al. (2012) examined high-yield investment programs and found that with relatively low interest payments and long mandatory investment periods, Ponzi schemes can expect to have a longer lifetime. Carey and Webb (2017) discussed models of trust creation and maintenance in Ponzi schemes and pointed out that understanding how operators create trust would help prevent fraud. Various approaches, such as big data methods (Xu, Lu and Chau, 2015) and blockchain technology (Chen, Zheng, Ngai, Zheng and Zhou, 2019), have also been proposed to detect Ponzi schemes.

Ezubao Ponzi scheme is one of the first peer-to-peer lending scandals to be exposed (Albrecht et al., 2017). Ezubao, which was established in 2014, was one of the largest and most famous P2P lending platforms in China. In less than two years, the total volume of loan transactions on Ezubao exceeded 73 billion Yuan, with 4.9 million lenders. However, on 8 December 2015, the media reported that the Chinese police had arrested more than 20 people associated with Ezubao's Ponzi scheme. On 9 December 2015, the company suspended operations and approximately 710,000 lenders have still not recovered their principal investment and interest. On 16 December 2015, police officials announced that Ezubao was under investigation on a charge of being a Ponzi scheme. Ezubao claimed that a project company, which was a borrower, had signed a financing agreement with them, and they then issued bids for financing in the form of debt transfers on the Ezubao platform. After raising funds, the project company paid out income and principal amounts to the lenders. Ezubao promised a return of between 9% and 14.6% per year. However, according to the investigation, Ezubao fictionalized financing projects, transferred the money to third parties with favourable treatment, and then transferred the funds back to their affiliated companies. It was discovered that out of 207 project companies, only one received actual funding from Ezubao (Guo, 2016).

According to Albrecht et al. (2017), the Ezubao Ponzi scheme was perpetrated through advertising to the public, faked successful loans, and the government-supported appearance of the platform. This allowed it to attract lenders easily. Without collateral, the trust of lenders plays a very important role in the P2P lending market. As mentioned previously, exposed Ponzi schemes could destroy the trust of investors in the financial out market. According to Gurun et al. (2018), on the Madoff investment scandal, it was pointed that the shock to the investors' trust could have led them to update their beliefs concerning the risk and caused them to withdraw investments from delegated managers in favour of the relative safety of banks. Therefore, in China, after the Ezubao scheme, in order to overcome a crisis in trust and attract lenders, P2P lending platforms launched 'The Premium Plan' to underwrite a promise to lenders that platforms would take responsibility for using the premiums to cover principal losses.

In this chapter, the objective is to discuss the impact of the Ezubao scheme on the Chinese P2P lending market from the perspective of the P2P lending platforms, especially the impact on the credit risk and the return of P2P lending platforms under the risk premium commitment.

3.3 Data and Variables

3.3.1 Data

For this study, I collected data from the Renrendai platform. Founded in 2010, The Renrendai platform is one of the biggest P2P lending platforms in China. As the leading P2P lending platform, since 2014, Renrendai has been awarded an AAA rating, the highest level in the Chinese P2P lending market. According to the 2019 annual report, the volume of transactions on the Renrendai platform by the end of 2019 was 99.5 billion Yuan with approximately one million borrowers, mainly self-employed or small business owners, and two million lenders.

To apply for a loan, borrowers provide their loan request with their personal information to the Renrendai platform. The platform is responsible for verifying the credibility of the borrowers' profiles as well as determining an appropriate amount of funding and lending rate for each borrower based on the historical credit report and personal information. Once the loan request has been accepted by the Renrendai platform, profiles of qualified borrowers are published on their website for showing to the lenders (shown in Figure B.1). Meanwhile, the Renrendai platform provides different portfolios with fixed interest rates to lenders. The funds of lenders would be diversified to hundreds of borrowers through the Renrendai platform in order to diversify risk. Furthermore, for all the lenders on the platform, Renrendai offers a guaranteed mechanism. It promises that when a loan is seriously overdue (i.e. more than 30 days overdue), Renrendai will pay the remaining principal and interest of the loan to lenders through the premium known as the "Risk Reserve Fund". It means that lenders would be compensated by the Renrendai platform if they suffered a loss.

According to the timeline of the Ezubao scheme, the police officially confirmed that Ezubao was under investigation on 16 December 2015. In this research, to limit the uncertainty factors such as algorithms and policy changes that affect the platform, data were collected three months prior to and three months after this date. I collected data on the Renrendai website for the period of October 2015 to March 2016. This data listed all the related loan information, including loan details and borrowers' demographic information. In addition, the Renrendai platform published and updated its average interest rate in its reports, on a quarterly basis (shown in Figure B.2). I collected them from the published Renrendai quarterly and annual reports from 2015 and 2016.

3.3.2 Variable Description

To examine the impact of the Ezubao scheme on the Renrendai platform, firstly, I set up the dummy variable, **Ponzi**. It is defined by the date that Ezubao was confirmed to be under investigation by the police. *Ponzi=0* when loans were funded successfully before 16 December 2015, otherwise, *Ponzi=1.* In addition, when a borrower registers on the Renrendai platform, they obtain a unique identification number (Borrower ID), and once their loan application is successfully funded, each loan for which they applied is also allocated a unique number (Loan ID). In collecting the data, I recorded their loan characteristics by loan ID, including the Disbursal date, Original Loan Amount, Lending Rate, Term, Loan Status, and Remaining Amount, as follows. ***Disbursal date*** is the date that the loan is funded successfully. Borrowers receive the funds on this date and are also required to make monthly repayments from this date. ***Original Loan Amount*** is the principal amount and ***Lending Rate*** is the price of borrowing, it is the annual percentage rate of borrowing. ***Term*** is the maturity of the loan; borrowers can apply for a loan for 3 months to 48 months on the Renrendai platform. These variables represent the essential loan information that is determined before a loan has been successfully funded by the platform.

Furthermore, the platform would update ***Loan Status*** based on borrowers' monthly repayment behaviour. There are three status levels shown in the dataset: 'In progress', 'Bad debt', and 'Closed'. When borrowers are in the repayment period, they are recorded as 'In progress'. 'Bad debt' records bad borrowers' default. At the 'Closed' level, there are two types of loans. In the first case, the borrower has a good credit standing and has paid off all the principal and interest. The second type is for loans that are under the 'Principal Protection Scheme', i.e. the borrowers' outstanding principal and interest are being paid by the premiums to the lender, and the platform has taken over the claim. And ***Remaining Amount*** is the amount still to be repaid by the borrower. Borrowers with good credit would keep zero in the Remaining Amount. If it is a positive number, it also signifies the amount by which Renrendai compensates the lender with a premium. It is caused by borrowers with bad credit defaulting on their repayments.

Interest Rate is the rate of return a lender receives by lending money to borrowers. On the Renrendai platform, lenders' investments are automatically diversified to a different number of borrowers, and the lenders' interest rate is dependent on the comprehensive yield of the portfolio they choose to invest in. Additionally, the platform does not disclose information about lenders' investment data. For a single borrower, the number of lenders and the amount they invest is not fixed. Therefore, I collected the average interest rate of lenders from the quarterly and semi-annual reports[1] disclosed by the Renrendai platform as a benchmark for measuring the expected return.

In order to measure credit risk, it is necessary to define risk-related variables. As the 'Principal Protection Scheme' promised, the platform will pay the premiums to the lenders. Therefore, even if the loan status is 'Closed', it cannot simply be assumed

[1]Example of a screenshot of the semi-annual report is shown as Figure B.2.

that the loan has involved a normal repayment. The default dummy variable is defined by combining the loan status and the remaining amount. Since the data were collected after the end of the entire repayment process, if the remaining amount still shows positive numbers, it will be regarded as a defaulted loan. And a binary variable, ***Default***, is defined as describing defaulted behaviour of loans. When *Default*=1, it describes borrowers who pay the principal and interest later than the date of repayment and those who fail to repay the principal and interest. In this study, loans are regarded as in default when the loan status is 'Bad Debt', and when the loan status is 'Closed' while the remaining amount remains positive. When a borrower has paid off the principal and interest, *Default*=0. ***Loss Given Default*** is the loss incurred if a borrower defaults, expressed as a percentage of the total principal.

Moreover, in this study, to capture the impact of the Ezubao scheme on other P2P lending platforms, the profit or return of platforms is important. Depending on the profit pattern of the Renrendai platform (Xing and Wang, 2015), I defined two variables: ***Expected Return*** and ***Real Return***. Based on Serrano-Cinca and Gutiérrez-Nieto (2016), the ***Expected Return*** of the platform is the difference between the loan repayment of principal and interest from borrowers and investment payment to lenders for individually funded loans on the Renrendai platform. This is the service fee for the Renrendai platforms, which is responsible for the profits and is a component of the risk premium. By subtracting the compensation amount from the expected return, it is the ***Real Return*** for each funded loan.

3.3.3 Data Description

During the period October 2015 to March 2016, there were 54,918 funded loan records on Renrendai platform; 29,846 were funded successfully before the date of the Ezubao scheme and 25,072 thereafter. There is a slight decline in the number of loans funded.

Descriptive statistics for the main variables are presented in Table 3.1. The original loan amounts range from 3,000 Yuan to 428,000 Yuan, and the average is 81,541.06 Yuan. It shows a wide range of loan amounts, while the average amount of borrowing

Table 3.1: Data description

Variable	(1) Obs	(2) Mean	(3) Std. Dev.	(4) Min	(5) Max	(6) P25	(7) P50	(8) P75
Original Loan Amount	54,918	81,541.06	44,167.83	3,000	428,000	49,100	74,600	96,900
Lending Rate (%)	54,918	10.9476	0.5617	8	13.2	10.8	10.8	10.8
Term	54,918	33.3009	7.5953	3	48	36	36	36
Remaining Amount	54,918	17,476.32	27,644.3	0	242,397.7	0	0	27,297.42
Interest Rate (%)	54,918	11.0089	0.2800	10.79	11.54	10.79	10.94	10.94
Default	54,918	0.4658	0.4988	0	1	0	0	1
Loss Given Default	54,918	0.1665	0.1961	0	1.1406	0	0	0.328
Expected Return (%)	54,918	-0.0613	0.5614	-2.94	2.26	-0.14	-0.14	0.01
Real Return (%)	54,918	-16.7130	19.5312	-112.60	2.26	-32.94	-1.34	-0.14
Ponzi	54,918	0.4565	0.4981	0	1	0	0	1

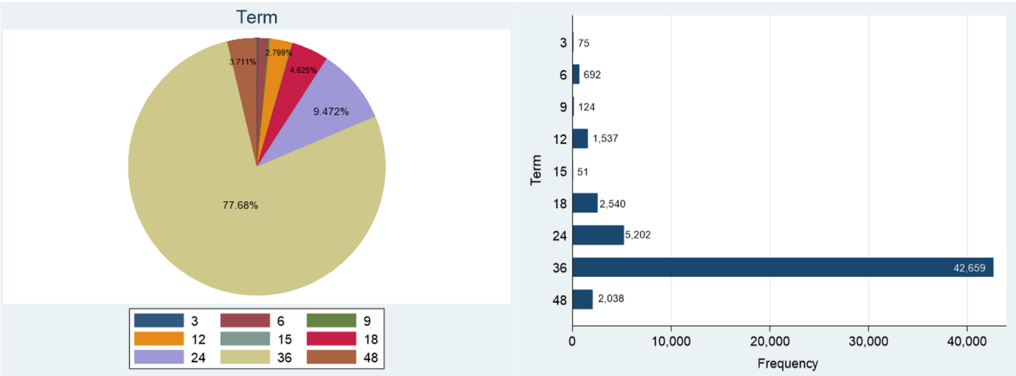
Note: This table shows the number of observations (1), mean (2), standard deviation (3), minimum (4), maximum (5), and quartiles (6)-(8) of the following variables. *Original Loan Amount* is the amount of principal. *Lending Rate* is the interest rate of borrowing money. *Term* is the length of borrowing. *Remaining Amount* is the principal and interest that should be repaid. *Interest Rate* is the average annual interest rate of investing on loans issued by the Renrendai platform. *Defualt* equals 1 if a borrower defaulted and 0 otherwise. *Loss Given Default* is the percentage of non-repayment principal to the original amount of principal. *Expected Return* is the expected return of each funded loan which is the difference between the loan repayment of principal and interest from borrowers and investment payment to lenders. *Real Return* is the real return of each funded loan. *Ponzi* is defined by the date that Ezubao was confirmed to be under investigation by the police. *Ponzi=0* when loans were funded successfully before 16 December 2015, otherwise, *Ponzi=1*.

is less than 100,000 Yuan, indicating that Renrendai primarily focuses on small loans. The lending rate charges are from 8% to 13.2%, while the interest rates for investors are from 10.79% to 11.54%, which are much higher than the corresponding lending and deposit rates offered by banks[2]. Based on the length of the repayment period, there are nine types of loan terms. The average term length is 33.3 months. Specifically, as shown in Figure 3.1, 77.68% of funded loans are on a 36-month term, for a total of 42,659. These basic descriptive statistics of loan characteristics are similar to those of studies that have examined the data from a similar period on Renrendai platform (Wang et al., 2021; Xu et al., 2020).

Furthermore, the average of the Ponzi dummy is 0.4565, which means 45.65% of loans are funded after the Ezubao Ponzi scheme. Table 3.2 reports the comparison with mean and standard deviation of loan characteristics before and after the Ezubao scheme. The data shows that there has been a significant increase in the amount and duration of borrowing by borrowers after the Ezubao Ponzi scheme. There is a greater standard deviation in the loan amount, meaning that borrowers seek loans that are much more or less than the average amount. Conversely, lending rates for

[2] The interest rate for loans from one to five years (inclusive) for financial institutions in 2016 is 4.75%; the deposit rate for three years is 2.75%. According to the People's Bank of China: http://www.pbc.gov.cn/tiaofasi/144941/3581332/3588280/index.html

Figure 3.1: Loan frequency by Term



Note: This figure shows the percentage and frequency of different lengths of loans.

borrowers and interest rates for investment by lenders have both fallen significantly and have less volatility.

Table 3.2: Summary statistics: pre-Ponzi and post-Ponzi scheme

Variables	Before (Ponzi= 0)			After (Ponzi= 1)			diff	t
	Obs	Mean	Std.Dev	Obs	Mean	Std.Dev		
Original Loan Amount	29,846	76,210.92	41,973.59	25,072	87,886.13	45,845.39	-11675.21	-31.1266***
Lending Rate	29,846	11.07506	0.6437745	25,072	10.79588	0.3940756	0.2791781	59.8848***
Term	29,846	31.62102	8.033925	25,072	35.30061	6.494031	-3.679593	-58.2717***
Interest Rate	29,846	11.16936	0.2915692	25,072	10.8179	0.05837	0.3514536	187.7284***

Note: This table reports the mean comparison before and after the Ezubao Ponzi scheme happened. Variables are including Original Loan Amount, Lending Rate, Term and Interest Rate. And, * p<0.10, ** p<0.05, *** p<0.01

The statistics related to the risk and returns are also shown in Table 3.1. The analysis of the remaining amount and default dummy variable indicates that half of the borrowers have poor credit. Approximately 46.5% of borrowers still have remaining amounts unrepaid by the closing date of repayment, which need to be covered by the use of the risk premium. The maximum remaining amount reaches 242,397.7 Yuan. On average, the amount remaining is 17,476.32 Yuan. And the average loss given default is 0.1665. It represents an average loss on each loan is 16.65% of the principal amount. It suggests that the Renrendai platform experienced a high level of risk as well as losses. And there are interesting findings that borrowers produced negative returns for the platform. The average expected return for the Renrendai platform is -0.0613%, while the average real return is -16.71%. The standard deviation of real return is 19.5312, which illustrates the high volatility of the real return per loan. The negative average expected return may arise from the presence of extremely negative rates of return (Serrano-Cinca and Gutiérrez-Nieto, 2016). And the high negative average real return may be generated by high credit risk borrowers causing losses and the compensation of principal promised by the platform.

Overall, descriptive statistics suggest that the Renrendai platform experienced a high level of risk as well as losses. In this study, the main aim is to examine whether the defaults of high-risk borrowers as well as losses on the platform are related to the risk of the Ezubao Ponzi scheme.

3.4 Empirical Strategy

3.4.1 The Credit Risk of P2P Lending Platform

In this section, I discuss how the credit risk faced by P2P lending platforms has changed after the Ezubao Ponzi scheme. There is very limited literature regarding Ponzi schemes and P2P lending. However, there are a few studies offering some ideas, for example, Zhang (2012) pointed out that financial emergencies often evolve into risk events through public opinion communication. The Ezubao scheme was the first and largest Ponzi scheme in the Chinese P2P market, and its negative impact is firstly manifested in the impact on the risk of other P2P platforms. Therefore, the first hypothesis is:
After the exposure of the Ezubao scheme, the credit risk on the existing P2P lending platform increased.

Based on the pre-post comparison evaluation (Pomeranz, 2017), it is to set up two groups: one is the comparison group before the policy event and the other is the treatment group after the policy event. In this study, using the fraud dummy variable, *Ponzi*, loans can distinguish between two groups: one comprises loans funded before the fraud and the other comprises loans funded following the fraud. To estimate the effect of the Ezubao scheme on the credit risk of other P2P lending platforms, credit risk will be discussed from three perspectives, which are the probability of default, the loss given default, and potential defaulters.

The primary discussion of credit risk in P2P lending is about the probability of default on the loan (Canfield, 2018; Đurović, 2017). I employ the Probit model to examine the probability of default and the fraud dummy variable. And the Probit model is conducted as:

$$Pr(\mathit{Default} = 1) = \Phi(\alpha + \beta Ponzi + \delta \mathbf{Features}_i + \epsilon_i) \tag{3.1}$$

where the dependent variable, *Default*, represents whether the borrower defaulted at the end of the repayment period. It is a binary variable. It equals 1 if the borrower defaulted and 0 otherwise. Pr(*Default*=1) indicates the probability that the borrower is unable to repay. *Ponzi* is the independent variable which is a binary variable as well. *Ponzi*=1 stands for a loan funded after the Ezubao scheme, otherwise *Ponzi*=0. The coefficient β indicates whether the fraud dummy would affect the probability of default. Furthermore, Φ is the cumulative normal distribution. And $\mathbf{Features}_i$ are a set of control variables such as the original amount of the loan, lending rate, and term.

In addition, the loss given default, which is an indicator of the severity of losses after default, is another measurement of credit risk (Zhou et al., 2018). It is calculated by:

$$\mathit{Loss\ Given\ Default} = \frac{RemainingAmount}{OriginalLoanAmount} \tag{3.2}$$

And to further estimate the loss given default by the following Tobit model:

$$\mathit{Loss\ Given\ Default} = \theta + \gamma Ponzi + \delta \mathbf{Features}_i + \mu_i \tag{3.3}$$

where *Loss Given Default* is the dependent variable, it represents the percentage of the loan amount remaining unpaid relative to the principal amount after the loan has matured. The fraud dummy variable, *Ponzi*, is the independent variable, and $\mathbf{Features}_i$ are a set of control variables as mentioned previously.

Furthermore, it is essential to distinguish good credit borrowers who never default from defaulters, according to Moffatt (2005). A potential defaulter can be transformed into an actual defaulter due to changes in certain circumstances, which increases the risk of default. The hurdle model could effectively identify potential defaulters with its first hurdle. The second hurdle will then measure the amount of loss caused by these defaulters. Hence, it is important to measure credit risk by identifying potential defaulters and estimating the losses they cause (Byanjankar et al., 2015; Zhou et al., 2019). The model is represented by:

$$Y_i = D_i * L_i \tag{3.4}$$

The first hurdle equation, which is to select defaulted borrowers, is:

$$D_i = \begin{cases} 1, & \text{if } D_i^* > 0 \\ 0, & \text{if } D_i^* \leq 0 \end{cases} \tag{3.5}$$

where

$$D_i^* = \rho + \tau\text{Ponzi} + \beta\mathbf{X}_i + \nu_i \tag{3.6}$$

And the second hurdle equation is for measuring the Remaining Amount of defaulters:

$$L_i = \varphi + \omega\text{Ponzi} + \beta\mathbf{X}_i + \varepsilon_i \tag{3.7}$$

where L_i is the remaining amount of defaulters. Ponzi is the fraud dummy estimator. In the hurdle, Equation 3.5 and 3.6, D_i^* is represented as the remaining amount of an individual funded loan after loans matured. When D_i^* is larger than 0, it means the probability of default is positive, in other words, it signifies a defaulted borrower, and D_i is equal to 1; otherwise, D_i equals 0, and it signifies a good quality borrower. Equation 3.7 is intended to estimate how much the potential defaulters contribute to the platform's loan default total. $\mathbf{X}_i$ are control variables.

The control variables mentioned in the three models are the set of basic characteristics of the loan, including the original amount of the loan, lending rate, and term. Many previous studies demonstrated that these three variables are found to have a significant relationship with credit risk in the P2P lending market (Chen, Dong, Liu and Sriboonchitta, 2019; Emekter et al., 2015; Everett, 2015).

3.4.2 The Profits of P2P Lending Platform

The key to keeping a P2P lending platform operating, as any business does, is profitability. Based on Sun (2019); Xing and Wang (2015), they pointed out that P2P lending platforms are mainly profit-making by charging a service fee to the borrower alone or to both borrowers and lenders. The service charge is raised from the difference between the interest rate charged by the borrower for the loan and the interest rate promised to the lender. At the same time, the P2P platform's guarantee mechanism, which is a promise to compensate lenders when a borrower has defaulted, also relies on service fee income.

According to research into the Madoff investment scandal, Gurun et al. (2018) identified that the trust shock could have led lenders to update their beliefs concerning risk, which led them to withdraw investments from delegate managers in favour of the relative safety of banks. Thus, when the Ezubao scheme was exposed, lenders' trust in P2P platforms would also be affected. In order to acquire lenders' trust, most P2P lending platforms have established a risk compensation plan. Once the borrowers have defaulted, the losses of the lenders are compensated by the P2P lending platform. However, this will take place at the cost of a reduction in profit for the P2P platforms. Therefore, the second hypothesis is:
After the exposure of the Ezubao scheme, the profits of existing P2P lending platforms decreased.

Equation 3.8 estimates the change in real return on the Renrendai platform after the Ezubao scheme collapsed.

$$R_i = \alpha + \delta \text{Ponzi} + \theta \text{Default} + \gamma \text{Interaction} + \epsilon_i \tag{3.8}$$

where R_i is the real return of an individual funded loan, Default is a dummy variable, and Ponzi is the fraud dummy estimator. The interaction term (Ponzi*Default) and its coefficient capture how much change of return is contributed by affected defaulters after the Ezubao scheme was exposed.

3.5 Empirical Results

In this section, I first examine the impact of the Ezubao scheme exposed on the credit risk of the Renrendai platform. And then I evaluate the change in returns of Renrendai after the Ezubao scheme. The aim is to discuss the impact of the Ezubao scheme on other P2P lending platforms.

3.5.1 Results on the Credit Risk

To estimate the effect of the Ezubao scheme on Renrendai, firstly, I performed a mean comparison of two groups of newly funded loans, the group funded before the Ezubao scheme and the group funded after. As shown in Table 3.3, after the Ezubao scheme, the number of funded loans decreased. It implies that after the Ezubao scheme, P2P platforms such as Renrendai consequently reduced the volume of loans funded.

By contrast, the average probability of default, the average loss given default and the average remaining amount increased after the Ezubao scheme. In detail, the average number of defaults in the group of loans that were funded after the Ezubao scheme is 0.5242, which is significantly higher than the group funded before the scheme at 0.4169. This means that in the three months following the Ezubao scheme, about 52% of new borrowers who received a loan on the Renrendai platform were delinquent, and the platform needed to use its risk premium to cover the lender's losses. This is a quite high percentage, which is consistent with the previous descriptive statistics showing that the credit risk of borrowers who successfully applied for loans on the Renrendai platform is very high.

Table 3.3: Mean comparison

Variables	Before (Ponzi= 0)			After (Ponzi= 1)			diff	t
	Obs	Mean	Std.Dev	Obs	Mean	Std.Dev		
Default	29,846	0.4169068	0.4930554	25,072	0.5241704	0.4994254	-0.1072636	-25.2449***
Remaining Amount	29,846	13,460.84	24,251.7	25,072	22,256.39	30,525.09	-8,795.55	-37.6147***
Loss Given Default	29,846	0.1294	0.1719	25,072	0.2107	0.2134	-0.0812	-49.4148***

Note: This table reports the mean comparison results before and after the Ezubao Ponzi scheme happened. Variables are including Default, Loss Given Default, and Remaining amount. And, * p<0.10, ** p<0.05, *** p<0.01

As for the losses resulting from defaulted behaviours occurred, it can be found by comparison that the average Remaining Amount, after the Ezubao scheme, value is approximately 22,256.39 Yuan, which is nearly twice as high as for the group funded before the scheme at 13,460.84 Yuan. Furthermore, it is similar to the average loss given default, in which the unpaid principal and interest as a percentage of the total loan amount significantly increase by approximately 8.12 percentage points after the Ezubao scheme. It illustrates that borrowers who received loans after the Ezubao scheme had a significantly higher amount of default. In order to guarantee that lender's losses do not increase, the platform needs to pay more risk premiums. Overall, as can be seen from the figures in the main comparison above, it is easy to show that after the Ezubao scheme, the platform suffered a higher default risk, which is evidenced by the higher probability of default and the increase in the size of average remaining amounts.

Table 3.4: Estimation results on credit risk

VARIABLES	(1) Default	(2) Loss Given Default	(3) Remaining Amount	(4)
Ponzi	0.0575***	0.0534***	0.1569***	11,085.02***
	(0.0044)	(0.0019)	(0.0120)	(473.79)
ln(Original Loan Amount)	0.0422***	0.0095***	0.1150***	23,012.02***
	(0.0043)	(0.0018)	(0.0118)	(468.32)
Lending Rate	0.0700***	0.0302***	0.1911***	7,979.287***
	(0.0042)	(0.0018)	(0.0114)	(465.37)
Term	0.0182***	0.0086***	0.0497***	1,543.249***
	(0.0004)	(0.0002)	(0.0011)	(44.35)
Pseudo R2	0.0738	0.1014	0.0738	0.0131
Method	Probit	Tobit	First Hurdle	Second Hurdle
Observations	54,918	54,918	54,918	54,918

Note: This table reports the results of the estimations by the Probit model (1), the Tobit model (2), and both the first hurdle (3) and the second hurdle (4) for the Hurdle model respectively. Standard errors are in parentheses. The dependent variables are *Default* which equals 1 if the borrower defaulted and 0 otherwise; *Loss Given Default* which is the percentage of non-repayment principal to the original amount of principal and *Remaining Amount* which is the principal and interest that should be repaid. *Ponzi* is defined by the date that Ezubao was confirmed to be under investigation by the police. *Ponzi=0* when loans were funded successfully before 16 December 2015, otherwise, *Ponzi=1. ln(Original Loan Amount)* is the natural logarithm of amount of principal. *Lending Rate* is the interest rate of borrowing money. *Term* is the length of borrowing. And *** $p<0.01$, ** $p<0.05$, * $p<0.10$

Column (1) of Table 3.4 shows the marginal effects of the probability of default and fraud dummy variable by estimating Model 3.1. It presents that the fraud dummy, Ponzi, has a significant positive impact on the probability of default. The coefficient is 0.0575, which indicates that the probability of loan delinquency has increased by 5.75 percentage points after the exposure of the Ezubao Ponzi scheme. The finding suggests that the probability of default on loans on the Renrendai platform is affected by the exposure of the Ezubao scheme. In addition, it is important to examine the extent to which the exposure of the Ezubao scheme affects the losses of the Renrendai platform based on Model 3.3. The results are shown in column (2) of Table 3.4 that the fraud dummy, Ponzi, takes a positive sign. It indicates that the exposure of the Ezubao Ponzi scheme has a positive and significant effect on the loss given default at the 1% significance level. The outstanding amount as a percentage of principal rose by 5.34 percentage points after the scheme. Combined with the finding on the probability of default, it can be suggested that the increased credit risk of the Renrendai platform is related to the exposure of the Ezubao Ponzi scheme. It is consistent with findings in the studies on risk contagion. According to Lang and Stulz (1992), they point out that the failure of a company could affect the probability of default of companies that have not defaulted.

Furthermore, I apply the hurdle model to support the findings above, the platform suffered a higher default risk after the Ezubao scheme. As shown in Figure B.3, approximately 53% of funded loans have a zero remaining amount, which infers a good quality of funded loans as well as good credit borrowers, with the rest in default. The remaining outstanding loans are mostly concentrated in amounts below 50,000 Yuan, which comprise approximately 75% of defaulters. According to the results in column (3) of Table 3.4, the potential defaulters on newly financed loans increase after the occurrence of the Ezubao scheme. It indicates that the probability of default increases when the number of potential defaulters increases. Specifically, results in the first hurdle show that the scheme had a significant positive effect on the probability of default, which is evidenced by the fraud dummy being positive at the 1% significance level. The empirical results of the second hurdle imply that due to the effect of the Ezubao Ponzi scheme, there are more borrowers tend to not repay in good time. With regard to default borrowers, the results of the second hurdle show how the value of the remaining amounts changed after the Ezubao scheme. Based on column (4) in Table 3.4, from the results shown in the loss, the number of remaining amounts of defaulters increased after the scheme, supported by the positive coefficient of the Ponzi dummy at a 1% significant level. In comparison to the number of remaining amounts before the scheme, the figure for defaulters increased by 11,085.02 Yuan on average.

Additionally, results for all three models show that credit risk is positively affected by three control variables: original loan amount, lending rate, and term. This implies that the larger the number of loan amounts funded, the higher the probability of default. Therefore, in charging a higher rate for lending and offering a longer repayment period, a higher default risk and a greater loss might be incurred in the future (Emekter et al., 2015; Everett, 2015).

Therefore, the collapse of the Ezubao scheme would affect other platforms such as Renrendai, especially their borrowers and newly funded loans. After the exposure of the scheme, the group of borrowers who were successfully funded demonstrated worse repayment behaviour compared to the group funded before the scheme. It shows that the probability of default increases with the increasing number of potential defaulters. For those defaulters, they might also tend to default on greater amounts of credit, which implies that those funded after the Ezubao scheme tend to default earlier than those funded prior to it. In fact, credit risk contagion is also found in traditional financial markets, such as the interbank market or bond markets. Studies of the interbank (Van Lelyveld and Liedorp, 2004) and bond markets (Davis and Lo, 2001) demonstrated that the failure of a financial institution could impose a considerable burden on other financial institutions and may provoke defaults by other financial institutions.

3.5.2 Results on Real Return

Lang and Stulz (1992) points out that the failure of a company not only affects the probability of default of non-defaulting companies but also their stock returns. In this section, I explore the impact of the scheme on peer-to-peer lending platforms' return. Previous findings show that after the Ezubao scheme, platforms such as Renrendai faced a higher risk of default and approved credit for more uncreditworthy borrowers. In addition, 'The Premium Plan', which is the promise that the platform would cover the default amount by using premiums would impose additional burdens on platforms. Zhu (2018) noted that under the guarantee mechanism, the capacity of P2P lending platforms to assess risk in selecting borrowers is distorted, leading to lower quality of borrowers' credibility and creating risk. And Zhang (2017) found that under the guarantee mechanism, the expected return on loans is affected not only by systemic risk but also by idiosyncratic risk. It is predicted that after the Ezubao scheme, platforms would earn less than before. Hence, to estimate the impact of the scheme on peer-to-peer lending platforms, it is important to measure how much the defaulters contribute to changes in real returns after the Ezubao Ponzi Scheme. This is shown in Model 3.8 as an interaction term (Ponzi*Default).

Table 3.5: Estimation results on real return

VARIABLES	(1) Real Return	(2) Real Return	(3) Real Return
Ponzi	-8.052***		0.193**
	(-0.164)		(-0.0898)
Default		-35.55***	-30.72***
		(-0.07)	(-0.0886)
Interaction			-9.444***
			(-0.13)
Constant	-13.04***	-0.151***	-0.230***
	(-0.111)	(-0.0478)	(-0.0572)
Observations	54,918	54,918	54,918
R-squared	0.042	0.824	0.851

Note: This table reports the results on real return.*Default* equals 1 if the borrower defaulted and 0 otherwise; *Ponzi* is defined by the date that Ezubao was confirmed to be under investigation by the police. *Ponzi=0* when loans were funded successfully before 16 December 2015, otherwise, *Ponzi=1*. And *Interaction* represents the extent to the defaulters contribute to changes in real returns after the scheme. Standard errors are in parentheses. And *** $p<0.01$, ** $p<0.05$, * $p<0.10$

The results support the previous hypothesis that the real return of the platform decreased after the Ezubao scheme. The main reason is the higher default risk driven by the rising number of potential defaulters and the increasing number of premiums needed to cover the default amounts. As Table 3.5 shows, in column (1), the Ponzi dummy is negatively related to the real return. It implies that after the Ezubao scheme, the real return decreased by about 8.052%. Meanwhile, the Default dummy is similar to the Ponzi dummy, it has a negative effect on the real return at 1% significance level. Moreover, as shown in column (3), the interaction term shows a negative relationship with the real return of the platform at 1% significant level. It suggests that default borrowers who were funded after the Ezubao scheme contributed to a situation in which the platform paid more premiums to cover their losses, which reduced the profit of the P2P lending platform.

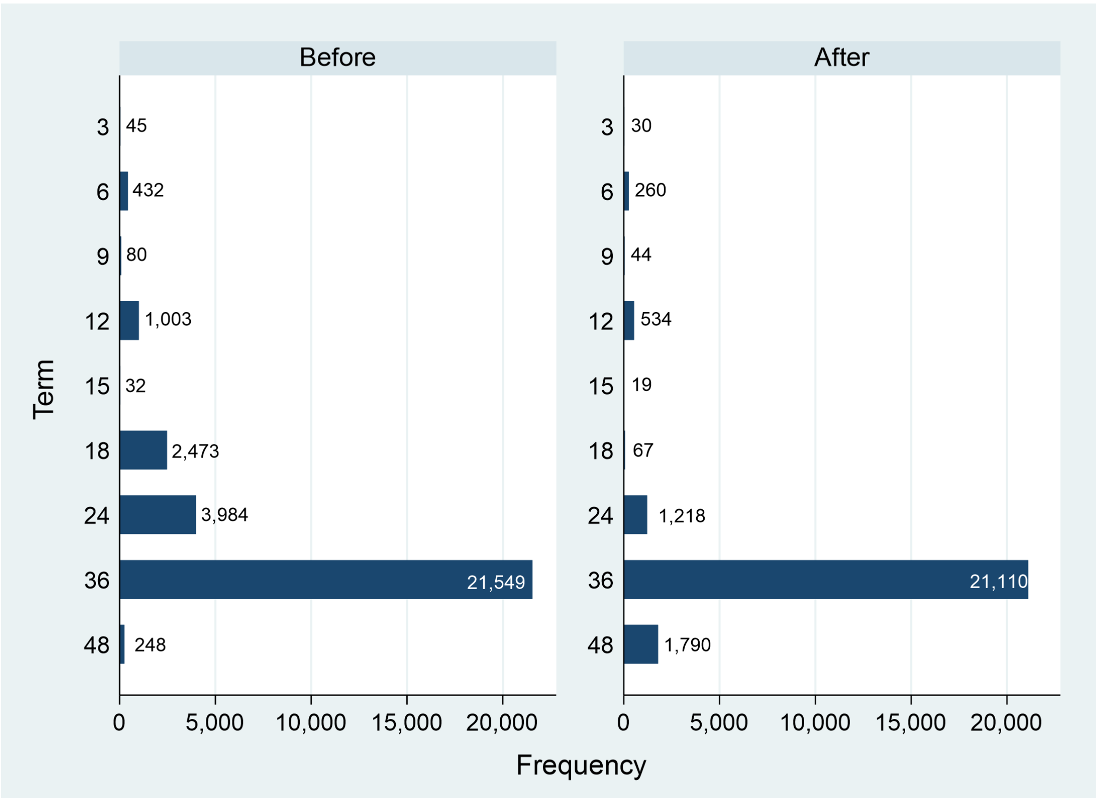
Overall, according to these results, the impact of the Ezubao scheme collapse on P2P lending platforms is significant. The increasing number of defaulters and outstanding loans led to the platform being burdened with more premiums to cover investors' losses and resulted in a cut in profits for P2P lending platforms. This finding is consistent with Lang and Stulz (1992), in which credit risk contagion also exists in the P2P lending market affecting the profits of other platforms. The trust of investors in the financial market will collapse due to the exposure of Ponzi schemes, and they will withdraw their investments in favour of safer financing products such as bank deposits (Gurun et al., 2018). The P2P lending market in China was under pressure from the Ezubao Ponzi scheme, and in order to reinstate lenders' trust, P2P platforms promised to cover lenders' losses by introducing risk premiums. However, this shifted the risk that was originally shouldered directly by lenders in the P2P lending market to P2P lending platforms themselves, which directly influences the returns of these platforms.

However, borrowers involved in the P2P lending market are higher-risk customers who cannot borrow from banks and suffer more uncertainty when confronted by the shock of negative market news. Specifically, they will become defaulters more easily, while the amount of their default will increase correspondingly, resulting in more losses, although P2P platforms charge higher lending rates to these subprime credit borrowers to ensure that such risks can be covered. However, in order to attract more lenders, P2P lending platforms in the beginning promised interest rates to lenders which are also high. Combined with the risk premium loss compensation promised, it is expected that P2P platforms did not actually gain positive returns, and under the impact of the Ezubao scheme, their revenue is even less as a result. A few platforms thus collapsed, concentrating the market on the top-ranked platforms that are still running. The expanded scale of lenders and borrowers makes the cost of managing risk for platforms more expensive until the credit risk accumulates and explodes (Gonzalez, 2010; Lützenkirchen et al., 2012). Therefore, even if payment of a risk premium was promised, it would not be sufficient to cover the losses of the lenders in the future.

3.5.3 Robustness Test

Figure 3.2 shows that although the platform offers various lengths of terms for loans, the 36-month term loan is the main product on the Renrendai platform. Comparing the frequency of funded loan terms prior to and after the Ezubao scheme, it is clearly shown that following the Ezubao scheme, the number of all types of funded loans decreased, except for the 48-month term. There is a slight decrease in 36-month funded loans from 21,549 before the date of the Ezubao scheme to 21,110 loans thereafter. As for the 6-month, 12-month, in the beginning, term loans, the number after the Ponzi fraud is approximately half the previous number, and for the 18-month term loans, the number almost reaches 0 following the Ponzi scheme.

Figure 3.2: Difference in loan term length before and after the Ezubao scheme



Note: This figure shows the difference in frequency of terms before and after the Ezubao scheme.

To test the robustness of the results, I chose to focus only on the data of 36-term loans to examine whether the previous results are valid. As shown in Figure 3.1 and Figure 3.2, of all successfully funded loans, 77.68% are 36-term loans. Of the remaining 22.32% of loans, some borrowers opted for 12-term, 18-term, 24-term, and 48-term loans. To confirm that the reduction in the platform's returns after the Ezubao scheme is not affected by the change in this small percentage of loans, the following robustness test focuses only on the data relating to 36-term loans.

Table B.1 shows a significantly increased in default from 0.5451 to 0.5803 with a decreasing number of funded loans after the fraud happened. The remaining amount, which is the amount of principal and interest on which borrowers defaulted, significantly increases from 17,577 Yuan to 24,300.5 Yuan. Meanwhile, the loss given default increased by 6.54 percentage points. It implies that after the Ezubao scheme happened, the Renrendai platform experienced an increase in the probability of default and the amount of default based on the funded loans it owned. As Renrendai promised to pay default premiums to their investors, the increase in these two figures means that the platform will have to pay more premiums, which is negative for the P2P lending platform business.

By April 2020, a total of 42,659 36-term loans successfully funded from October 2015 to March 2016 had finished being repaid. Followed by the Model 3.1, results from the Probit model are shown in column (1) of Table B.2. It is found that the fraud dummy, Ponzi, has a positive and significant effect on the probability of default at the 5% significance level. Additionally, examining the Model 3.3, the results show that the loss given default increased after the Ezubao Ponzi scheme. The coefficient associated with the fraud dummy is positive and statistically significant at the 1% significance level. Column (3) and (4) in Table B.2 reports results from the hurdle model. In the first hurdle, showing results after the Ezubao scheme happened, there is a significant positive coefficient on the post Ponzi dummy when controlling the original principal amount and lending rate. That means once the scheme happened, the number of potential defaulters increased. Moreover, in the second hurdle, the remaining amount rises. According to the figures in Table B.2, there is a positive coefficient of Ponzi on Remaining Amount, or in other words, the default principal and interest significantly increased after the fraud happened. Compared to the period before, each defaulter might increase their default amount by about 5416.07 Yuan on average. Overall, the estimated results for 36-term loans are consistent with previous findings that the exposure of the Ezubao scheme has impacted the credit risk of the Renrendai platform, resulting in an increase in both the probability of default and the loss.

Having shown that the credit risk increases after the Ezubao scheme, the next step is to estimate changes in the real return on 36-term loans after the scheme unravelled. This is shown in Table B.3 as an interaction term (Ponzi*Default). Firstly, the results reported in column (1) in Table B.3 show that the difference in real returns on the platform represents a 6.66% decline after the fraud happened. In addition, taking no account of the fraud, the real return of non-performing loans is lower by about 34.67%than that of performing loans, which are shown in column (2), Table B.3. Furthermore, in column (3), the estimate of the interaction coefficient indicates that the real return decreased significantly by 9.458% after the fraud was exposed. Therefore, the estimated results from the analysis of 36-term loans support the previous findings regarding potential defaulters and the real return on the platform.

Overall, the results of the 36-term robustness analysis were consistent with the previous findings. After the Ezubao scheme happened, the quality of funded loans declined. The probability of default increased, meaning more potential defaulters, while the remaining amount of non-performing loans increased. It implies that the platform should pay more risk premiums to investors as it promised. In terms of the P2P lending platform, Renrendai, took more credit risk after the Ezubao scheme was exposed. These findings support the previous hypotheses and also provide an interesting insight that the P2P lending market experiences the same credit risk contagion as other traditional financial markets. The failure of one financial institution may affect the probability of default and profits of other financial institutions (Davis and Lo, 2001; Lang and Stulz, 1992; Van Lelyveld and Liedorp, 2004).

3.6 Conclusion

The Ezubao scheme is the largest Ponzi scheme that has been exposed in the history of Chinese P2P lending markets. In this study, I attempted to analyze the impact of a major fraudulent scheme on an immature financing market. The success of the Ezubao scheme relied on lenders' trust, according to Wang et al. (2019). They analyzed data on the Ezubao scheme and observed that lenders' trust in the Ezubao platform originated from their own experience, peer effects, and advertisements on social media. Lenders believed in their past trading experience in the P2P lending market, and they also considered the investment decisions of peer lenders as support. Additionally, continuous advertising on a reliable television station such as China Central Television (CCTV) promoted trust in P2P lending. However, as the unexpected financial scandal was exposed, the Ezubao scheme taught lenders a lesson on the P2P lending market. To determine how this fraud affects the market, it is necessary to undertake an analysis from the point of view of the P2P lending platforms. Using the data collected from one leading P2P lending platform, Renrendai, the results show that the impact of the Ezubao scheme is significant.

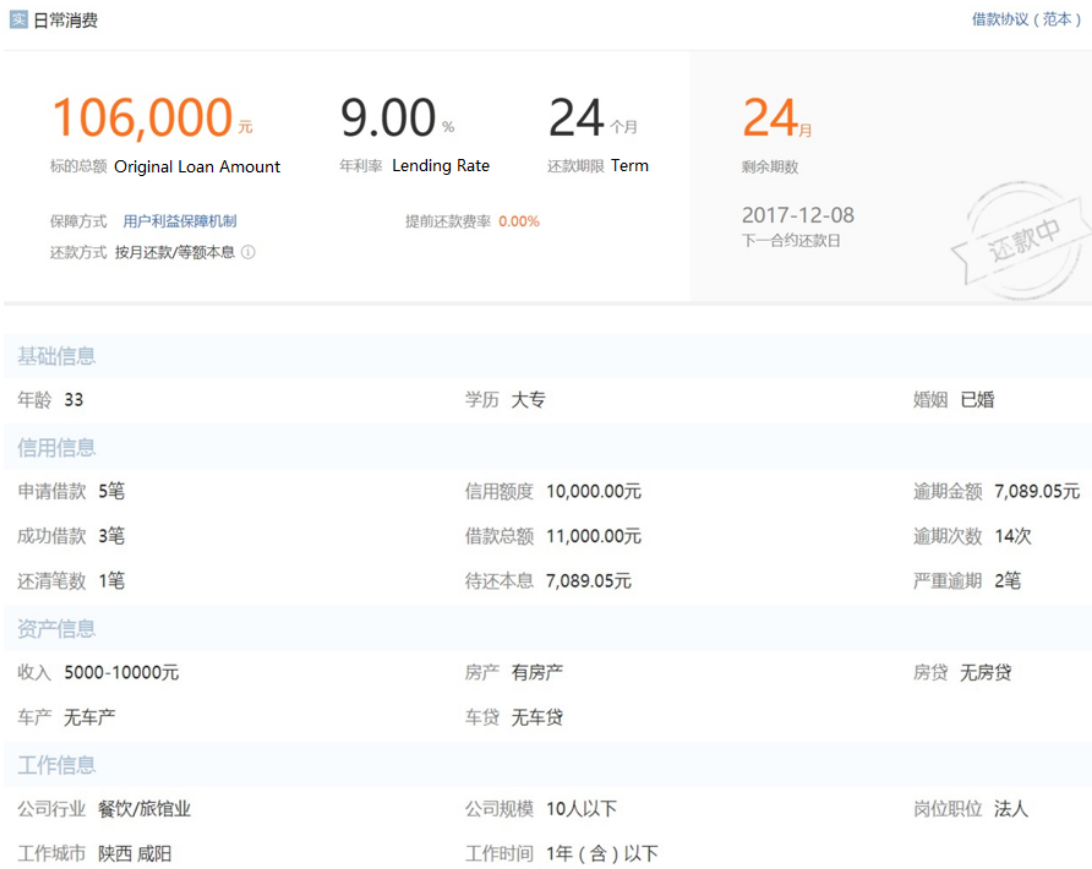
I found after the Ezubao scheme is exposed, the credit risks that P2P lending platforms undertake increased. It is found that the probability of default increased significantly. The number of potential defaulters on funded loans increased. High-risk borrowers were more likely to default. Second, the risk premiums that P2P platforms promised increased. With the increase in potential defaulters, the remaining amount of principal and interest increased. It was considered that this might cause lenders to lose more, however, due to the promised risk premiums, the risk was transferred to the platforms. This implies that there is an increase in the amount of risk premium required. Furthermore, it could lead to a decline in profits by P2P lending platforms. The results show that the real return on funded loans decreased significantly when compared to the figures prior to the fraud. Therefore, the impact of the Ezubao scheme is significant on the P2P lending market, especially on existing platforms.

Overall, there is some evidence provided in this study that there is the existence of credit risk contagion in the P2P lending market. According to Allen and Gale (2000), it is shown that a small shock initially affects only a small group of institutions in the market, but it can spread to the whole market through risk contagion. As for the impact of the Ezubao scheme, in the long term, the increase in risk premiums required by platforms could result in higher charges for their service or increased lending rates. This would increase the probability of default borrowers. Through higher default rates and higher premiums, it could result in platforms collapsing due to higher default risks in the future, or they could choose to create a new Ponzi scheme to cover the higher premiums. Unfortunately, there was a second wave of collapsing P2P lending platforms brought about by higher default rates, which affected the development of the Chinese P2P lending market until its eventual downfall.

While the previous discussion provides some interesting and new findings, there are still some limitations regarding data disclosure and availability on platforms. Firstly, data disclosure for P2P lending platforms in China is incomplete and insufficient, and due to limitations in data availability, I have not been able to obtain data from other platforms for further study and discussion. In addition, other external factors such as the media are also important regarding the credit risk contagion in the P2P market which could be further studied in the future.

Appendix B

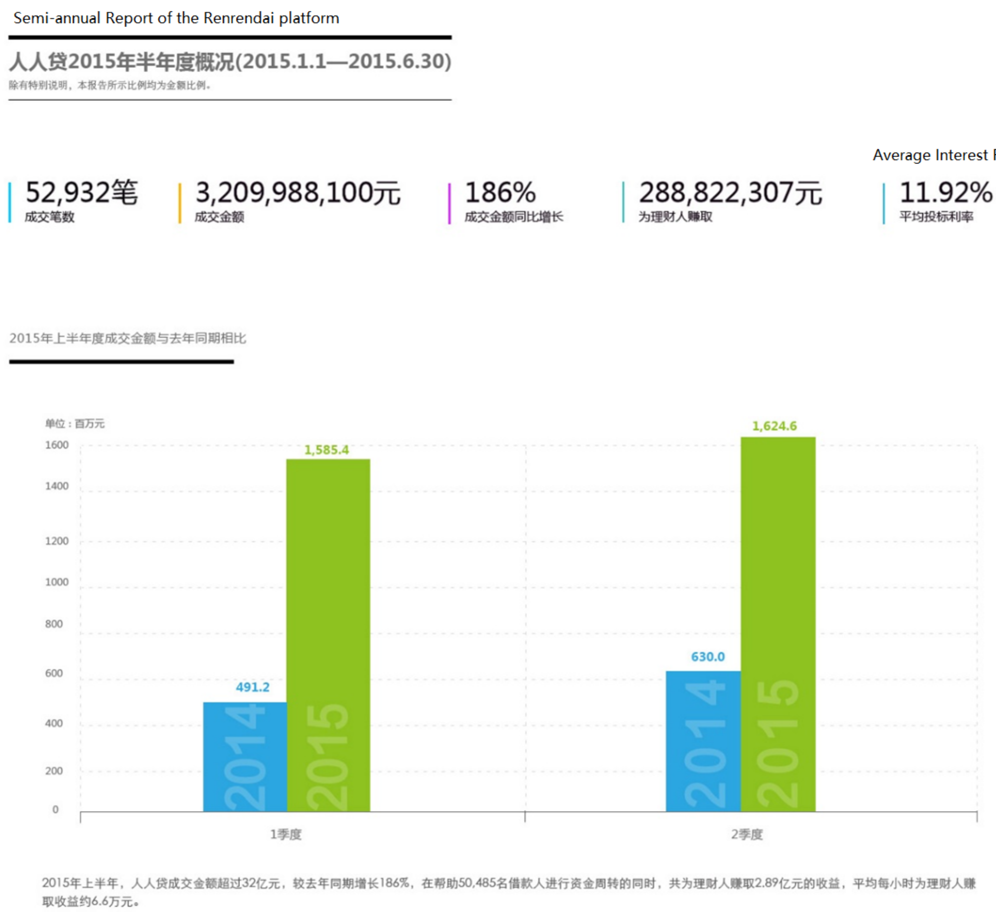
Figure B.1: The profile of qualified borrower



Note: As shown in Figure B.1, examples of the profiled qualified borrowers are displayed on the Renrendai website. These screenshots are taken on 1st April 2020. Every registered investor can read that information including the basic information of the loan and the demographic information about the borrower. All data of borrowers in this Chapter are collected by those profiles.

Appendix B

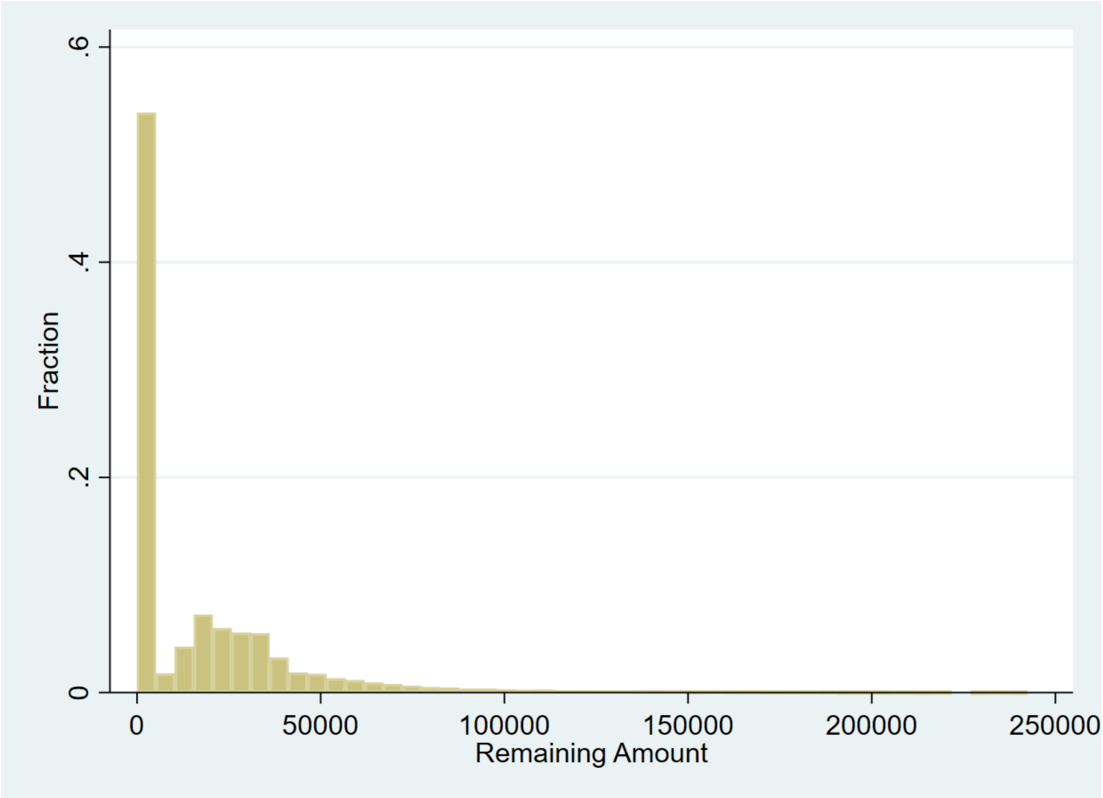
Figure B.2: Annual report on Renrendai



Note: As shown in Figure B.2, examples of the semi-annual report are displayed on the Renrendai website. These screenshots are taken on 1st April 2020. They listed figures about the number of funded loans, the number and the growth rate of the total amount of funded loans, the estimated earning profit and the average interest rate for investors.

Appendix B

Figure B.3: Fraction of remaining amounts



Note: This figure shows the fraction distribution of the remaining amounts. It is observed that approximately 53% of funded loans have a zero remaining amount.

Appendix B

Table B.1: Mean comparison on 36-term loans

Variables	Before (Ponzi= 0)			After (Ponzi= 1)			diff	t
	Obs	Mean	Std.Dev	Obs	Mean	Std.Dev		
Default	21,549	0.5451	0.4980	21,110	0.5803	0.4935	-0.0353	-7.3439***
Remaining Amount	21,549	17,577.00	26,033.74	21,110	24,300.50	30,272.17	-6,723.50	-24.6111***
Loss Given Default	21,549	0.1626	0.1616	21,110	0.2280	0.2025	-0.0654	-36.9285***

Note: This table reports the mean comparison results before and after the Ezubao Ponzi scheme happened. Variables are including Default, Loss Given Default, and Remaining amount. And, * p<0.10, ** p<0.05, *** p<0.01

Table B.2: Estimation results on credit risk of 36-term loans

VARIABLES	(1)	(2)	(3)	(4)
	Default	Loss Given Default	Remaining Amount	
Ponzi	0.0137**	0.0376***	0.0348**	5,416.07***
	(0.0054)	(0.0022)	(0.0139)	(488.90)
ln(Original Loan Amount)	0.0549***	0.0191***	0.1399***	27,126.19***
	(0.0054)	(0.0022)	(0.0138)	(487.76)
Lending Rate	-0.0430***	-0.0351***	-0.1095***	-4,861.49***
	(0.0062)	(0.0026)	(0.0160)	(574.71)
Pseudo R2	0.0037	0.0234	0.0037	0.0058
Method	Probit	Tobit	First Hurdle	Second Hurdle
Observations	42,659	42,659	42,659	42,659

Note: This table reports the results of the estimations by the Probit model (1), the Tobit model (2), and both the first hurdle (3) and the second hurdle (4) for the Hurdle model respectively. Standard errors are in parentheses. The dependent variables are *Default* which equals 1 if the borrower defaulted and 0 otherwise; *Loss Given Default* which is the percentage of non-repayment principal to the original amount of principal and *Remaining Amount* which is the principal and interest that should be repaid. *Ponzi* is defined by the date that Ezubao was confirmed to be under investigation by the police. *Ponzi=0* when loans were funded successfully before 16 December 2015, otherwise, *Ponzi=1. ln(Original Loan Amount)* is the natural logarithm of amount of principal. *Lending Rate* is the interest rate of borrowing money. And *** p<0.01, ** p<0.05, * p<0.10

Appendix B

Table B.3: Estimation results on real return on 36-term loans

VARIABLES	(1)	(2)	(3)
	Real Return	Real Return	Real Return
Ponzi	-6.660***		-0.119
	(0.177)		(0.0900)
Default		-34.67***	-29.84***
		(0.0694)	(0.0840)
Interaction			-9.458***
			(0.120)
Constant	-16.18***	0.0258	0.0824
	(0.125)	(0.0521)	(0.0620)
Observations	42,659	42,659	42,659
R-squared	0.032	0.854	0.891

Note: This table reports the results on real return. *Default* equals 1 if the borrower defaulted and 0 otherwise; *Ponzi* is defined by the date that Ezubao was confirmed to be under investigation by the police. *Ponzi=0* when loans were funded successfully before 16 December 2015, otherwise, *Ponzi=1*. And *Interaction* represents the extent to the defaulters contribute to changes in real returns after the scheme. Standard errors are in parentheses. And *** p<0.01, ** p<0.05, * p<0.10

Chapter 4

The Development of Chinese Peer-to-Peer Lending Industry: An Industry Lifecycle Perspective

Abstract

From 2007 to 2020, P2P lending in China experienced rapid growth and then significant decay in just 13 years. In this chapter, I use a total of 6,151 registered P2P lending platforms data and the monthly data from the P2P lending market from January 2014 to December 2019. The aim is to explore and present a detailed picture of the development of the Chinese P2P lending market by drawing on an industry lifecycle theory perspective. Even though the lifespan of the Chinese P2P market is short, the market still experienced five stages as predicted by the lifecycle theory. In addition, I find that the earlier entrants in the market have a higher chance of survival. This is also in line with the predictions from the theory.

4.1 Introduction

The Peer-to-Peer (P2P) lending market in China has experienced not only rapid growth but also significant decline. In China, the first P2P lending platform, Paipaidai, was launched in June 2007. Developing at a slow pace during the first six years, the market expanded rapidly after 2013 and boomed in 2015, but by the end of 2020, the market had been cleared out by the People's Bank of China. In 13 years, a total of 6,151 registered P2P lending platforms had entered the market.

There are three mainstream topics in the literature about Chinese P2P lending. The first relates to research on the information provided by borrowers when they apply for loans. Based on the information provided by borrowers, studies examine whether loans can be successfully applied for and whether there is a relationship between the information provided and borrowers' subsequent default behaviour (Li et al., 2014, 2013; Liao, Ji and Zhang, 2015; Wang and Liao, 2014). The second topic concerns research into investors' behaviour, examining investors as individuals and whether their investment behaviour is rational (Caglayan et al., 2021; Chen and Lin, 2014; Gao, Caglayan, Li and Talavera, 2021). The third topic is the analysis of relevant government regulatory policies for P2P lending platforms and the market (Chen, Kavuri and Milne, 2020; Huang, 2018; Wu and Cao, 2011). However, research rarely focuses on the characteristics of the entire Chinese P2P lending market, i.e. assessing whether the changing number of platforms in the different periods of development would affect the participants in the P2P lending market. Therefore, in my research, the aim is to explore the detailed picture of the development of the Chinese P2P lending market by drawing on an industry lifecycle perspective. Previous studies focus on the traditional manufacturing market whose lifespan is more than 30 years; whether the short history of this new financing market represents a complete lifecycle is a question I set out to answer in this study.

This study focuses on the development of the Chinese P2P lending market. All data in this chapter were obtained from WangDaiZhiJia (WDZJ). I collected and selected data, which comprises the platform dataset and the market report data from WDZJ, in March 2020. The platform dataset, containing the records of all P2P lending platforms that existed in the market up until March 2020, describes the characteristics of the platforms' participants. And the market report data covers six years of monthly statistics on the Chinese P2P lending market, from January 2014 to December 2019. Drawing on the five stages of industry lifecycle theory (Gort and Klepper, 1982) and summarizing the data about the net entry of P2P lending platforms in the market, I found that the Chinese P2P lending market experienced five stages as predicted by the lifecycle theory. Stage I, from 2007 to 2013, is the P2P lending industry's emergence. Stage II, from 2014 and 2015, covers the rapid growth in the P2P lending industry. Stage III, from 2016 to 2017, shows the maturity phase of the industry, and Stage IV, after 2018, shows the market shrinking. Stage V is in 2020. This is the end of the market.

Moreover, I identify and discuss the character of stages by using monthly data from the P2P lending market from January 2014 to December 2019. It is found that in the introduction stage, the new market experienced slow and unregulated growth. The business model of platforms is in the trial phase and there is also a lack of publicly available data. In Stage II, the expansion of the market is reflected in the growth in the number of platforms, investors, and borrowers. In Stage III, the decreasing number of P2P lending platforms contributed to the largest trading volume of loans. The number of investors and borrowers is reaching its peak at this stage. Stage IV spans the shrinkage of the P2P lending market after 2018. A decreasing number of lenders and borrowers is accompanied by a rising number of bankrupt platforms. Finally, in Stage V in 2020, all P2P platforms exit the market; the market is cleared out by strict government policy. Furthermore, I use survival analysis to examine whether the entry of P2P lending platforms into the market at different stages has an impact on their survival. The findings show that the later a P2P lending platform enters, the higher the risk and the lower the probability of survival in the market. Compared to other markets, the P2P lending market experienced a shorter lifespan of only 13 years in China. However, the market did experience a whole life-cycle process.

The rest of the chapter is organized as follows. Section 4.2 is a review of the literature about the Chinese P2P lending market and the concept of the industry lifecycle theory. Section 4.3 introduces the dataset and constructs the framework of the lifecycle model in the Chinese P2P lending market. The phases of the Chinese P2P lending market are characterized by the volume of trading, the number of borrowers and investors, and the number of P2P lending platforms. In Section 4.4, I discover the survival length of registered P2P platforms according to their entry stages. Section 4.5 extends the discussion on the development of the P2P lending market in China. Finally, Section 4.6 concludes with the findings.

4.2 Literature Review

4.2.1 Peer-to-Peer Lending in China

As this is a new and developing topic in the area of finance, previous studies of the Chinese P2P lending market mostly focused on three streams: borrower information, the behaviour of investors, and government regulation.

First, research on borrower information relates to the analysis of the determinants for successful loan applications and the prediction of borrowers' default behaviour. For example, Li et al. (2013) found that information provided by borrowers when they apply for loans has a significant impact on the success rate of their applications. Information includes the loan amount, interest rate, borrowing terms and other borrowing order information, the basic characteristics of the borrower, and the borrower's social relationships. Chen et al. (2017) used data from the Paipaidai platform and pointed out that a borrower's gender is one of the key factors in the P2P lending market. Their analysis shows there is obvious gender discrimination in the Chinese P2P lending market. Female borrowers have a higher probability of obtaining loans with higher lending rates. In addition, Wang and Liao (2014) found that the combination of online and face-to-face authentication mechanisms can effectively reduce the information asymmetry between borrowers and investors, which is conducive to improving the success rate of an application and reducing borrowing costs. P2P lending platforms offer information found on borrowers' applications to investors. Research on loan descriptions showed that the longer the length of the loan description, the higher the success rate of the application and the lower the default rate. Borrowers with low credit ratings are more willing to provide more descriptive information (Li et al., 2014; Liao, Ji and Zhang, 2015). Furthermore, there are some fixed words in loan descriptions, such as entrepreneurship, family, urgency, and integrity, which are conducive to improving the success rate of borrowing but are not related to the default rate. Li et al. (2015) discussed the issue of the number of friends a borrower has. They showed that a borrower who has many friends can easily acquire funding, his or her lending rate is relatively low, and his or her future loan performance is better than that of others.

Second, research on investors in the Chinese P2P lending market features discussions of the herd effect. Gao, Caglayan, Li and Talavera (2021) found that ordinary lenders would emulate the bids of expert lenders, following their actions. Expert lenders performed herd behaviour even though they rarely imitated others. Chen and Lin (2014) found that there is a significant herd effect on Paipaidai and that this effect is harmful to the interests of investors. The herd effect reduces the borrowing interest rate but cannot reduce the borrower's default rate, causing a decrease in the rate of return for investors. Caglayan et al. (2021) studied the Renrendai platform, which provided evidence of herding behaviour among P2P lenders in China. Lenders' herding behaviour was related to the amount of time spent on the platform and their experience. Renrendai is similarly impacted by the herd effect according to (Liao, Li, Wang and He, 2015), who found that the further the progress of a loan order completion, the more investors can be attracted to participate in it. A loan application with stronger information asymmetry will cause more obvious herding behaviour in the initial stage. Investors will not be able to obtain more information on the behaviour of other investors, so the herding effect gradually drops to a certain level.

The third area of research analyzes relevant government regulatory policies for P2P platforms and the market. P2P lending companies take on the same types of risk as traditional financial institutions, such as market risk, operational and other risks, and especially credit risk. Without collateral and face-to-face investigation, there could be a higher probability of default than in the case of normal loans from banks (Westland et al., 2018). The market is exposed to high risks. Therefore, some studies, for example Wu and Cao (2011), suggested that the Chinese government should strengthen supervision of the P2P lending market to avoid fraud and the risk of failure to redeem due to high default levels. Huang (2018) stated that implementing laws and regulations would provide direction to P2P lending. He compared the regulations that had been implemented by 2016 in the United Kingdom, the United States, mainland China and Hong Kong and pointed out that the regulations in the Chinese P2P lending market provided a valuable experience in maintaining the right balance. However, Chen, Kavuri and Milne (2020) reviewed the regulations in the Chinese P2P lending market, tracing the absence of regulations to the development of a comprehensive framework, and concluded that the Chinese P2P lending market faces substantial uncertainties under the strict new regulations.

Overall, research related to P2P lending in China has concentrated on participants in the market at the micro level. For example, leading platforms in the market such as Paipaidai and Renrendai became popular sample platforms for empirical research on the P2P lending market because of their detailed data disclosure. Regarding the macro level, research on the development of the Chinese P2P lending market from a market perspective is scarce. In this chapter, I will contribute the market perspective of the development of this new financing innovation by describing the industry lifecycle of the Chinese P2P lending market.

4.2.2 The Industry Lifecycle Theory

The term 'industry' usually refers to a group of firms that produce a closely related set of products or services. Industry lifecycle refers to the process of the changing behaviour of producers, especially entry and exit behaviour, and comprises stages from the emergence to the decline of an industry. The study of the industry lifecycle (ILC) theory developed in the 1980s and evolved from the study of the product lifecycle theory, which was introduced by Vernon (1966). Abernathy et al. (1978) stated that there are three patterns for products, which are the fluid pattern, the transitional pattern, and the specific pattern, depending on the rate of innovation. Based on their studies of the product lifecycle theory and innovation in American car manufacturing, the topic of the ILC theory emerged.

Gort and Klepper (1982) analyzed 46 new products and constructed the ILC theory with a five stages model of the development of industries. In Gort and Klepper's five-stage ILC theory, the change in entry and exit rates is one of the key themes. Klepper and Graddy (1990) expanded the number of firms in new industries to demonstrate their three new stages in the ILC theory. Those three stages show that the number of firms first grows, then declines dramatically, and finally levels off.

The other key theme in the ILC theory is firm survival. Agarwal and Gort (1996) expanded the ILC theory by introducing the hazard rate. They emphasize the impact of the industry's lifecycle stage and the firm's age on firm survival. Their research explains the comprehensive impact of ILC stages on the entry and exit of firms, which is reflected by the changing patterns of hazard rates at the different stages between entry and market. Results show a negative relationship between the age of the firm and the hazard rate. Furthermore, Klepper (2002) discussed firm survival and the evolution of oligopoly by collecting data on four industries. His research shows that the earliest entrant has the greatest innovation efficiency, grows into the largest producer, conducts further innovation, and has the strongest competitive advantage.

4.3 Institutional Environment of the Chinese P2P Lending Market

In China, the P2P lending market went from its introduction in 2007 to a boom, then to a fall, and finally to its termination at the end of 2020. From the beginning to the end, the 13-year history of the P2P lending market in China, in spite of its shortness, is still a valuable experience in Chinese alternative finance in the financial market. In this section, I would like to discuss the development and characteristics of China's P2P lending market from the perspective of the industry life cycle theory.

4.3.1 Data

This study focuses on the development of the Chinese P2P lending market. All data in this chapter were obtained from WangDaiZhiJia (WDZJ), which was the first reliable P2P lending industry portal in China. Since the Chinese government does not release authoritative data on the P2P lending market, only a few third-party websites display updates and provide data to the public. WDZJ provides information on industry data reports and professional research for participants and followers of the P2P lending industry. To get a picture of the P2P lending market, I collected and selected data, which comprises the platform dataset and the market report data from WDZJ, in March 2020.

The platform dataset, containing the records of all P2P lending platforms that existed in the market up until March 2020, describes the characteristics of the platforms' participants. More specifically, it provides basic information on these platforms, including the launch date, the registered capital, the registered location, the current business status, the exit date, and other relevant registered P2P lending information. The launch date is the date that each P2P lending platform was established. The registered capital is the total amount of registered funds received from investors. The registered location is the city in which the P2P platform is registered and denotes the local government under whose regulations it falls. The current business status refers to the operational status of the P2P lending platform at the time of data collection. There are five statuses displayed in the dataset: 'In-running', 'Transformed', 'Closed', 'Defaulted', and 'Recorded by police'. P2P lending platforms that are staying in business are recorded as 'In-running'. Those platforms which are still running financing businesses online but have stopped matching borrowers and lenders are recorded as 'Transformed', and those that closed and wrote off their P2P lending platforms are recorded as 'Closed'. P2P lending platforms that suffered from borrowers being unable to pay their principal and interest back on time, and where investors were unable to receive their investment or withdraw are recorded as 'Defaulted'. The status 'Recorded by police' denotes fraudulent platforms that are registered to scam funds from investors, and in which the police have been involved in an investigation. The date of any business status changes for each P2P lending platform is noted in the exit date.

In addition, the market report data covers six years of monthly statistics on the Chinese P2P lending market, from January 2014 to December 2019. The statistics show the average lending rate, which is the price for borrowing money from lenders; the average length of borrowing; the volume of loans trading; the number of existing platforms; the number of bankrupt platforms; the number of borrowers; and the number of lenders. It tracks the development of the market over time.

4.3.2 Hypotheses

The ILC theory of Gort and Klepper (1982) focuses on the change in the number of producers in a market and presents five stages. Stage I begins when the first producer introduces a new product and ends with a rapid increase in the number of new producers entering the market. At this stage, the number of producers is limited, and the scale of the market is small with slow growth in demand. The barriers to entry for producers are low and the competition level is relatively weak. Stage II experiences a high rate of entry of competitors. In detail, as a large number of producers enter, the scale of the market increases with rapid growth in demand. After this sharp increase in the number of producers, Stage III ensues, where the numbers of entrants and exiting producers are balanced. The net entry of producers is equal to zero or very low. In this stage, there are some barriers to entry for producers in that the earlier entrants may be more efficient at production, which makes it more costly for the new entrant producers. The scale of the market stabilizes, while the growth in demand tends to increase relatively slowly. This is followed by a negative net entry in Stage IV in which the number of producers decreases while demand gradually reduces and competitiveness declines. The second period of zero net entry is Stage V. This cycle continues until the industry shrinks or new technology introduces a new lifecycle.

The P2P lending service can be referred to as an innovative financial product, and P2P lending platforms can be regarded as producers in a market offering those financial products (Davis, 2016; Wang et al., 2015). Based on the previous ILC theory model, this study is discussed whether the development of the Chinese P2P lending market follows a five-stage ILC theory model. To prove this hypothesis, firstly, it is necessary to discuss whether the number of entries and exits of Chinese P2P lending platforms follows the ILC theory, which is performed by calculating the net number of platform entries. Therefore, the first hypothesis is:

Hypothesis 1: The development of the Chinese P2P lending market can be separated into five stages based on the net entry of P2P lending platforms.

Secondly, it is necessary to discuss whether the classified stages are consistent with the ILC theory's predictions for the output of each stage. In the P2P lending market, the components that measure the output are the volume of loan trading, the number of borrowers participating in the trading, and the number of lenders participating in the trading. Therefore, I assume:

Hypothesis 2: In Stage II, the number of platforms is positively correlated with the output. In Stage III, the number of platforms is negatively correlated with the output. In Stage IV, the number of platforms is positively correlated with the output.
And,
Hypothesis 3: There are significant structural changes between each stage.

4.3.3 Conceptual Framework

In this section, following the ILC theory, the different stages of the Chinese P2P lending market are identified through the net entry number of P2P lending platforms. The net entry is the difference between the number of platforms that entered the market and the number that exited the market during the year. Table 4.1 shows the statistics on the number of registered P2P lending platforms entering and exiting the market, the number of platforms operating normally in the market, and the net entry of platforms each year.

As shown in Table 4.1, in the first three years (2007, 2008, and 2009), there were only nine P2P lending platforms in the business. In the years that followed, until 2012, fewer than 100 new P2P platforms were entering the market each year. No platforms are shown to have exited until 2011, when 10 platforms exited, followed by six platforms in 2012 withdrawing from the market. The net entry number stayed positive and at a low level, which is less than 100. However, in 2013, the number of P2P platforms began to increase. A total of 488 new platforms entered the market in 2013, almost five times the number in 2012. Even though the number of exiting platforms increased to 70, the net entry number of platforms still rose significantly to 418. This indicates that new P2P platforms gradually started to enter the market in 2013, with an increasing number of platforms available in the market to provide P2P lending services. The P2P lending market moved from emergence to rapid growth

Table 4.1: Entry and exit of platforms

Year	Launched			Exited			Total	Net Entry
	Freq.	Percent	Cum.	Freq.	Percent	Cum.		
2007	1	0.02	0.02	0	0	0	1	1
2008	1	0.02	0.03	0	0	0	2	1
2009	7	0.11	0.15	0	0	0	9	7
2010	14	0.23	0.37	0	0	0	25	14
2011	42	0.68	1.06	10	0.16	0.16	57	32
2012	83	1.35	2.41	6	0.1	0.26	134	77
2013	488	7.93	10.34	70	1.14	1.4	552	418
2014	1,874	30.47	40.81	273	4.44	5.84	2,153	1,601
2015	2,390	38.86	79.66	1,173	19.07	24.91	3,370	1,217
2016	802	13.04	92.7	1,562	25.39	50.3	2,610	-760
2017	381	6.19	98.89	677	11.01	61.31	2,314	-296
2018	66	1.07	99.97	1,363	22.16	83.47	1,017	-1,297
2019	1	0.02	99.98	710	11.54	95.01	308	-709
2020	1	0.02	100	307	4.99	100	0	-306

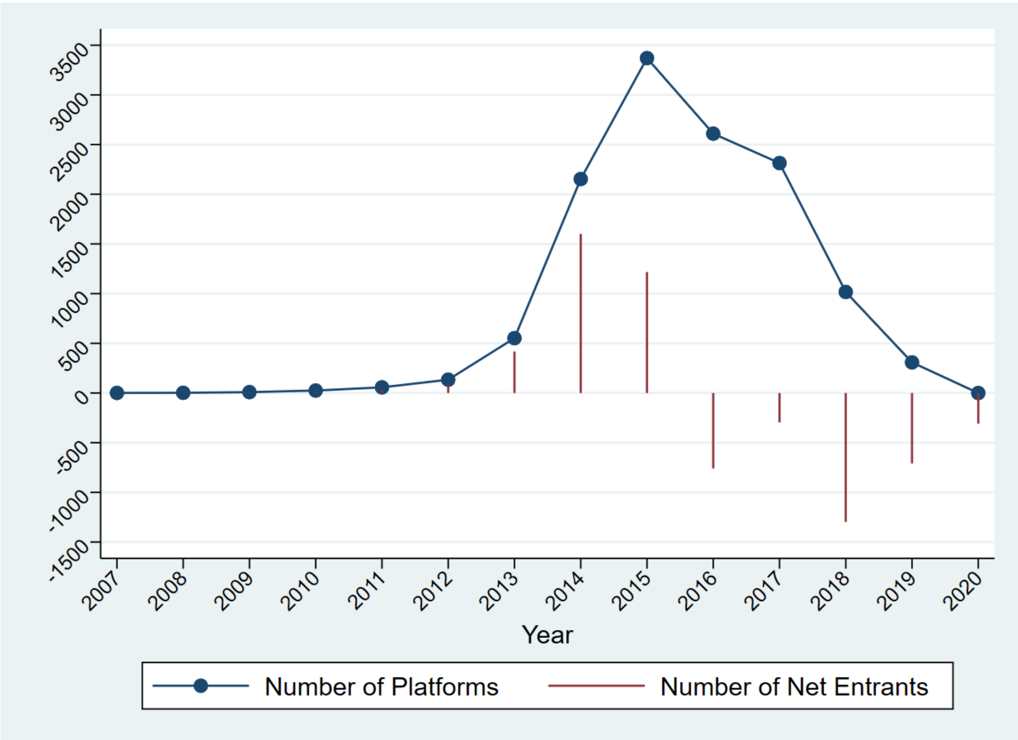
Note: This table reports the frequency and percentage of P2P lending platforms entering and exiting the market from 2007 to 2020 as well as the total number of platforms in existence in the market and the net number of entrants.

due to the increasing number of entrants.

The number of new P2P platforms entering the market jumped to 1,874 in 2014, which is roughly 30.47% of the total number of P2P platforms that entered the market during the 13-year history. In addition, 2,390 new platforms entered the market in 2015, which is approximately 4.89 times as many as the number of new entrants in 2013. At the same time, the number of exited platforms also started to grow remarkably from 70 in 2013 to 273 in 2014. The number of exited platforms in 2015, representing about 19.07% of the total number of exits, was 1,173. As for the net entry, the number increased to a peak of 1,601 in 2014. In the following year, the number of net entrants remained positive but slightly decreased to 1,217. According to the statistics in the table, it can be illustrated that the number of net entrants grew rapidly and significantly from 2014 and peaked in two years. The scale of the P2P lending market in China expanded very rapidly during this period.

However, the net number of entries turned negative beginning in 2016. The number of new entrants in the P2P lending market dropped significantly, while the number of exiting platforms increased. To be specific, there were 802 new platforms launched in 2016, while 1,562 platforms shut down their businesses. The situation slightly recovered in 2017. It witnessed the entry of 381 new P2P lending platforms with the withdrawal of 677. Moreover, 1,363 platforms left the P2P industry in 2018, and only 66 were new entrants. The declining trend in the P2P lending industry seemed to be irreversible. In 2019, only one new platform entered the market. At the end of 2020, all the platforms withdrew from the industry. Overall, these figures are similar to those studies and reports that have discussed the development of the Chinese P2P lending market (Deer et al., 2015; Ding et al., 2021; Fong, 2018; Huang, 2018).

Figure 4.1: Platforms in P2P lending market



Note: This figure reports the trend in the number of P2P lending platforms in existence and the number of net entries in the market from 2007 to 2020.

Figure 4.1 shows the basic trend in the number of P2P lending platforms in normal operation and the number of net entries in the market over a 13-year period. According to the five-stage of the theory of ILC (Gort and Klepper, 1982), the first two stages can be identified by comparing the net entry number. Stage I, from 2007 to 2013, marks the emergence of the P2P lending market, and Stage II shows rapid growth in the P2P lending market in 2014 and 2015. Stage IV is also obvious and easy to identify by the shrinkage in the P2P lending market after 2018. The last stage, Stage V, is in 2020. The market is terminated, and all P2P platforms exit.

However, in contrast to the theory, Chinese P2P lending platforms did not experience an equilibrium period of net entry after the second stage of rapid growth but rather began to decline from 2016 to 2017. However, the development of the Chinese P2P lending market in this way is consistent with the industry life model developed by Klepper and Graddy (1990). They proposed that there are only three different stages in the industry life cycle: expansion, knockout, and up to equilibrium. Compared to the theory of Gort and Klepper (1982), the shake-out stage is shown as a decline in output with a decrease in the net entry. Between 2016 to 2017, there was a slight recovery, where a balance was nearly reached. Considering the above, I temporarily marked this special two-year period from 2016 to 2017 as Stage III, as a pre-shrinkage stage. In the following sections, I will continue to further identify stages in the life cycle of the Chinese P2P lending market by comparing the outputs in different stages, especially stage III.

4.3.4 Stages Identification Strategy

To identify the different stages, I first used a mean comparison to confirm the difference in output. I expect to capture the difference in the volume of output between stages. Additionally, to further test whether there is a structural change across stages, I constructed a regression model for the platform and output elements, which was set as follows:

$$Output_{it} = \alpha + \beta_i Platforms_{it} + \epsilon_{it} \tag{4.1}$$

$Output_{it}$ is the monthly output indicator for stage i which represents Stage II, Stage III or Stage IV. The $Output_{it}$ indicator for measuring the P2P market includes the volume of trading loans, the number of investors, and the number of borrowers. $Platform_{it}$ indicates the monthly number of operating platforms in stage i, and ϵ_{it} indicates the error term.

The model is conducted by following a classical econometric test for structural change, the Chow test(Chow, 1960). Based on the Chow test, the data is grouped into two segments, and parameters are estimated for each segment, and then tested for equality of parameters with the help of F-statistics(Hansen, 2001). In the following test, parameters for each stage will be estimated, and then test them whether they are equivalent. To be specific, in Model 4.1, if $\beta_{II}=\beta_{III}$ or $\beta_{III}=\beta_{IV}$ is significant, then it can be inferred that the difference between Stage II and Stage III (or between Stage III and Stage IV) is insignificant, i.e., there is no structural change between stages. Conversely, it indicates that there is a structural change between stages.

4.3.5 Results

Mean Comparison

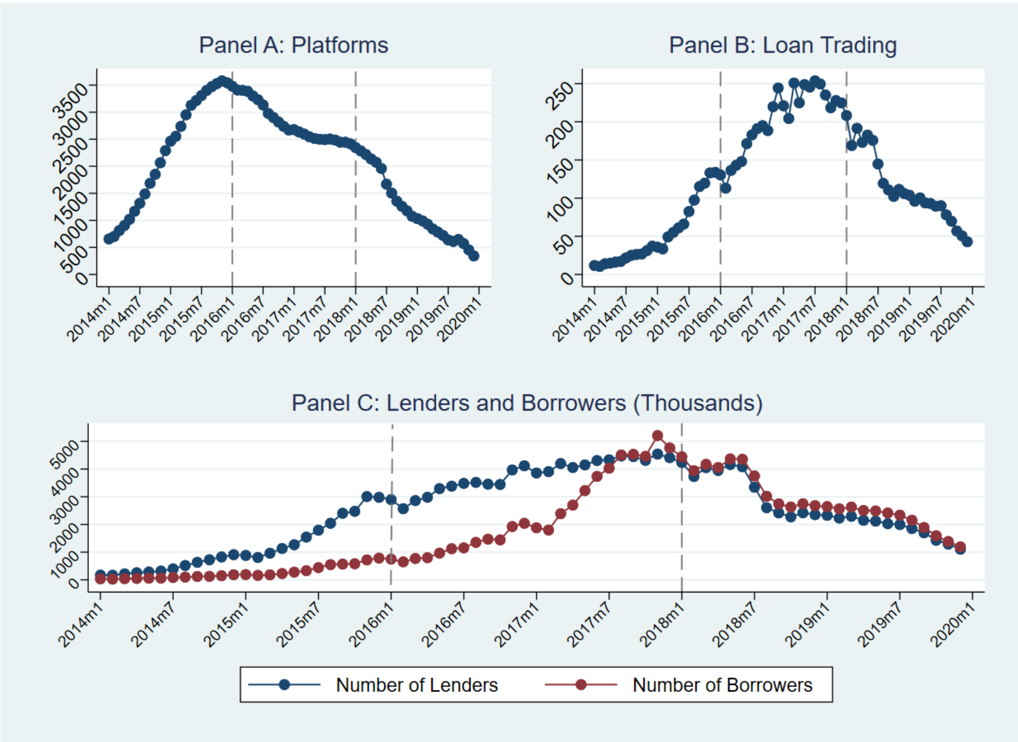
Figure 4.2 provides monthly data about P2P lending outputs from January 2014 to December 2019, including the number of platforms, the total loan trading, and the number of investors and borrowers. It covers the period from Stage II to Stage IV.

As shown in Panel A in Figure 4.2, the plot displays the development of the number of P2P lending platforms in existence in the market. At first, in Stage II, the number of platforms running normally in the market is also growing month by month, showing that a large number of P2P lending platforms were established in the two years between 2014 to 2015. The number of platforms smoothly increased from 657 to the peak number of 3,579 in November 2015, followed by a slight drop to 3,543 in December of that year. Beginning from Stage III, the number experiences a continuous decline. Between 2016 to 2017, the number of P2P lending platforms began to decrease month by month, from 3,480 to 2,414. Furthermore, there is a dramatic decrease in Stage IV, in which the number of platforms fell from 2,345 to under 500.

According to Table 4.2, comparing Stage II and Stage III, the mean number of P2P platforms is significantly different with a significance level of 5%. The mean of Stage II, 2243.08, is significantly less than the mean of Stage III, which is 2820.58. In the meantime, Table 4.3, detailing the mean comparison between Stage III and Stage IV, shows clearly that the mean of Stage III is significantly different from that of Stage

IV. The mean of Stage IV is 1234.33, which is less than half of the mean of Stage III. Based on the theory of ILC with respect to the number of producers, the number in Stage II should experience a sharp increase and maintain a stable, high level in Stage III, as the equilibrium between entry and exit is maintained, and then it would fall.

Figure 4.2: Number of platforms



Note: This figure reports the number of platforms, the total loan trading, and the number of investors and borrowers from January 2014 to December 2019.

Furthermore, in Stage II, in addition to the growth in the number of platforms, the expansion of the scale of the P2P lending market is also evidenced by the increase in the volume of trading loans. According to Panel B in Figure 4.2, the volume showed a slow increase from approximately 10 billion yuan in January 2014, followed by a trend of sharp increase, from about 35.7 billion yuan in January 2015 to around 130 billion yuan per month at the end of this stage in December 2015. The volume of trading loans experienced a significant increasing trend that remained in place from January 2016 to July 2017. The growth reached its peak at 253.676 billion yuan in July 2017. After that, during the last six months of Stage III, changes in the volume of trading loans fluctuated. After Stage III, the volume of trading loans fluctuated, decreasing from 208.19 billion yuan to 175.72 billion yuan. Then, in July and August 2018, it plunged from around 175.72 billion yuan to approximately 110 billion yuan, and at the end of stage IV, there are only 42.89 billion yuan in trade loans in the market.

Table 4.2: Mean comparison results on Stage II and Stage III

Variables	Stage II			Stage III			diff	t
	Obs	Mean	Std.Dev	Obs	Mean	Std.Dev		
Platforms	24	2,243.08	1,043.35	24	2,820.58	369.647	-577.5	-2.5559**
Loan Trading	24	51.4634	40.6274	24	202.863	42.8968	-151.4	-12.5538***
Number of Lenders	24	1,113.092	892.1316	24	3,790.029	583.3067	-2,676.938	-12.3034***
Number of Borrowers	24	252.5375	229.6401	24	2402.7	1,503.971	-2,150.162	-6.9236***

Note: This table reports the results in mean comparison between Stage II and Stage III. Variables are including the number of platforms, the total loan trading, and the number of investors and borrowers. Both the number of lenders and the number of borrowers are counted in thousands. And, * p<0.10, ** p<0.05, *** p<0.01

The results in Table 4.2 and Table 4.3 provide evidence that in Stage III, the trading volume of the loan is significantly different from Stage II and Stage IV, respectively. The mean of the trading volume at 202.863 billion yuan in Stage III is almost four times as much as that in Stage II which is 51.4634 billion yuan. In Stage IV, the mean of trading loans declines to 114.971 billion yuan or almost half as much as Stage III. Combined with the results about the number of platforms, this shows that the declining number of P2P platforms in business in Stage III makes a significant contribution to the loan trading volumes.

Table 4.3: Mean comparison results on Stage III and Stage IV

Variables	Stage III			Stage IV			diff	t
	Obs	Mean	Std.Dev	Obs	Mean	Std.Dev		
Platforms	24	2,820.58	369.647	24	1,234.33	638.993	1,586.25	10.5269***
Loan Trading	24	202.863	42.8968	24	114.971	46.3077	87.892	6.8213***
Number of Lenders	24	3,790.029	583.3067	24	2,589.837	965.6596	1,200.192	5.2118***
Number of Borrowers	24	2402.7	1,503.971	24	2862.2	959.5489	-459.5001	-1.2618

Note: This table reports the results in mean comparison between Stage III and Stage IV. Variables are including the number of platforms, the total loan trading, and the number of investors and borrowers. Both the number of lenders and the number of borrowers are counted in thousands. And, * p<0.10, ** p<0.05, *** p<0.01

Lenders and borrowers are the two key participants in the P2P lending market. Figure 4.2 shows the number of investors and borrowers trading per month. According to Figure 4.2, the numbers of lenders and borrowers both experience a significantly increasing trend in Stage II and Stage III. For lenders, there is a sharp increase from 160 thousand to about 3 million per month in Stage II and a steady growth in most of Stage III until the peak of about 4.5 million in November 2017. After that, in Stage IV, the number experiences a huge drop from roughly 4 million to 3.34 million to 2.60 million in the three months from June to August 2018.

Unlike the number of lenders, the number of borrowers witnesses a slight climb in Stage II lasting until the middle of Stage III with growth from 37 thousand in January 2014 to almost 2 million in February 2017. From March 2017 to the end of Stage III, there is a dramatic increase in the number of borrowers, reaching a peak in November 2017 as well. The most important moment is in September 2017, when the number of borrowers exceeds the number of lenders. Although the pattern of increase is different, the path of decline is similar. The number of borrowers also experiences a plunge in the three months from June to August 2018.

The mean comparison in Table 4.2 and Table 4.3 shows a statistical difference between the mean of lenders in Stage II and that in Stage III. There are 3.79 million lenders in Stage III, more than three times as many as the 1.113 million lenders in Stage II. Similarly, at the 5% significance level, there is a statistical difference between Stage III and IV. In Stage III, the P2P lending market attracts the highest number of participating lenders. For borrowers, based on the results in Table 4.2, there is a statistically significant difference in the mean between Stage II and Stage III. In Stage II, the mean number of borrowers is only 252.5 thousand and that increases to 2.4027 million in Stage III. However, between Stage III and Stage IV, based on Table 4.3, there is not found to be a statistically significant difference in the means. Although the trend in the number of borrowers in Stage IV goes down, the average number for each month is not smaller than before.

To sum up, based on the results above, there is a preliminary indication that the P2P lending market experiences an expansion in Stage II, which reflects an increase in the number of platforms, trading volume, lenders, and borrowers. In Stage III, there is a great contribution of trading volume with the largest scale of lenders, even if the number of platforms goes down. Furthermore, in Stage IV, it is unexpected that the number of borrowers is no different from Stage III.

Regression Results

After classifying the data into three sub-datasets according to different stages, the model was regressed separately according to the stages. The regression results are shown in the following tables.

In Table 4.4, it is shown that in Stage II, the number of P2P lending platforms is significantly correlated with all three output factors. To be specific, in Stage II, the number of P2P lending platforms has a significant positive effect on the loan trading amount. As the number of platforms in the market increases, the loan trading amount increases with it. Similarly, the regression coefficients of the number of lenders and the number of borrowers are significant at the 5% confidence level. In Stage II, as the number of platforms increases, the number of lenders also increases; meanwhile the number of borrowers also increases. This is consistent with Hypothesis 1 and suggests that Stage II is also consistent with the characteristics of the expansion phase described in the ILC theory.

Table 4.4: Regression results

Variables	Loan Trading Amount			Number of Lenders			Number of Borrowers		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Stage II	Stage III	Stage IV	Stage II	Stage III	Stage IV	Stage II	Stage III	Stage IV
Platforms	0.0346***	-0.109***	0.0707***	0.769***	-1.514***	1.468***	0.191***	-3.499***	1.445***
	(-0.00381)	(-0.00849)	(-0.00343)	(-0.0795)	(-0.095)	(-0.0762)	(-0.0233)	(-0.443)	(-0.0873)
Constant	-26.11**	510.3***	27.75***	-612.7***	8,060***	777.4***	-176.0***	12,272***	1,079***
	(-9.402)	(-24.13)	(-4.75)	(-196)	(-270.2)	(-105.4)	(-57.43)	(-1,259)	(-120.8)
R-squared	0.789	0.882	0.951	0.81	0.92	0.944	0.753	0.74	0.926
Observations	24	24	24	24	24	24	24	24	24

Note: This table reports regression results for each stage. Dependent variables are the total volume of loan trading, the number of lenders and the number of borrowers.Both the number of lenders and the number of borrowers are counted in thousands. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

In contrast, in Stage III, the number of P2P lending platforms has a significant negative effect on the three output factors. As shown in Table 4.4, more specifically, the loan trading amount increases, and the number of lenders increases when the number of P2P lending platforms in the market decreases, as does the number of borrowers. It indicates that in Stage III, the Chinese P2P markets experience an increasing concentration of P2P lending platforms and more efficient transactions, with lenders and borrowers clustering on the P2P lending platforms which are still surviving in the market to transact. It is consistent with the predictions for Stage III in Hypothesis 2. Combined with the ILC theory, Stage III can be considered as the mature stage of the Chinese P2P lending market, even if its net entry number is not exactly consistent with the theory.

According to Table 4.4, Stage IV is similar to Stage II, where the number of P2P platforms is positively and significantly related to the three output factors. In particular, in Stage IV, the number of P2P lending platforms has a significant positive effect on the loan trading amount. As the number of platforms in the market decreases, the loan trading amount also reduces with it. Meanwhile, the number of lenders and the number of borrowers are also significantly and positively correlated with the number of P2P lending platforms at the 5% significance level: as the number of P2P lending platforms declines, the number of lenders also decreases; meanwhile, the number of borrowers also reduces. This is consistent with Hypothesis 2, which means that stage IV is consistent with the characteristics of the decline stage in the ILC theory.

Table 4.5: Chow test results

Variables	F-statistics	
	(1)	(2)
	Stage II v.s. Stage III	Stage III v.s. Stage IV
Loan Trading Amount	411.64***	195.57***
Number of Lenders	862.73***	347.32***
Number of Borrowers	83.69***	197.07***

Note: This table reports the chow test results. * p<0.10, ** p<0.05, *** p<0.01

Table 4.5 shows the Chow tests for the differences in the regression coefficients between Stage II and Stage III, and between Stage III and Stage IV, respectively, in order to examine whether there is a significant structural change between the different stages, as predicted by Hypothesis 3. To be specific, in terms of the F-test for each output variable, the F-statistics are 411.64, 862.73, and 83.69, respectively, between Stage II and Stage III, all rejecting the null hypothesis. It indicates that there is a significant difference in the regression coefficients between Stage II and Stage III, i.e. there is a significant structural change between Stage II and Stage III. Similarly, the results of the F-test between Stage III and Stage IV, both reject the null hypothesis, which indicates that there is also a significant structural change between Stage III and Stage IV.

In summary, it is observed that the Chinese P2P lending market has experienced five stages even though it has had a very short lifespan. Based on the ILC's five-stage theory (Gort and Klepper, 1982), the first stage of the P2P lending market emerged from 2007 to 2013, and the second stage experienced rapid growth in the P2P lending market from 2014 to 2015. The reasons include the problem of defaults and the exposure of fraud to the police and the public. For example, the Ezubao scheme, the largest Ponzi scheme in China in recent years, was exposed in December 2015 (Guo, 2016). This became an important turning point in the development of the industry. The third stage spanning from 2016 to 2017 witnessed the maturing of the P2P online lending market, and the fourth stage started in 2018 with a gradual shrinkage of the P2P online lending market. The strict regulatory policies introduced by the government in the P2P lending market in 2018, as well as the explosion of default risks on a number of P2P lending platforms in the middle of the year 2018, with many loans failing to repay the principal and interest to lenders after the maturity date, led to the decline of the entire market (Hsu et al., 2021). Until 2020 the last stage, the fifth stage, the market is being terminated and all P2P platforms exit.

4.4 Survival of Chinese P2P Lending Platform

Following the previous section identified the five stages of development of the P2P lending market in China, this section will examine whether the different stages chosen by P2P lending platforms to enter the market could have an impact on their survival. It is important to show the survival of firms, as this is relevant to the development of a market or a new industry (Agarwal and Gort, 1996). Firms are referred to as P2P lending platforms in this study.

4.4.1 Platform Description

The emergence of the P2P lending market in China began in June 2007, when the first P2P lending platform, Paipaidai, was launched. Between then and March 2020, according to the platform dataset on WDZJ, there were 6,151 registered platforms in existence in the market. At the end of 2020, The People's Bank of China reported that all P2P platforms had been terminated. Over 13 years, the P2P lending market in China experienced not only rapid growth but also significant decline. Based on the platform dataset, I calculated the survival time of each platform by using their year of launch and year of closure. The survival time of the platforms is calculated in months because many P2P lending platforms, especially those with fraudulent purposes, survive for less than a year. Counting survival length in months will enable more platform data to be captured to reduce bias. Then summarized them by the five different current business statuses as well as by five stages.

Firstly, Table 4.6 shows the frequency of lifespans of P2P lending platforms in China. It shows the length of survival of P2P lending platforms in the market. To be specific, there are 2,306 platforms (37.49%) that existed for less than 12 months. And approximately half of the platforms (47.70%) lasted between 13 and 48 months which are 2,934 platforms. A total of 876 P2P lending platforms (14.24%) stayed in the market between 49 and 84 months. Few platforms managed to stay in operation for more than 84 months and even fewer for more than 120 months. Only 4 P2P lending platforms operated for more than ten years. It shows that P2P lending platforms in China have short lifespans as well as the P2P lending market.

Table 4.6: Frequency of lifespans of P2P lending platforms

Length	(1) Freq.	(2) Percent	(3) Cum.
less than 12 months	2,306	37.49	37.49
13-48 months	2,934	47.70	85.19
49-84 months	876	14.24	99.43
85-120 months	31	0.50	99.93
More than 120 months	4	0.07	100
Total	6,151	100	

Note: This table reports the frequency and the proportion of survival length of P2P lending Platform.

In addition, classified by the different statuses for P2P lending platforms, Table 4.7 shows the summary statistics of the lifespans of P2P lending platforms. It shows that the average lifespan of Chinese P2P lending platforms is about 24.35 months. By 2020, there is a total of 299 P2P lending platforms still running, and their average lifespan is 61.37 months. 'Transformed' platforms and 'Defaulted' platforms are the two types that had longer lifespans than the average. There are only 94 'Transformed' platforms in the market, which experienced an average lifespan of 32.60 months.

'Defaulted' platforms are the high default risk platforms. With an average of 29.24 months in business, there is a total of 1,775 defaulted platforms in the market. Furthermore, the 2,489 'Closed' platforms have an average lifespan of 21.25 months. However, there are 1,494 platforms classified as 'Recorded by Police', which are the highest-risk platforms in the market. They experienced the shortest lifespan, only 15.75 months on average. These figures are similar to those of studies on the survival of Chinese P2P lending platforms (He and Li, 2021; Liu et al., 2019).

Table 4.7: Summary of P2P lending platform by status

Status	(1) Obs	(2) Mean	(3) Std. Dev.	(4) Min	(5) Max	(6) P25	(7) P50	(8) P75
In-running	299	61.37124	14.22775	3	125	53	62	68
Transformed	94	32.59574	20.8349	1	149	18	30	47
Closed	2,489	21.25713	15.38401	0	118	10	18	30
Defaulted	1,775	29.24451	20.37249	0	121	10	29	46
Recorded by Police	1,494	15.74632	18.26611	0	124	2	9	22
Total	6,151	24.34677	20.23061	0	149	8	19	39

Note: This table reports the number of observations (1), mean (2), standard deviation (3), minimum (4), maximum (5), and quartiles (6)-(8) of the survival length for different statuses for P2P lending platforms in the market. In-running describes platforms which are still running financing businesses. online but have stopped matching borrowers and lenders are recorded as Transformed. Closed P2P lending platforms are recorded as Closed. P2P lending platforms that suffered from default risk are recorded as 'Defaulted'. Recorded by police denotes fraudulent platforms and in which the police have been involved in an investigation.

Table 4.8: Summary of P2P lending platform by Stage

Status	(1) Obs	(2) Mean	(3) Std. Dev.	(4) Min	(5) Max	(6) P25	(7) P50	(8) P75
Stage I	636	39.42453	27.32244	0	149	17	35	61
Stage II	4,264	24.52486	19.38325	0	75	8	19	41
Stage III	1,183	16.63483	13.09455	0	51	5	13	26
Stage IV	67	6.373134	4.785824	1	27	3	5	9
Stage V	1	3	-	3	3	3	3	3
Total	6,151	24.34677	20.23061	0	149	8	19	39

Note: This table reports the number of observations (1), mean (2), standard deviation (3), minimum (4), maximum (5), and quartiles (6)-(8) of the survival length for different stages for P2P lending platforms in the market.

Furthermore, Table 4.8 shows statistics based on the different stages of entry into the market for P2P lending platforms. In particular, the average length of survival of the 636 P2P lending platforms that entered Stage I is 39.42 months, with 50% of the platforms surviving for more than 35 months. In Stage II, there are 4,264 P2P platforms entering the market and 50% of them survived for more than 19 months, with an average survival time of 19.38 months. The average length of survival in Stage III is 16.63 months. As a result of the decline in the market, the average length of survival of P2P platforms in Stage IV is 6.37 months. Stage V is the most special, as only one entered the market with a survival time of 3 months.

Overall, Chinese P2P lending platforms generally had short lifespans in the market. Agarwal and Gort (1996) pointed out that firm survival could be affected by each stage in the industry life cycle. In the next section, it is examined whether the stage of the platforms' entry into the market has any impact on their survival.

4.4.2 Survival Analysis Strategy

To examine the relationship between the stage of the platforms' entry into the market and their survival, the survival analysis is employed in this section. Survival analysis has been applied to most of the research on P2P lending to discuss the determinants of loan defaults (Byanjankar, 2017; Serrano-Cinca et al., 2015) and the impact of regulatory policy on P2P platforms (He and Li, 2021; Liu et al., 2019; Wang et al., 2016). I use the Kaplan-Meier method, the log-rank test, and the Cox proportion hazard model in this analysis. Firstly, the survival time is defined as the length of time that a P2P lending platform's business is normally in operation. The start time is when the company is established by registration and the end time is when the business stops. Specifically, there are five business statuses of P2P platforms as mentioned previously, of which, with the exception of the 'In-running', the remaining four statuses have recorded a clear end of the business date and can be counted. The survival time of 'In-running' platforms is right-censored because it cannot be observed at the date I collected the data. And the survival analysis is available for the right-censored data (Kleinbaum and Klein, 2012).

The Kaplan-Meier method is a non-parametric maximum likelihood method to estimate the survival function with incomplete observation data (Kaplan and Meier, 1958). The Kaplan-Meier method and the Log-rank test are applied to test for differences in survival time between different groups (Goel et al., 2010).

The survival function is indicated as follows:

$$\hat{S}(t) = \prod_{j|t_j \leq t} (\frac{n_j - d_j}{n_j}) \tag{4.2}$$

where S(t) represents the probability of surviving to time t, t_j is the times at which failure occurs, i.e. the time at which the P2P lending platform has stopped business. n_j is the number of platforms has not experienced failure before time t_j and d_j is the number of failures at time t_j.

However, the log-rank test only provides information for testing whether the difference in survival time between the groups is statistically significant and it cannot test the effect of other independent variables on survival time (Goel et al., 2010). Therefore, the Cox proportion hazard model is employed. The model is represented as:

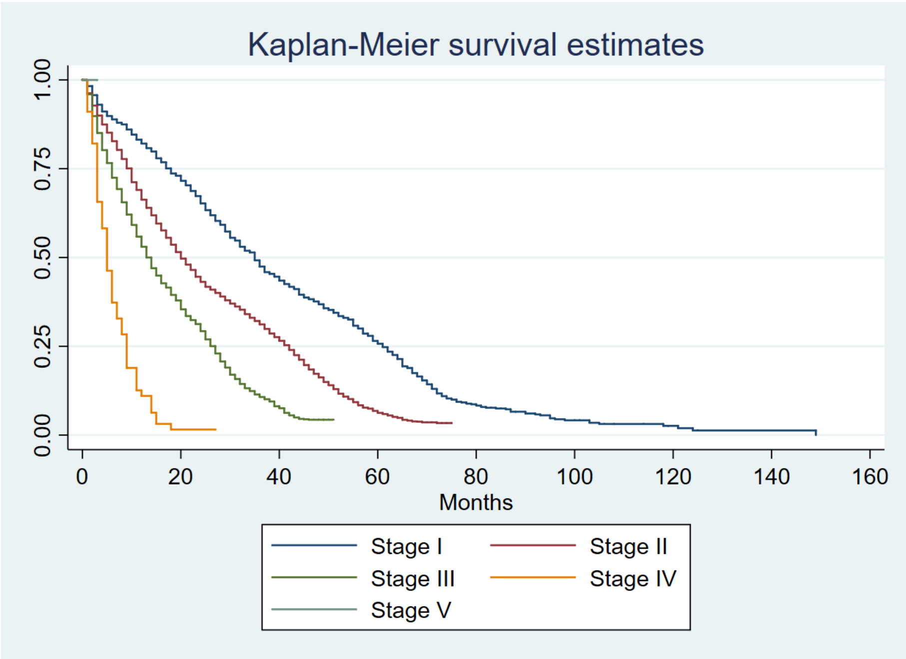
$$h(t) = h_0(t)exp(\beta_1 x) \tag{4.3}$$

where h(t) is the hazard at time t. And the hazard is the dependent variable and can be defined as the probability of failure of P2P lending platforms at a given time assuming that the platforms have survived up to that given time. The independent variable, in this study, is *stage*. Stage equaled 1 to 5 represent the P2P lending platforms entering the market at Stage I to Stage V respectively. The model provides an estimation of the coefficient, beta. But the estimation of the baseline hazard function h(t) cannot be estimated (Cox, 1972).

4.4.3 Survival Estimations Results

The number of months each platform survived is used as survival time, while the time at which it exits the market is marked as the time when the platform exit event occurs. According to the statistics, 211 of the 6,151 registered P2P lending platforms survived less than one month. After removing these platforms, a total of 5,940 platforms remained. Of these, 5,641 P2P lending platforms exited the market, and 299 are still operating. With the date on which individual P2P lending platforms started business corresponding to different stages of the development of the P2P lending market, platforms can be divided into five groups of different stages. After grouping the statistics of the corresponding survival length of platforms and plotting the Kaplan–Meier survival estimates, it can be shown clearly in Figure 4.3. that the survival length of platforms at each stage is also different.

Figure 4.3: Kaplan-Meier survival estimates



Note: This figure plots the survival functions from Stage I to Stage V by using the Kaplan-Meier method.

Figure 4.3 shows that the survival coefficients of the platforms in the first four stages are quite different, except for the survival coefficient of 1 observed in Stage V for the single platform that entered the market last and is still operating. However, when compared to the survival length of the platforms corresponding to each survival coefficient, it is evident that when 25% of the platforms in each stage exit the market, the longest survival length experienced by the platforms in Stage I is 18 months. The platforms that entered the market at Stage II saw 25% of their number exit the market when they had reached 10 months of operation. The shortest survival length was in Stage IV, where 25% of platforms exited the market after 3 months of operation. Comparing the length of survival of 50% of the platforms that exited the market at each stage reveals the following: platforms that entered the market at Stage I and are still operating survived 35 months, platforms entering in Stage II experienced 20 months, and platforms entering in Stage III experienced 13 months.

Whereas 50% of the platforms that entered at Stage IV only experienced 5 months before exiting the market. It is observed that the survival length of the platforms that entered the market in Stage I is much longer than that of the remaining platforms, which is related to the time sequence of market entry.

Since each platform entered at a different time in different stages, the survival length cannot simply be explained by comparing the length of months to show that there is a difference between stages, so I next applied the log-rank test to examine whether there is a significant difference in the survival time of P2P lending platforms between stages, and the results are shown in Table 4.9.

Table 4.9: Summary of hazard rate of P2P platforms

Stages	Events observed	Events expected	Relative hazard
Stage I	601	1009.81	0.5753
Stage II	3874	3921.76	1.0399
Stage III	1101	694.22	1.7428
Stage IV	65	15.1	4.9213
Stage V	0	0.11	0
Total	5641	5641	1
LR chi2(3)= 538.63		Pr>chi2=0.0000	

Note: This table reports the results of the log-rank tests.

As listed in Table 4.9, there are three indicators: events observed, events expected, and relative hazard. Events observed represents how many P2P lending platforms have exited the market during this stage. Events expected represents how many P2P lending platforms are predicted to exit the market at this stage. Relative hazard represents the percentage risk of P2P lending platforms exiting from the market happening at this stage. Table 4.9 shows that the relative hazard is 0.5753 for platforms entering at Stage I, 1.0399 for platforms that entered at Stage II, 1.7428 for platforms that entered at Stage III, and the highest figure is for platforms that entered at Stage IV at 4.9213. Also, the Chi2 value is 538.63 and the p-value is 0.0000. The p-value is less than 0.001, which rejects the null hypothesis of the log-rank test that there is no difference in survival length between groups. Therefore, it could be indicated that the survival rates between stages differ significantly from each other. This means that P2P lending platforms that entered the market at Stage I have survived longer than other platforms. It is consistent with the previous finding that the survival length of the platforms that entered the market in Stage I is much longer than that of the remaining platforms and has less risk.

Table 4.10: Results of the Cox proportion hazard model

VARIABLE	hazard
stage	0.570***
	(0.0247)
chi2 = 0.93	Prob> chi2 = 0.3337

Note: This table reports the results of the Cox proportion hazard model and the test proportional-hazards assumption.

Furthermore, to examine the effect of stages on the survival time of P2P lending platforms, the Cox proportion hazard model is applied. Table 4.10 presents results as modelled in Model 4.3. It is shown that the coefficient associated with stage is positive and statistically significant at 1 % level. It suggests that the later the stage of entry into the market results in a higher hazard ratio. In addition, the p-value for the test proportional-hazards assumption is 0.3337, which is greater than 0.05, the null hypothesis cannot be rejected. Therefore, the proportional-hazards assumption holds. It means the stage has a positive effect on the hazard ratio. The later a P2P lending platform enters, the higher the risk and the lower the probability of survival in the market. It supports the previous finding related to the Kaplan-Meier method, the log-rank test.

The finding also suggests that the development of P2P lending platforms in China is consistent with the idea of industry life cycle development (Agarwal and Gort, 1996). And this finding is similar to that of the study by Wang and Zhao (2021). Early entrants to the P2P lending platform have conducted their business cautiously and with a high level of risk tolerance. While the industry experienced rapid growth, a large number of P2P platforms enter with the risk increasing. A large number of high-risk platforms are subsequently eliminated. Competitive pressures and stringent regulation results in higher operating costs for P2P platforms, further exacerbating the risk of exit. In the next section, an extended discussion of the development of the P2P lending market in China is presented.

4.5 Extended Discussion

P2P lending was introduced in China in 2007. With the development of the economy in China, small and medium-sized enterprises started playing an increasingly important role. These enterprises had been troubled by the difficulties of securing bank financing for a long time. According to the report *The Operation and Financing of Small and Micro Business in 36 Cities* (2012), more than 62% of small and micro enterprises did not have any form of bank loan. Fungacova and Weill (2014) pointed out that small and medium-sized enterprises and individual businesses pursue alternative financing as they have limited access to acquire credit support from banks, which may contribute to the growth of shadow banking. Due to the high demand for financing from the public, P2P lending began to expand in 2013. During this early stage, the method of business operation for P2P lending platforms was borrowed from famous platforms in Europe and the United States, such as Zopa and Lending Club. At the time, research related to P2P lending in China was more focused on the development of P2P lending in Western countries (Zhang and Hu, 2013). Due to the absence of government regulation and the lack of secure financing, research also focused on the risks associated with the business of P2P lending, and regulatory suggestions for P2P lending (Wu and Cao, 2011; Zhang and Hu, 2013).

The development of the P2P market was encouraged by the government, and the tolerance of regulation allowed the P2P lending market to grow rapidly (Wang et al., 2016). In July 2015, the government issued guidelines for the P2P market, clarifying the boundaries of P2P lending platforms in China. At the same time, the risks of P2P platforms were gradually exposed, such as platforms suspected of online fraud, fictitious loans, and the defrauding of lenders' investments; the most famous case was the Ezubao Ponzi scheme. This is one of the biggest Ponzi schemes in the Chinese financial market, and its explosion made the government regulation of the P2P market significantly stricter, ending the violent expansion of the P2P market under deregulation.

Between 2016 and 2017, the government issued a series of guidelines to regulate the registration of P2P lending platforms for business, establishing a policy regulatory framework for the P2P market. This caused a portion of high-risk platforms to begin exiting the market. Zheng et al. (2017) pointed out that strict regulation resulted in an improved credit environment in the market, reducing the cost of covering risk while cutting operating costs. Borrowers and lenders on P2P lending platforms started to concentrate on high-ranked platforms with a better reputation. However, an increase in the number of borrowers meant that the P2P lending market extended credit to a larger pool of borrowers. This led to more cases of non-repayment of loans and raised the default risk of borrowers (Gonzalez, 2010; Lützenkirchen et al., 2012). The following stage, Stage IV, shows many P2P lending platforms going bankrupt because of the expansion of borrowers.

The shrinkage of the Chinese P2P lending market was first caused by the government. In 2018, with the implementation of various regulatory policies, the P2P lending industry entered a stage of unprecedented strict compliance requirements. The various regulatory measures greatly hindered the development of the industry (Feng et al., 2020). The more requirements in the industry and the more severe the regulations, the fewer P2P lending enterprises could fully comply. Most P2P lending platforms closed or were transformed in accordance with the regulatory authorities' policies. This indirectly led to the second reason for shrinkage: a large number of P2P platforms experienced the problem of defaulting and went bankrupt in July 2018. The main reason for this was the extending of credit to more borrowers in Stage III.

After the imposition of strict government regulations for P2P lending platforms, only 299 platforms remained in the market by March 2020. However, the impact of COVID-19 would make it more difficult for P2P platforms to operate (Nigmonov et al., 2020). The months of shutdowns greatly increased the risk of delinquency by borrowers. By the middle of November 2020, the government announced the termination of the P2P lending industry. The lifecycle of the P2P lending industry ended.

4.6 Conclusion

By combining technology and finance, P2P lending became a new direct financing approach available to the public. From 2007 to 2020, the P2P lending market in China experienced a whole lifecycle, from emergence to decline. According to the ILC theory of Gort and Klepper (1982), an industry will experience five stages, identifiable by the entry and exit of producers. According to the information collected from the registered platform dataset, those five stages were evident in this market. Even though I collected incomplete monthly records, missing some Stage I and Stage V data, the lifecycle of the P2P lending industry could still be pictured.

I find that P2P lending in China experiences the complete five stages lifecycle. Stage I, from 2007 to 2013, witnesses the introduction of the P2P lending market, with a small number of entries and barely any exits. At this stage, as a new kind of financing product, P2P lending without collateral was hard to trust for investors. In addition, the interest rate for borrowers and the platforms that entered the market is unregulated by the government. From 2014 to 2015, the expansion in the P2P lending market was at Stage II. With a high net entry number, the market expansion reflects the growth in the number of platforms, investors, and borrowers. The exit of platforms begins to increase in this period characterized by the highest price but the shortest loan term. However, the difference between the ILC theory proposed by Gort and Klepper (1982) and the P2P lending market is that both Stage III and Stage IV present a negative number of net entries. Stage III shows a slight balance from 2016 to 2017. In Stage III, the decreasing number of P2P lending platforms contributes the largest volume of loans. Both the number of investors and the number of borrowers reach their peak during this stage. Stage IV was the period of shrinkage in the P2P lending market after 2018. It was marked by a decrease in all three participants, and the number of P2P lending platforms in the business declined due to the rising number of bankrupt platforms. The number of investors declined significantly, as did the number of borrowers, although the ratio did not change. In Stage V, in 2020, all P2P platforms exited, and the market was terminated by strict government policy.

Another interesting finding is the later a P2P lending platform enters, the higher the risk and the lower the probability of survival in the market. Early entrants to the P2P lending platform have conducted their business cautiously and with a high level of risk tolerance. Overall, although P2P lending experienced a relatively short but complete lifecycle, it was still a valid experiment in Chinese fintech for the public. It will provide useful experiences for the development of fintech in the world.

While the previous discussion provided some interesting findings, there are still some limitations in terms of the availability of data. Due to limitations in the early data summaries, the availability of monthly data only from 2014 onwards makes it impossible to discuss the characteristics of the first phase. In addition, other factors that may affect the risk of survival of P2P platforms are important. Because of limitations in data availability, there are no additional factors that could be collected, so in this study, we only focus on the impact of the different stages of market entry on survival time. Other factors such as geographical location are left for future research.

Appendix C

Table C.1: Survival length of platforms by status

Survival Length		0 Year	1-3 Years	4-6 Years	7-9 Years	More than 10 Years	Total
In-running	Freq.	1	10	259	26	3	299
	Percent	0.33	3.34	86.62	8.7	1	100
	Cum.	0.33	3.68	90.3	99	100	
Transformed	Freq.	4	56	33	0	1	94
	Percent	4.26	59.58	35.11	0	1.06	100
	Cum.	4.26	63.83	98.94	98.94	100	
Closed	Freq.	343	1768	228	6	0	2489
	Percent	14.06	74.05	11.65	0.24	0	100
	Cum.	14.06	88.11	99.76	100	100	
Defaulted	Freq.	278	932	552	12	1	1775
	Percent	15.66	52.51	31.09	0.68	0.06	100
	Cum.	15.66	68.17	99.26	99.94	100	
Recorded by Police	Freq.	595	731	162	5	1	1494
	Percent	39.83	48.93	10.85	0.34	0.07	100
	Cum.	39.83	88.76	99.6	99.93	100	
All	Freq.	1228	3572	1296	49	6	6151
	Percent	19.96	58.07	21.07	0.8	0.11	100
	Cum.	19.96	78.04	99.11	99.9	100	

Note: This table summarizes the frequency and percentage of the survival time of the platform according to five different platform states. Source of data from WDZJ.com

Appendix C

Table C.2: Number of status of platforms by stages

		In-running	Transformed	Closed	Defaulted	Recorded by Police	Total
Stage I	2007	0	1	0	0	0	1
	2008	0	0	1	0	0	1
	2009	1	0	4	1	1	7
	2010	2	0	4	3	5	14
	2011	4	0	15	11	12	42
	2012	5	0	16	35	27	83
	2013	17	12	157	201	101	488
Stage II	2014	101	27	767	526	453	1,874
	2015	109	36	1,081	562	602	2,390
Stage III	2016	49	17	328	232	176	802
	2017	8	1	99	177	96	381
Stage IV	2018	1	0	17	27	21	66
	2019	1	0	0	0	0	1
Stage V	2020	1	0	0	0	0	1
Total		299	94	2,489	1,775	1,494	6,151

Note: This table summarizes the frequency of the final status of platforms that opened in each year at different stages. Source of data from WDZJ.com

Appendix C

Table C.3: Survival length of platforms by stages

Survival Length		0 Year	1-3 Years	4-6 Years	7-9 Years	More than 10 Years	Total
Stage I	2007	0	0	0	0	1	1
	2008	0	0	0	1	0	1
	2009	0	1	0	3	3	7
	2010	0	0	9	3	2	14
	2011	9	3	18	12	0	42
	2012	5	27	39	12	0	83
	2013	65	247	158	18	0	488
Stage II	2014	196	1058	620	0	0	1874
	2015	569	1418	403	0	0	2390
Stage III	2016	242	511	49	0	0	802
	2017	86	295	0	0	0	381
Stage IV	2018	55	11	0	0	0	66
	2019	0	1	0	0	0	1
Stage V	2020	1	0	0	0	0	1
Total		1228	3572	1296	49	6	6151

Note: This table summarizes the number of years of survival for platforms that launched in each year at different stages. Source of data from WDZJ.com

Chapter 5

Conclusion

As a new form of direct financing investment, P2P lending was born in 2005 and contributed to the global boom in financing markets. This new financing model, developed through online technology, rapidly expanded after its emergence, especially in China. Unlike traditional bank lending, it connects borrowers' credit needs with investors' funds directly through a peer-to-peer lending platform. Since P2P lending does not require collateral from borrowers, it can cover more borrowers who are not accepted by traditional banks. Therefore, peer-to-peer lending is seen as a complement to traditional banks (Balyuk, 2019; Havrylchyk et al., 2017; Tang, 2019).

However, covering more subprime borrowers also means that P2P lending carries a higher risk of default compared to traditional bank lending. Following the P2P lending framework, borrowers apply for funds from lenders via a P2P lending platform. Once borrowers have acquired funds, they are obliged to pay principal and interest to their lenders on time. Credit risk is the default risk that borrowers fail to make payments to lenders, leading to a loss for lenders. Unlike bank loans, loans on the P2P lending market are mostly unsecured loans. This renders the cost of default for borrowers relatively low. In addition to the credit risk, Ponzi schemes in the emerging P2P market, especially in China, have caused many P2P investors to lose their principal and interest.

Taking an overview of the development of the P2P lending market in China, I found that it followed the same lifecycle process as other mature industries. When the market was first introduced, the public needed to gain experience with it; it then passed a significant growth stage, reached maturity, and then began to decline until it ended.

Based on my findings, either positive or negative news about the market would affect the platforms and market growth as a whole. Comparing the impact on the market of the new policy announced in the United Kingdom to the impact of the shocking financial scandal in China, there are similarities in that with the growth of the market, the number of potential defaulters increased after an external event. Whether positive or negative, news on social media about this new financial market attracted high-risk subprime-credit borrowers to apply for a loan. However, high-risk borrowers who were affected by the financial scandal, as in the Chinese market example, tended to default earlier on their repayment period and on a greater amount of principal and interest. However, for the high-risk borrowers in the UK market, their default amount was not affected by the policy announcement. In this way, it was easy to identify high-risk borrowers in the UK market by improving the borrower selection algorithm at the beginning. In the Chinese market, it is hard to identify such borrowers when financial scandals explode. Hence, it required P2P lending platforms to offer greater compensation guarantees to win the trust back from investors. Therefore, the second round of default crises in the Chinese P2P lending market was forecast, and it accelerated the decline of the market.

Studying the life cycle of the development of the Chinese P2P lending market and the length of survival of P2P platforms can offer insights into P2P lending markets in other countries. The results of the previous study show that P2P lending platforms that enter the market earlier survive longer and can also expand their businesses as the P2P market develops, for example, by attracting more borrowers and lenders. However, attracting high-risk borrowers also raises the risk of default. As the Chinese P2P lending market entered a recession, a large number of P2P lending platforms exploded in a default crisis due to their early expansion. The high default rate not only resulted in investors suffering losses, but in the face of high default risks even P2P lending platforms that promised to cover the losses of lenders with risk premiums were unable to afford the promised compensation, which led to the widespread bankruptcy of P2P platforms. This eventually brought the whole market to an end.

Despite its short-lived existence, the Chinese P2P lending market has also contributed to the alternative financing market of China. After the failure of P2P lending, the difficulty of financing SMEs remains a concern, and I notice that some of the transformed P2P lending platforms mentioned in Chapter 4 still provide loans to SMEs. The lenders are no longer public individuals, but large investors such as banks, trust companies, and insurance companies. The business model is also no longer online, but more similar to microfinance. In the long run, this approach may become a new alternative finance industry model. The study of the P2P lending market found a preference for high-risk borrowers to enter new lending markets, which can provide some lessons for the future development of alternative finance in China; for example, future alternative financial service providers can avoid some default risks by anticipating the rise of default risks in advance during the expansion process. In addition, investors should not only anticipate the risks of new alternative financial products, but also be cautious of possible financial scams, such as Ponzi schemes. In summary, it is foreseeable that alternative finance, especially Internet-based alternative finance, will continue to be worthy of focus and research, especially in the Chinese market. The focus of my research will be on the future development of alternative finance as well as internet finance in China.

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