Peer-to-peer Lending Market and Shadow Banking in China

Thesis submitted in accordance with the requirements of the University of Liverpool for the degree of Doctor in Philosophy by

Jiaqi Kuang

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Dr. Xudong Ji	Original idea, intellectual guidance and suggestions with reference to the writing up, methodological issues, and interpretation of results
Dr. Peng Cheng	Intellectual guidance and suggestions on literature review and interpretation of results
Dr. Kallinterakis Vasileios	Intellectual guidance and suggestions on structure, literature review, interpretation of results

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Jiaqi Kuang	Main idea, Literature review, collection of data, empirical estimation, interpretation of results and writing up
Dr. Xudong Ji	Intellectual guidance and suggestions with reference to the writing up, methodological issues, and interpretation of results
Dr. Peng Cheng	Intellectual guidance and suggestions on literature review and interpretation of results
Dr. Kallinterakis Vasileios	Intellectual guidance and suggestions on literature review and interpretation of results

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Jiaqi Kuang	Main idea, Literature review, collection of data, empirical estimation, interpretation of results and writing up
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Table of Contents

Abstract

The fast development and high risk of Chinese peer-to-peer lending market has attracted more scholars' the attention. This thesis studies the Chinese peer-to-peer lending market from the platform level (see chapter 2 and 3) and market level (see chapter 4).

Firstly, this thesis examines the various information (third-party provided information and voluntary information disclosure) and government regulation effect on the default probability and cost of capital of platforms by the specific dataset which combines the data collected from CSMAR (control variables), WDZJ (third-party provided index), and platforms' website (voluntary information disclosure). This study finds that both third-party provided information and voluntary financial information disclosure help on reducing the default probability and cost of capital of platforms, meanwhile, the government regulatory intervention could decrease the cost of capital (Chapter 2).

Secondly, by using the artificial intelligence technology, this thesis examines the sentiment impact of different types of public information (media news and social media posts) on the performance of peer-to-peer lending platforms. Based on the unique news dataset that collected and analyzed by Python and Snownlp (which used to run the sentiment analysis), this study reveals that the higher levels of media sentiment and social media sentiment dampen the default probability, and the asymmetry effect exists in the peer-to-peer lending market which display that only positive change on sentiment of news has a significant impact on reducing default probability and cost of capital of platforms, while negative change on sentiment does not. Furthermore, this study tries to explain the results by examining the sentiment effect on investors' participation, which does help to explain the role of news sentiment. (Chapter 3)

Finally, this thesis examines the effect of central government monetary policy and the local government financial demand on the scale of peer-to-peer lending market, which is a new type of shadow banking market in China. The results show that the central government monetary policy has significant effect on the future rising of the scale of the peer-to-peer lending market; meanwhile, the local financing demand has the significant positive effect on the scale of the peer-to-peer lending market. This study also suggests that the size of existing shadow banking facilitates the future expanding of the peer-to-peer lending market (Chapter 4).

1. Introduction

The peer-to-peer lending market originated in the UK from 2005 and developed in the US since 2006. In 2007, the first peer-to-peer lending platform Ppdai appeared in China and subsequently gained a mushroom growth in China. With the further development of block-chain technology, the peer-to-peer lending market has been accelerated in recent years and becomes a burgeoning lending market among individuals and small businesses, who normally have difficulty to access bank loans. This fast growth brought 1,931 operating peer-to-peer lending online platforms and 244.3 billion RMB trading volume by the end of 2017.[1]

There are three reasons for the explosive growth in Chinese peer-to-peer lending market: (1) the risk control in the peer-to-peer lending market seems looser than traditional banks; (2) peer-to-peer lending platforms could address financing difficulties faced by small businesses and individuals; (3) peer-to-peer lending market facilitates and promotes the financial innovation (Lufax, 2014).

The fast growth and the large demand for funds of small businesses and individuals has brought some special characteristics of Chinese peer-to-peer lending market. The first one is all operations and transactions in P2P market are based on platforms rather than

[1] The data was published by WDZJ, which is a third-party information dissemination intermediary that publishes the data of the whole Chinese peer-to-peer lending market and individual platforms in Chinese peer-to-peer lending market.

between investors and borrowers. This operational mechanism is different from that in the UK, Germany, and the US where the lending transactions are based on individuals. There is a huge gap in the number of platforms in different countries. There are more than 1000 operating platforms in the Chinese peer-to-peer lending market at the end of 2017 and 343[2] operating platforms at the end of 2019 after the government regulatory intervention, which are far more than the total number of peer-to-peer lending platforms existed in other countries.

The second characteristic is the business models of the P2P market in China have been changing throughout 2010-2019. The main business model has changed from peer-to-peer direct lending to sale of wealth management products[3] which is different from the business models of peer-to-peer lending platforms in other countries where peer-to-peer lending focuses primarily on matchmaking lending transactions between individual borrowers and lenders. Till the 2019, there are three different business models in Chinese peer-to-peer lending market: (1) peer-to-peer lending with guarantee (secured by the borrower's personal asset or guaranteed by the platform or a third party), (2) peer-to-peer lending without guarantee, (3) and financial products selling.[4]

The third characteristic of Chinese P2P market is most Chinese peer-to-peer lending

[2] Many platforms are not in the operating platform list but they are not default, most of them have transformed into loan assistance and micro-loan companies, still operating personal loan business, and paying the interest and capita on schedule.
[3] Wealth management products: the financial products that sold on peer-to-peer lending platforms.
[4] Sale of wealth management products issued by the peer-to-peer lending platform and/or on-commission sales of financial products issued by banks, trust companies, and insurance companies.

platforms provided principal guarantees to individual lenders in the event of loan defaults which is quite different from the American peer-to-peer lending platform (Wang et al., 2016). Each peer-to-peer lending platform is more like a small bank in China; therefore, the peer-to-peer lending market is regarded as one of shadow banking systems in China.

These unique characteristics also bring some differences between Chinese peer-to-peer lending market and peer-to-peer lending market in other countries (such as US, UK, Japan). First, there is a huge gap in the number of platforms in different countries. There are more than 1000 operating platforms (and over 6000 cumulative platforms) in the Chinese peer-to-peer lending market at the end of 2017 and 343 operating platforms at the end of 2019 after the government regulatory intervention, which are more than the total number of peer-to-peer lending platforms existed in other countries (At the end of 2019, there were 251 P2P platforms available outside mainland China; 146 of them are located in Europe, 35 in North America, 43 in Asia, 9 in Australia, and 18 in South America and Africa). Second, the business model in Chinese peer-to-peer lending platforms is quite different from platforms in other countries. The main business model of peer-to-peer platform in other countries is matchmaking lending transactions between individual borrowers and lenders, but for Chinese P2P platforms, except the directly peer-to-peer lending, another one important business model is the sale of wealth management products (which means peer-to-peer platforms works as a small fund management firms). Third, some Chinese peer-to-peer lending platforms provided principal guarantees to individual lenders, but platforms in other countries usually does not.

However, the rapid growth of Chinese P2P lending market had resulted in increasing number of default platforms from 2015-2019 because the information asymmetry and high risk in the Chinese shadow banking system. Till the end of 2019, there were over 2000 default platforms in total (from 2010-2019) and the default rate is over 29%. In order to deal with the high risk and serious default rate in the P2P lending market, Chinese government issued two regulations[5] on the peer-to-peer lending market. The regulations promote the fresh and healthy development of the peer-to-peer lending market and boosts the changing in the business model of the peer-to-peer lending market. After that, the Chinese P2P lending market entered into the decreasing period with the 343 operating peer-to-peer lending platforms and 42.9 billion RMB trading volume at the end of 2019.[6] The market growth and lending rate have decreased because problematic platforms dropped out from P2P market.

The special characteristics (discussed above) and the full development cycle (start period-rapid growth period-declining period) of Chinese peer-to-peer lending market

[5] In August 2016, the China Banking Regulatory Commission published 'P2P Platforms Management Document', which is available at www.cbrc.gov.cn.
In March 2018, the China Banking Regulatory Commission - Office of the Leading Group for the Special Campaign against Internet Financial Risks published the 'Notice on Intensifying the Corrective Action on Asset Management Business through the Internet and Conducting Acceptance Work' (available at: http://www.wfgx.gov.cn/GXQXXGK/TRZZX/201804/t20180408_2759009.html).

[6] The data was published by WDZJ, which is a third-party information dissemination intermediary that publishes the data of the whole Chinese peer-to-peer lending market and individual platforms in Chinese peer-to-peer lending market.

make it become a suitable market to study the information asymmetry, risk, behavior of participators, and policy effect in the innovative market. This thesis focuses on investigating the effect of information disclosure, public sentiment, and government policy on the performance of firms and the market.

This thesis consists of three chapters: Chapter 2: Disclosure sources, regulatory changes and market performance: Evidence from the Chinese peer-to-peer lending market; Chapter 3: The Effect of Media News and Social Media Information on the Default Probability and Cost of Capital: Evidence from Chinese Peer-to-peer Lending Market; Chapter 4: The Effect of the Central Government Monetary Policy and the Local Government Financing Demand on the Scale of the Shadow Banking: Evidence in P2P Lending.

As a newly innovative shadow banking market, the high default rate and high risk of P2P lending market have always been criticized. Information asymmetry has been viewed as the cause of the inefficient market and the high default probability of firms (Akerlof, 1970). Information disclosure has been regarded as the critical factor to alleviate information asymmetry and for improving the efficiency of the financial market (Diamond and Verrecchia, 1991; Botosan, 1997; Sengupta, 1998; Healy et al.,1999a; Lambert et al., 2007; Goldstein and Yang, 2017; Ahmad et al., 2019; etc.). Chapter 2 shows the effect of information disclosure on the firms' performance (default probability and cost of capital) in Chinese P2P lending market in detail. With using different sources of information disclosure (third-party provided information, voluntary operational and financial information disclosure) and the unique dataset which combines all types information, the influence of information disclosure on Chinese P2P lending market is investigated from three different perspectives: the effect of voluntary information disclosure, third party provided information, and government regulation.

In this Chapter, I find that both third-party provided information and voluntary financial information disclosure have the significant impact on reducing default probability and cost of capital of platform. Additionally, the significant effect of voluntary operational information disclosure can only be found on default probability, and the government regulation has a significant effect on reducing cost of capital. Besides, the results of this Chapter prove that information disclosure has significant impact on reducing information asymmetry and risk of P2P lending market which may contribute important policy inspirations for government on the future innovative market.

Except the information disclosure, the public information (includes the media news and social media posts) has always displayed the excellent effect on reducing information asymmetry in the financial market (Nofsinger, 2005; Fang and Peress, 2009; Cahan et al., 2015; etc.). Chapter 3 studies the effect of the sentiment of media news and social media posts on P2P platforms' performance (default probability and cost of capital) in Chinese P2P lending market in detail. The comprehensive data of both media news and social posts were collected from the largest two P2P lending information platforms

(WDZJ and P2PEYE[7]). With using the artificial intelligence technology, the sentiment of media news and social media posts was quantified. A new set of keywords in P2P lending market are used in doing the sentiment analysis. The study suggests that media sentiment and social media sentiment have a significantly negative effect on the platform's default probability, meanwhile, only positive change on sentiment of news has significantly impact on reducing default probability and cost of capital of platforms, while negative change on sentiment does not. The results point out an asymmetry effect on public information on P2P market performance.

As an innovative financial market, the P2P lending market is also a new type of shadow banking. The fast growing and less regulated P2P lending market brings a lot of concerns in the world. Chapter 4 studies the P2P lending market from national and provincial aspects, by examining the relationship between the existing shadow banking[8] and P2P lending market[9] and the influence of the Chinese central government monetary policies, the local government bond issued on P2P lending market as well as on shadow banking sector. The results in Chapter 4 show that the central government's contractionary monetary policy and local government bond issued could significantly increase the scales of existing shadow banking and the P2P lending market. The existing shadow banking is a major contributor for the fast growth of P2P lending market. This

[7] WDZJ and P2PEYE are two most popular and largest information intermediaries in Chinese Peer-to-Peer lending market. Although the data published in WDZJ is no longer public, we have downloaded and saved all rating indexes data and information (media news and social media posts).
[8] Existing shadow banking: the traditional shadow banking before the Fintech and recent financial innovation.
[9] New shadow banking: the new type shadow banking after the Fintech and recent financial innovation, such as the P2P lending market.

Chapter also reveals the effect of local government bond issued on the P2P lending market which may offer some policy implications to government that is the local government debt should be strictly regulated because it has a significant impact on the increasing scale of the shadow banking (including P2P lending market) which will increase the risk of the financial system (Epstein, 2005; Brunnermeier ,2009; Adrian and Shin, 2009; Delottei, 2009; Hsu and Moroz, 2010; Pozsar et al., 2010; Adrian and Ashcraft, 2012) and eventually will harm the development of Chinese economy (Adrian and Shin, 2009; Adrian and Ashcraft, 2012; Moreira and Savov, 2017). Furthermore, the results of this Chapter suggest the capital in existing shadow banking should also be monitored since it is the important factor affects the scale of P2P lending market.

Chapter 5 of the thesis is the conclusion chapter, after studying the development of P2P lending market and shadow banking system through different perspectives, my study concludes there are significant impacts of various sources of information disclosure, the different public sentiments, and the government policies on the performance of platforms (firms) and peer-to-peer lending market. These results inspire the future study on the innovative market and shadow banking system by providing some enlightening evidences, e.g., the different effects of third-party provided information, operational and financial information disclosed by platforms; the asymmetry effects of media sentiment and social media sentiment; the surprisingly relations between existing shadow banking and P2P lending market. Therefore, this study provides valuable insights for the participants (individuals, firms, platforms, intermediaries, and government) in this innovative market.

2. Disclosure Sources, Regulatory Changes and Market Performance: Evidence from the Chinese Peer-to-Peer Lending market

Abstract

Information disclosure in the peer-to-peer (P2P) lending industry is affected by various stakeholders (financial authorities; industry self-regulation; ratings agencies), yet no study to date has investigated the differential impact of each of those elements over P2P markets' performance. This study provides seminal evidence on this issue from China, home to the world's largest P2P lending market, by assessing how two distinct aspects of its performance (default probability; cost of capital) are affected by each of those elements during the 2015-2019 period. The findings suggest that higher levels of third-party provided information (by ratings agencies) and voluntarily disclosed financial information (by P2P platforms) dampen both the default probability and the cost of capital of P2P platforms. Additionally, I find government regulatory intervention leads to lower cost of capital. The evidence presented here indicates that P2P platforms' performance benefits from the presence of multiple disclosure sources and offers actionable implications for such platforms internationally.

Keywords: information disclosure; third-party provided information; voluntary operational and financial information disclosure; government regulation; P2P lending market

JEL classification: F3, G14, G18

2.1.Introduction

Peer-to-peer (P2P, hereafter) lending platforms are market settings subject to enhanced risk due to asymmetric information between borrowers and lenders (Freedman and Jin, 2008; Lin et al., 2018). With the further development of block-chain technology, the peer-to-peer lending market has been accelerated in China and becomes a burgeoning lending market among individuals and small businesses, who normally have difficulty to access bank loans. The rapid development has also brought up some problems, such as the high default probability of platforms and borrowers. The lagging regulation in the emerging peer-to-peer lending market and the high information asymmetry between borrowers, platforms, and investors have resulted in the high default rate of platforms and borrowers. Therefore, it is critical to study how to reduce the default risk in peer-to-peer lending market. Different from peer-to-peer lending market in other countries, there are large number of platforms in China. The more than 5000 cumulative peer-to-peer lending platforms[10] increases the information asymmetry in Chinese peer-to-peer lending market which also makes it necessary to study the risk and problems in platform level instead of focusing on individual level research as most previous studies (Berkovich, 2011; Herzenstein et al., 2011; Pope and Syndor, 2011; Duarte et al., 2012; Michels, 2012, Ge et al.,2017) have done.

[10] The cumulative P2P lending online platforms reached 5,970 and the cumulative trading volume reached 6,103.60 billion RMB at the end of 2017.

One of the theories that could significantly reduce the risk and the information asymmetry is the information disclosure. Existing literatures have shown the significant effect of information disclosure on firms' performance in stock market (Diamond and Verrecchia, 1991; Botosan, 1997; Sengupta, 1998; Healy et al., 1999a; Verrecchia, 2001; Lambert et al., 2007, Goldstein and Yang, 2017; Ahmad et al., 2019) and the impact of voluntary non-financial information disclosure on loan performance of individual borrowers in the peer-to-peer lending market (Jiang et al., 2019; Herzenstein et al., 2011; Michels, 2012; Pope and Syndor, 2011; Duarte et al., 2012; Lin et al., 2018; Ge et al.,2017). Research to date has largely focused on the performance-impact of borrowers' voluntary non-financial information disclosure (Berkovich, 2011; Herzenstein et al., 2011; Pope and Syndor, 2011; Duarte et al., 2012; Michels, 2012, Ge et al.,2017), with very little attention (Wang et al., 2020) having been devoted to the effect of disclosure motivated via diverse regulatory stakeholders (financial authorities; platforms; ratings agencies) in the P2P-industry. This study aims to fill this gap by exploring the impact of two distinct sources of disclosure (voluntary operational and financial information disclosure by platforms; third-party provided information) and government regulatory intervention over two distinct aspects of P2P-platform performance (default probability; cost of capital) in the context of the Chinese P2P lending market, the world's largest.[11] Unlike previous studies, which document a significantly negative effect of information disclosure on the borrowers' performance (default probability; lending rate) in P2P platforms internationally based on single

[11] According to the report published by ACCA, Chinese P2P lending market was the world's largest P2P lending market (ACCA, 2016).

platforms (due to the small number of platforms in most countries) and voluntary information disclosure only (due to the lack of any other third party information), this study is the first study to investigate the relationship between various types of information disclosure and P2P platform performance at a multi-platform level.

Drawing on data from 170 Chinese P2P lending platforms between 2015 and 2019, This study empirically addresses a series of research questions. First, I examine whether those platforms' default probability is impacted by voluntary (operational and financial) information disclosure, as well as by third-party provided information. Second, I assess the extent to which voluntary (operational and financial) information disclosure, as well as third-party provided information, affects the cost of capital across platforms. Third, I explore whether the above results hold during periods of increased regulatory control by the Chinese authorities and whether government regulations have had an impact on those platforms' default probability and cost of capital.

My results suggest that both voluntary (operational and financial) and third-party provided information contributes significantly to the reduction of the default probability on P2P platforms, with the accuracy of my empirical default probability predictions rising with the amount of information disclosure provided. Moreover, I find that third-party provided information helps reduce the cost of capital for P2P platforms, with a similar effect being observed for voluntary financial (yet not operational) information disclosure. I attribute the insignificant effect of voluntary operational information disclosure on the cost of capital to the fact that the operating data and reports reveal details exclusively related to the operational status of a platform (e.g., operating days, borrowing and lending amount, investor and borrower number); to the extent that investors may be far from familiar with the operational structures of P2P lending platforms, operational information is likely to be of lower salience for P2P investors. As per government regulation, I report evidence suggesting that it dampens the cost of capital of P2P platforms, while bearing less of an effect on their default probability.

This study contributes significantly to the corporate finance literature on information disclosure (Diamond and Verrecchia, 1991; Botosan, 1997; Sengupta, 1998; Healy et al., 1999a; Verrecchia, 2001; Lambert et al., 2007, Goldstein and Yang, 2017; Ahmad et al., 2019) by demonstrating for the first time that multiple sources of disclosure can confer a positive impact over the performance of the P2P lending industry by reducing the cost of capital on platforms and allowing only those platforms with the strongest financial health to survive. Second, to the extent that default probability and cost of capital (average return from investor's perspective) on P2P platforms can reflect (and help shape) the behavior of participants (lenders and borrowers) on those platforms, the evidence produced here contributes to the debate on the role of regulatory evolution over investors' behavior (Gerding, 2007; Hirshleifer, 2008; Bohl et al., 2020; Krokida et al., 2020; Andrikopoulos et al., 2021). Third, since participants in the P2P lending market are predominantly small size participants, mainly retail investors and small/micro enterprise owners (Deer et al., 2015; Chen and Tsai, 2017; Lu, et al, 2020) and likely to be subject to noise trading in their behavior[12], my findings also contribute to the literature on the role of information in retail investors' behavior.[13] Last, this study contributes to the literature on newly innovative financial markets (i.e., P2P lending market, FinTech market) by presenting views from three distinct parties (third-party, platform, government), which significantly departs from previous studies of P2P lending markets, e.g., individual behaviors (Breuer et al., 2020; Tian et al., 2021), individual voluntary information disclosure (Berkovich, 2011; Herzenstein et al., 2011; Pope and Syndor, 2011; Duarte et al., 2012; Michels, 2012, Ge et al.,2017; Wang et al., 2020), and impacts of FinTech market (Fung, et al., 2020; Lyons et al., 2021). Therefore, this paper can inspire future research on financial innovation from multiple perspectives.

My results bear important implications for the authorities entrusted with the regulation of P2P lending platforms internationally, as they showcase that the performance of P2P lending platforms is not only affected by the disclosure requirements of state regulation, but also by information disclosed both via platforms, as well as by rating agencies. To that end, I suggest that P2P platforms' regulators should strive to ensure (perhaps even rendering it legally mandatory) the active engagement of both the platforms themselves, as well as third parties (like rating agencies), in the production and dissemination of information in order to help enhance this market's efficiency. Such regulation is

[12] See, for example, the literature on retail traders' behavior cited in Andrikopoulos et al. (2021).

[13] See, for instance, the evidence from Ke et al. (2017) and Chen et al. (2020) on the role of information in reducing the effect of numerological superstitions among retail traders in Taiwan and Hong Kong, respectively.

particularly needed when the less sophisticated background of the predominantly retail participants of P2P platforms is considered, as this raises serious concerns over the potential for adverse/irrational behavior in the market (the case e.g., of platforms with Ponzi scheme features) and the impact on social welfare (Chen and Tsai, 2017). In this context, state regulators would be wise to impose rules which prevent adverse selection issues from arising between rating agencies and platforms. These issues could arise, for example, in instances where platforms assign the rating of their products to specific rating agencies in anticipation of more positive ratings (prompting other rating agencies to offer more positive ratings in order to attract more business), thus undermining the integrity of such ratings (Zhi, 2016). Furthermore, regulatory authorities could consider improving the financial education of P2P platform participants via *ad hoc* designated financial literacy initiatives, as this could improve investors' understanding of the products on offer by those platforms. In general, for the innovative market (such as peer-to-peer lending market), government supervision should be pre-positioned rather than post-positioned of the market development; meanwhile, the third-party provided information and voluntary information disclosure should be considered during regulation because they have significant effect on reducing the risk and information asymmetry of market. My results are also of key relevance to P2P lending platforms participants, since the probability of default is an inverse function of the information available on a platform, suggesting that platform participants need to thoroughly evaluate the available information about each platform before deciding which one to opt for. This increased awareness can reduce the potential for adverse outcomes in participant investments. From the platforms' perspective, this also implies that platforms should maintain a high level of transparency in their informational environment, to ensure that they are able to both attract high-quality investors, and are also able to offer an environment where investors have the information necessary to perform their function as borrowers or lenders without issues of asymmetric information hampering their participation.

The rest of this paper is organized as follows: Section 2.2 outlines the development of the P2P lending market internationally (section 2.2.1.), the role of information disclosure in the industry (Section 2.2.2.) and how this industry has evolved in China (Section 2.2.3.). Section 2.3. presents my hypotheses, each motivated via the extant literature. Section 2.4. discusses the data employed and section 2.5. introduces my empirical design. Section 2.6. presents my empirical results and section 2.7. offers concluding remarks and discusses some implications from my findings.

2.2.Literature Review

2.2.1. P2P Platforms

P2P lending constitutes a financial innovation, whereby individual borrowers can receive money directly from individual lenders at a fixed interest rate, without the involvement of traditional financial intermediaries. As a general observation, P2P lending markets internationally act as intermediaries, allowing lending transactions to be undertaken on their online platforms; the loan products offered may be either unsecured or secured, are usually not protected by government insurance and (for some platforms only) their ownership can be transferred. According to the data published in Paypers[14], P2P lending markets are more popular in developed countries, with the demand for and size of the markets expected to grow rapidly in these developing countries, as the income levels and technology penetration for their populations increase.

The first P2P lending platform in the world, Zopa, was established in the UK in 2005, followed by similar platforms launched shortly thereafter in the United States, Japan and Italy. At first, Zopa provided P2P community micro-loan services with borrowing amounts averaging between $1,000 and $25,000, and interest rates being completely negotiable among the parties to the transaction. To rate the reliability of borrowers, platforms employed a four-level credit scoring method (A*, A, B, and C), allowing the lender to tailor loans according to the borrower's internal credit rating, loan amount and loan time limit.[15] This allowed the borrower to choose a loan interest rate they found acceptable. To reduce risk, Zopa automatically divided the lender's funds into small tranches of £50. The lender could lend these small tranches to different borrowers, and

[14] Paypers (https://thepaypers.com/) is a Netherlands-based leading independent source of news analysis for the global fintech, payments and ecommerce industry.

[15] In October 2019, Zopa changed this rating method into a new 'Borrowing Power' tool, which offers would-be borrowers a personalized score between 1 and 10, as a measure of their attractiveness to lenders. It's calculated using a combination of credit score data (Experian, Equifax and Transunion), how much credit the customer is using, credit limits, hard searches and affordability. The tool is part of Zopa's app, available on Apple and Android, and is free to use (one does not need to have or be applying for a Zopa product to be able to use it). Zopa claims the tool only uses 'soft' credit searches to get information, so credit scores shouldn't be affected by using it.

each borrower would repay the overall loan in monthly instalments. Zopa has provided nearly 500,000 borrowers with more than £5 billion in loans until 2020, and more than 60,000 investors have received more than £350 million in income during the past fifteen years.[16]

After the appearance of Zopa, the P2P lending market started to develop in the US, with the launch of Prosper in 2006 and the Lending Club in 2007. As of 2020, there were 251 P2P platforms available outside mainland China; 146 are located in Europe, 35 in North America, 43 in Asia, 9 in Australia, and 18 in South America and Africa.[17] The pace of P2P platform growth accelerated after the global financial crisis in 2008; although most financial institutions suffered major losses during that crisis, P2P lending platforms endured fewer losses and managed to maintain the stability of their market segment (in terms of both market value and market size) during this period (CreditEase Research Institute, 2020). Post 2008 saw P2P platforms enjoying widespread attention from the financial industry and recording rapid growth internationally; the size of the global P2P lending market reached $67.93 billion by the end of 2019, and is predicted to grow further through 2027 (Khan, 2020).

[16] These data and information published on the website of Zopa. Available at: https://www.zopa.com.
[17] Source: https://p2pmarketdata.com/p2p-lending-platforms-of-the-world/

2.2.2. P2P Platforms and Information Disclosure

Information disclosure constitutes a key response to issues of information asymmetry (Akerlof, 1970) and agency problems (Jensen and Meckling, 1976; Smith and Warner, 1979) between transacting parties. Evidence suggests that information disclosure helps reduce a firm's cost of capital (Diamond and Verrecchia, 1991; Botosan, 1997; Sengupta, 1998), enhance equity performance (Healy et al., 1999a) and increase firm-profitability (Diamond and Verrecchia, 1991; Botosan, 1997; Sengupta, 1998, Verrecchia, 2001; Ahmad et al., 2019). Much of this disclosure emanates from financial intermediaries that reduce information asymmetry issues by acting as delegated monitors (Diamond, 1984; Boyd and Prescott, 1986), thus helping to allocate capital efficiently at minimum cost (Merton, 1989; 1993). In addition, government regulation has been found to alleviate the information asymmetry problem and mitigate market failures (Stiglitz, 1993; Kim et al., 2013; Li et al. 2017).

Recent investigations on information disclosure in P2P lending markets have focused on the risks inherent in asymmetrical access to information about borrowers' creditworthiness. Serrano-Cinca et al. (2015) find that loan purpose, the status of property ownership, credit history, and personal debt conditions are information types that could help explain the default of borrowers. Pope and Syndor (2011) assess the effect of borrowers' profile pictures on default and showed that loans taken from borrowers with no profile picture have a higher default rate. Herzenstein et al. (2011)

investigate whether identity claims affect loan performance. They find that narrative identity claims which include terms such as “trustworthy”, “successful”, “hardworking”, “economic hardship”, “moral” and “religious” have a negative effect on the default probability of borrowing and average lending rate; they were also found to have a greater impact on a lender's decision making compared to objective variables that reflect credit grade, gender, race, marital status, and family status. Michels (2012) finds that voluntary non-financial disclosures are significantly and negatively related to interest rates and future loan default probabilities of borrowers, and significantly and positively related to bidding activity on loans; these effects are amplified for borrowers with a relatively poor credit rating. Duarte et al. (2012) state that borrowers who have a more trustworthy appearance have lower default probabilities but will likely face increased lending rates for loans. Freedman and Jin (2008) and Lin et al. (2018) argue that voluntary information disclosure on behalf of platforms eliminates the information asymmetry between borrowers and lenders in the P2P lending market, with higher lending rates compensating for the voluntary information disclosure.

2.2.3. P2P Platforms and Information Disclosure in China

In 2007, the first P2P lending platform, Ppdai, appeared in China and subsequently led to mushrooming growth of P2P platforms in the country. The cumulative P2P lending online platforms reached 5,970 and the cumulative trading volume reached 6,103.60

billion RMB at the end of 2017[18]. Behind the rapid growth is the high default risk, it reached nearly 30% at the end of 2019 (see Chapter 1). The fast development and high risk of Chinese peer-to-peer lending market attracted the attention of researchers, prior studies have investigated loan performance (Zhang et al., 2019; Xiang et al., 2019; Li et al., 2020), investors' behavior (Zhang, et al., 2021; Tian, et al., 2021), and market competition (Wang, et al., 2021) in the Chinese P2P lending market, few have investigated the effect of information disclosure over these platforms' performance to date. Wang et al. (2020) constitutes the sole exception here, showcasing that platforms' audit information helps decrease the default probability among their financial products, with research on the impact of a broader variety of disclosure sources lacking at the moment.

2.3.Hypotheses Development

This study investigates the impact of various information disclosure sources (voluntary operational and financial information disclosure by platforms and third-party provided information) and considers government regulation's effect on the default probability and cost of capital of platforms in the Chinese P2P lending market.

[18] This is the cumulative number of platforms and trading volume. The number of operating platforms is 1,931 and the trading volume for 2017 is 244.3 billion RMB.

2. *Disclosure Sources, Regulatory Changes and Market Performance: Evidence from the Chinese Peer-to-Peer Lending Market*

Prior literature state that financial intermediaries have some intrinsic functions that could solve the moral hazard problem caused by information asymmetry (Campbell and Kracaw, 1980), and could overcome asymmetric information problems by acting as delegated monitors (Diamond, 1984; Boyd and Prescott, 1986). The third-party information dissemination platform or a rating agency in peer-to-peer lending market act as an important information intermediary to collect information of active peer-to-peer lending platforms and to provide indices and ratings of individual peer-to-peer lending platforms, which could be highly useful for investors. The third-party provided information could help on decreasing the information asymmetry, and then, increase the information transparency, in turn, could reduce the default probability of firms and platforms. Meanwhile, based on prior literature (Diamond and Verrecchia, 1991; Botosan, 1997; Sengupta, 1998; Verrecchia, 2001; Lambert et al., 2007), information disclosure could help reduce the information asymmetry in the financial market. In the P2P lending market, information disclosure can enhance investors' confidence in platforms (because of the publication of platforms' financial/operational information), reduce platforms' opportunistic behavior (given the greater transparency it fosters) and signal an image of a platform encompassing sufficient internal control and risk management systems. Furthermore, prior studies (Serrano-Cinca et al., 2015; Xiang et al., 2019; Wang et al., 2020) also find voluntary operational and/or financial information disclosure could reduce platforms' default probability. To test for these effects, my first set of hypotheses is stated as follows:

H1a: third-party provided information about P2P lending platforms has a significantly negative effect over these platforms' default probability.

H1b: voluntary operational and financial information disclosure made by P2P lending platforms has a significant negative impact on these platforms' default probability.

Gurley and Shaw (1960) state that intermediaries could reduce the transaction cost by diversification. Based on that, Merton (1989; 1993) develops a model which demonstrates that intermediaries can allocate risk efficiently at minimum cost. In P2P lending market, third-party intermediaries (such as WDZJ and P2PEYE) provide the third-party provided information, which also could help on reduce cost of capital of platforms.

In addition, bulk of extant research (Diamond and Verrecchia, 1991; Botosan, 1997; Sengupta, 1998; Verrecchia, 2001; Easley and O'hara, 2004; Wei and Gaofeng, 2004; Indjejikian, 2007; Lambert et al., 2007; Armitage and Marston, 2008; Dutta and Nezlobin, 2017; Zhou et al., 2018) investigate the effect of information disclosure on the cost of capital. Many studies find that the information disclosure could reduce firm's cost of equity capital (Diamond and Verrecchia, 1991; Botosan, 1997; Indjejikian, 2007) and debt capital (Sengupta, 1998), in addition, they find both compulsory and voluntary information disclosure (Verrecchia, 2001; Wei and Gaofeng, 2004), both quantity and quality of firm's information disclosure (Easley and O'hara, 2004) are associated with a lower cost of capital. Moreover, Lambert et al. (2007) show that the quality of a firm's information disclosure affects the cost of capital both directly. Recently, Armitage and Marston (2008) find that information disclosure could not only help decrease a company's cost of capital, but also help improve a company's reputation; Dutta and Nezlobin (2017) state that disclosure quality and cost of capital have a negative relationship for firms with low growth; and Zhou et al. (2018) find that water information disclosure level decreased the risk-taking of companies in high-water risk industry.[19] Moreover, most of the existing papers (Herzenstein et al., 2011; Michels, 2012; Duarte et al., 2012; Freedman and Jin, 2008; and Lin et al., 2018) state the significant effect of borrowers' voluntary information disclosure on the lending rate in the peer-to-peer lending market, these results indicate the significant power of voluntary information disclosure in P2P lending market.

I extend this research to the P2P lending market (which is a representative innovative and less developed market in the last decade) by examining both the effect of third-party provided information and platforms' voluntary operational and financial information disclosure on the platforms' cost of capital. Following prior literature (Campbell and Kracaw, 1980; Diamond, 1984; Merton, 1989; 1993), I expect rating indices provided by third-parties to be able to reduce the cost of capital. What is more, it is expected (based on Verrecchia, 2001; Wei and Gaofeng, 2004; Francis et al., 2008;

[19] Water risk mainly refers to the risk of water shortages faced by residents, enterprises and the natural world, including water-related physical, operational, regulatory, social reputation, economic and financial risks. High water risk industries/enterprises refer to industries/enterprises that are extremely vulnerable to water shortages.

Herzenstein et al., 2011; Duarte et al., 2012; Michels, 2012; Cheynel, 2013; Clinch and Verrecchia, 2015; and Lin et al., 2018) that voluntary operational and financial information disclosure will reduce the cost of capital. To test for these effects, the second set of hypotheses is as follows:

H2a: third-party provided information about P2P lending platforms has a significantly negative impact on platforms' cost of capital.

H2b: voluntary operational and financial information disclosure made by P2P lending platforms has a significant negative impact on platforms' cost of capital.

Government regulation has been viewed as a remedy for market failure caused by adverse selection and moral hazard problems associated with information asymmetry (Stiglitz, 1993). Prior literature documents positive effects of government regulation on the real economy and the capital market, with the net benefits of regulations accruing to both consumers and producers (Schwert, 1981). Aikins (2009) analyses the role of government regulation on financial markets during the global financial crisis (2008-2009) and demonstrates the positive effect of government regulation in terms of reducing market risk and fostering economic recovery from a theoretical perspective. More recently, Li et al. (2017) find that government regulation has a positive effect on the relationship between corporate environmental responsibility (CER) and corporate financial performance (CFP). Ashraf (2020) demonstrates that government policies and announcements (including public awareness programs; testing and quarantining policies; and income support packages) during the COVID-19 crisis had a positive effect on stock returns. But Kim et al. (2013) state that different regulations may have different effects; some regulations (e.g., limiting the banks' activity and entry requirements) can reduce the likelihood of a banking crisis, while other regulations (such as capital controls) can foment a currency crisis; Similarly, Zhou and Chen (2021) also state the different platforms have different responses to government regulation which indicate the multiple effect of government regulation. Moreover, Weiss (2008) uses three US government regulatory cases to argue that government regulation will encourage individuals and businesses to pay less attention to future expected risks which will in turn increase the risk-levels in the market. Pennathur et al. (2014) show that government regulations reduce wealth and increase market risk by investigating government regulations on banks, savings and loan associations (S&Ls), insurance companies, and real estate investment trusts (REITs) from 2007-2009. Also, recent evidence (Lo et al., 2019), finds that government regulation can influence P2P investors' preferences for private platforms, which tend to rely on higher return and – concomitantly - higher default probability rates.

In general, prior literature state the significant positive effect of government regulation on reducing information asymmetry (Stiglitz, 1993; Aikins, 2009) market risk (Aikins, 2009), but some studies also provide the evidence of the negative market effect of government regulation (Weiss, 2008; Pennathur et al., 2014). As an innovative market, P2P lending market has experienced the process of government regulation from scratch.

The gradually strict government regulation could also alleviate information asymmetry and reduce market risk. Therefore, government regulation is also considered to negatively affect the default probability (which is the measurement of risk) and cost of capital (since the decreasing information asymmetry will increase the market transparency, which help on reducing transaction cost) of platforms. To test for the effects of government regulatory intervention, my third set of hypotheses is as follows:

H3a: government regulatory intervention has a significant negative impact on P2P platforms' default probability.

H3b: government regulatory intervention has a significant negative impact on platforms' cost of capital.

2.4.Sample Selection

My sample consists of all Chinese P2P lending platforms which were both active at any point in time from September 2015 to December 2019 and for which data is available, in the CSMAR, WDZJ[20] and platforms' official website. I used the combined sample from three datasets: the dependent variables (Default probability (*DEFAULT*), cost of capital (*CC*)) and control variables (investor number (*IN*), net capital inflow (*NCI*), average loan time (*ALT*), and cumulative repay (*CR*)) were collected from CSMAR; all the rating indexes (trading index (*TRADI*), popularity index (*POPI*), technology index

[20] WDZJ is a third-party information dissemination intermediary that publishes the data of the whole Chinese peer-to-peer lending market and each of its individual platforms in the Chinese peer-to-peer lending market. Although the data published in WDZJ is no longer public, we have downloaded and saved all rating indexes data.

(*TECI*), leverage index (*LEVI*), liquidity index (*LIQI*), dispersity index (*DISI*), transparency index (*TRANI*), brand index (*BRAI*), revenue income index (*REVI*), and development index[21] (*DEVI*)) were collected from WDZJ (even though the data in WDZJ is not publicly available now, but we have downloaded all the data, and the data is available if requested); and all the information disclosure data (operational data (*OD*), operational report (*OR*), audit report without financial information (*ARWOFI*), unaudited financial data (*ADO*), audited informal financial data (*AFD*), audited formal financial statement (*AFS*), operational and financial disclosure[22] (*FDIS*)) were collected from official website of each peer-to-peer platform (this data is also available if requested).

Insert Table 2.1 about here

As shown in Table 2.1, after merging the platforms' rating indices'[23] dataset published by WDZJ with the CSMAR dataset, my final sample includes monthly data from 170 P2P lending platforms between September 2015 and December 2019. The total number of observations is 4,813; 3,410 of them are in the survival subsample, while 1,403 of them in the default subsample. My study starts from September 2015 (because CSMAR and WDZJ began publishing information about P2P lending platforms since that date) and ends in December 2019.

[21] The development index is a composite index, calculated as the weighted average of these nine individual rating indices. The weights calculated and published by WDZJ. DEVI = TRADI*12% + POPI*11% + TECI *5% + LEVI*6% + LIQI*12% + DISI*5% + TRANI*11% + BRAI*20% + REVI *18%

[22] Operational and financial disclosure is a quality measure of financial disclosure. It is calculated by the sum of *OD*, *OR*, *ARWOFI*, *FDO*, *AFD*, and *AFS*.

[23] Rating indices published by WDZJ include nine separate indices and one composite index. WDZJ publishes the top 100 platform's rating indices every month since September 2015.

To evaluate the effect of voluntary information disclosure on the default probability and the cost of capital at the platform level, I develop a measure of voluntary operational and financial disclosure. There are two levels of voluntary operational and financial information disclosure: (1) operational information, which can either involve informal operational data or a formal operational report; and (2) financial information, which can be an audit report without published financial information, unaudited financial data, audited informal financial data, or an audited formal financial statement. One point is awarded for each item of operational data, operational report, audited report without financial data, unaudited financial data, audited financial data, and audited financial statement. The sum of all points awarded to a platform is the index of operational and financial disclosure (*FDIS*).

I manually collected operational and financial information disclosure data (totaling 4,813 monthly platform-observations) from my sample platforms' respective websites. Table 2.1 shows that 729 platform-observations involve no disclosure of operational and financial information, while 4,084 platform-observations involve disclosure of operational and/or financial information voluntarily, which means most of my sample platforms disclose at least one kind of operational and/or financial information. I then separate different types of operational and financial information disclosed voluntarily by platforms and find that 3,842 platform-observations correspond to disclosed operational information (1,046 platform-observations correspond to disclosed operational data only; 1,756 platform-observations correspond to disclosed operational reports only; and 1,040 platform-observations correspond to both operational data and operational reports disclosed), while 2,384 platform-observations correspond to disclosed financial information (653 platform-observations correspond to audit reports disclosed without financial data and financial statements; 52 platform-observations correspond to disclosed financial data only; 1,004 platform-observations correspond to audit reports disclosed with financial data; and 2,282 platform-observations correspond to disclosed audited financial data and financial statements).

2.5.Models

The following Probit regression[24] in model (1) is the base model for default probability (*DEFAULT*) which is built up based on prior literature findings.[25] *DEFAULT* represents default probability of platforms, which is measured as 1 if the platform has defaulted, and 0 if the platform has survived. *CC* represents cost of capital of platform, which is also the average return provided and accepted to investors. *IN* represents investor number of platform, which is the monthly total investor numbers of platform. *NCI* represents net capital inflow of platform, which is the monthly net capital inflow of platform. *ALT* represents average loan maturity of platform, which is the monthly average loan period of platform. *CR* represents cumulative repay of platform, which is

[24] The Probit regression and Logistic regression are usually used for regression where the dependent variable is dichotomous. The dependent variable in the Probit and Logistic model can be of the class of binary nonlinear difference equations or multi classification, but the binary classification is more commonly used and easier to explain.

[25] The definitions of all variables are shown in Appendix 2.1.

the monthly cumulative outstanding loans of platform. *BD* represents banking deposits, which is measured as 1 if the capital custody in banks is implemented (the capital of the platform has been put into a banking account) and 0 otherwise. *DEAR* represents disclosed external assessment report, which is measured as 1 if external assessment report given, 0 otherwise. *L* represents platform geographical location and *B* represents the background of platform. Research has shown that cost of capital (*CC*) will significantly increase the default probability of platforms (Gilchrist and Zakrajsek, 2007; Chava and Purnanandam; 2010); location (*L*) and background (*B*) could affect the default probability of platforms (Jiang et al., 2019; Lufax, 2014); the liquidity of platforms (net capital inflow (*NCI*) could reduce the default probability of platforms (Jiang et al., 2019); the size of platforms (investor number (*IN*)) (Fama and French, 1993; 1996; Carhart, 1997; Vassalou and Xing, 2004) have significant negative effect on default probability of platforms; the higher average lending period (*ALT*), the higher default probability of platforms (Serrano-Cinca et al., 2015); and the lower solvency (which means the higher cumulative repay[26] (*CR*)), the higher default probability of platforms. Moreover, banking deposits (*BD*)[27] and disclosed external assessment reports (*DEAR*)[28] are regarded as safeguarding mechanisms of platforms, so I expect they will produce a significant effect on the default probability of platforms (Feinman,

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[26] It is the outstanding loans of platforms.

[27] Banking deposits represents whether the platform butt joints with banks (the capital of the platform has been put into a banking account).

[28] An external assessment report is suggested by the Chinese government and is issued by a legal firm to confirm the compliance of the platform.

1993). To begin with, I assess the default probability of platform *i* at time *t* via the following specification:

$$
\begin{aligned}
DEFAULT_{it} = {} & \alpha_{it} + \beta_1 CC_{it} + \beta_2 IN_{it} + \beta_3 NCI_{it} + \beta_4 ALT_{it} \\
& + \beta_5 CR_{it} + \beta_6 BD_{it} + \beta_7 DEAR_{it} \\
& + \sum_{n=1}^{4} \beta_8 L_{it} + \sum_{n=1}^{4} \beta_9 B_{it} + \varepsilon_{it} \quad (1)
\end{aligned}
$$

To test the effect of the third-party provided information on the default probability, I create the model (2) that controls all the independent variables in the model (1) as *Controls*. Model 2 is specified as:

$$DEFAULT_{it} = \alpha_{it} + \beta_1 DEVI_{it} + \sum_{n=2}^{n} \beta_n Controls_{it} + \varepsilon_{it} \quad (2)$$

In model (2), the dependent variable is *DEFAULT*, which measures the default probability of a platform; it assumes the value of 1 if the platform has defaulted, and 0 if the platform has survived. The key explanatory variable is *DEVI* (development index), reflecting third party provided information represented via rating indices; the latter are published by WDZJ and are calculated according to the different conditions of platforms (such as safety condition, technology condition, percentage loan amount of top ten borrowers, the percentage lent amount invested by top ten lenders and so on).[29] *DEVI* is a composite index comprised of 9 sub-indices, namely: trading index (*TRADI*), popularity index (*POPI*), technology index (*TECI*), leverage index (*LEVI*), liquidity

[29] All the detailed calculations are offered in the appendices.

index (*LIQI*), dispersity index (*DISI*), transparency index (*TRANI*), brand index (*BRAI*) and revenue income index (*REVI*). Following the literatures (Gurley and Shaw, 1960; Merton, 1989; Merton, 1993), I expect that rating indices provided by third-party financial intermediaries (such as WDZJ here) will reduce P2P platforms' default probability, as I mentioned in H1a.

To account for the impact of voluntary operational and financial information disclosure, the following model (3) is established:

$$DEFAULT_{it} = \alpha_{it} + \beta_1 DEVI_{it} + \beta_2 FDIS_{it} + \sum_{n=3}^{n} \beta_n Controls_{it} + \varepsilon_{it} \quad (3)$$

In model (3), *FDIS* (voluntary operational and financial information disclosure) is added as an additional explanatory variable based on model (2). Operational and financial disclosure is an index that describes the quantity of operational and financial information disclosed voluntarily by platforms. *FDIS* is a composite index representing the sum of 6 disclosure proxies: *OD* (disclosing operational data); *OR* (disclosing operational report); *ARWOFI* (disclosing audit report without financial information); *FDO* (disclosing financial data only); *AFD* (disclosing audited financial data); and *AFS* (disclosing audited financial report). According to prior studies (Serrano-Cinca et al., 2015; Xiang et al., 2019)[30], it is expected that voluntary operational and financial information disclosure will reduce platforms' default probability.

[30] Serrano-Cinca et al. (2015) state that borrowers' information disclosure could decrease the default probability. Xiang et al. (2018) demonstrate that platforms that disclose operational information could witness a decrease in their default probability.

Model (4) below is the base model for investigating the determinant of cost of capital (*CC*). Prior theories and studies show that the risk free rate (*RF*) and the consumer price index (*CPI*) have positive relations on cost of capital on platforms (Feldstein and Eckstein, 1970; Barth, et al., 2013; Hussain, et al., 2019); location (*L*) and background (*B*) of a platform (Jiang et al., 2019); Lufax, 2014) could affect the cost of capital; the liquidity of platforms (net capital inflow (*NCI*) (Diamond and Verrecchia, 1991; Omran and Pointon, 2004) will decrease the cost of capital of platforms; the size of platforms (investor number (*IN*)) (Fama and French, 1993; 1996; Carhart, 1997; Vassalou and Xing, 2004; Barth, et al., 2013; Hussain, et al., 2019) could reduce the cost of capital; the average lending period (*ALT*) (Michels, 2012) can significantly increase the cost of capital. Also, for the cumulative repay[31] (*CR*), I expect it will help on reducing cost of capital of platforms. As safeguarding mechanisms of platforms (Feinman, 1993), banking deposits (*BD*) and the external assessment report (*DEAR*) are expected to impact the cost of capital (*CC*) of platforms. Based on the above-noted literature, I assess the cost of capital of platform *i* at time *t* via the following specification:

$$\begin{aligned} CC_{it} = \alpha_{it} + \beta_1 RF_{it} + \beta_2 CPI_{it} + \beta_3 IN_{it} + \beta_4 NCI_{it} \\ + \beta_5 ALT_{it} + \beta_6 CR_{it} + \beta_7 BD_{it} + \beta_8 DEAR_{it} \\ + \sum_{n=1}^{4} \beta_9 L_{it} + \sum_{n=1}^{4} \beta_{10} B_{it} + \varepsilon_{it} \quad (4) \end{aligned}$$

To investigate the impact of third-party provided information over the cost of capital of

[31] Outstanding loans of platforms.

P2P platforms, I employ the model (5) that controls all the independent variables in model (4) as *Controls* and model (5) is shown in the following equation:

$$CC_{it} = \alpha_{it} + \beta_1 DEVI_{it} + \sum_{n=2}^{n} \beta_n Controls_{it} + \varepsilon_{it} \quad (5)$$

In model (5), I test whether rating indices provided by third-parties are able to reduce cost of capital. Following prior literatures (Diamond and Verrecchia, 1991; Botosan, 1997; Sengupta, 1998; Verrecchia, 2001; Easley and O'hara, 2004; Wei and Gaofeng, 2004; Indjejikian, 2007; Lambert et al., 2007; Armitage and Marston, 2008; Dutta and Nezlobin, 2017; Zhou et al., 2018), I expect that rating indices provided by third-party financial intermediaries will reduce P2P platforms' cost of capital, as I mentioned in H2a.

To account for the impact of voluntary operational and financial information disclosure over the cost of capital, I extend Equation (5) as follows:

$$CC_{it} = \alpha_{it} + \beta_1 DEVI_{it} + \beta_2 FDIS_{it} + \sum_{n=3}^{n} \beta_n Controls_{it} + \varepsilon_{it} \quad (6)$$

In model (6), *FDIS* (voluntary operational and financial information disclosure) is added as an explanatory variable. This is motivated by prior studies (Herzenstein et al., 2011; Michels, 2012; Jiang et al., 2019; Freedman and Jin, 2008; Lin et al., 2018) which show that information disclosure will reduce information asymmetry and significantly affect returns for investors. Therefore, it is expected that voluntary operational and financial information disclosure made by platforms will decrease the cost of capital.

In addition, the impact of government regulatory intervention on the relationship between disclosure and platform default probability and cost of capital are examined by the following specification:

$$DEFAULT_{it} = \alpha_{it} + \beta_1 DEVI_{it} + \beta_2 FDIS_{it} + \beta_3 GR_{it} + \beta_4 DEVI*GR_{it} + \beta_5 FDIS*GR_{it} + \sum_{n=6}^{n} \beta_n Controls_{it} + \varepsilon_{it} \quad (7)$$

$$CC_{it} = \alpha_{it} + \beta_1 DEVI_{it} + \beta_2 FDIS_{it} + \beta_3 GR_{it} + \beta_4 DEVI*GR_{it} + \beta_5 FDIS*GR_{it} + \sum_{n=6}^{n} \beta_n Controls_{it} + \varepsilon_{it} \quad (8)$$

In Models (7) and (8) *DEVI*GR* and *FDIS*GR* are two interaction terms employed to assess whether government regulatory intervention (proxied here by *GR*, a dummy which equals 1 for the period after the regulation, 0 otherwise) displays a moderating effect or not on the relation between the dependent variables (*DEFAULT*, *CC*) and testing variables (*DEVI*, *FDIS*). Previous studies (Schwert, 1981; Stiglitz, 1993; Weiss, 2008; Aikins, 2009; Kim et al., 2013; Pennathur et al., 2014; Li et al., 2017; Lo et al., 2019; Ashraf, 2020; Zhou and Chen, 2021) state the effect of government regulation could be positive (Schwert, 1981; Stiglitz, 1993; Aikins, 2009; Li et al., 2017; Ashraf, 2020) or negative (Kim et al., 2013; Zhou and Chen, 2021; Weiss, 2008; Pennathur et al., 2014; Lo et al., 2019), since peer-to-peer lending market is an innovative and high risk market, I expected the government regulation has the power on reducing default probability and cost of capital of platforms.

2.6.Empirical Results and Analysis

2.6.1. Descriptive Statistics

Descriptive statistics for my sample variables are reported in Table 2.2. The mean of default probability (*DEFAULT*) is 0.292, which implies that the majority of observations are survivors during my sample window.[32] The mean of the cost of capital (*CC*) of the platform is 9.466 and the average risk-free rate (*RF*) is 3.368, thus suggesting that P2P lending platforms in China extend financing at almost 6 points over the country's risk-free rate. The mean value of *ALT* is 8.237, indicating that the life of the average loan is 8 months. Among my control variables, investor number (*IN*), net capital inflow (*NCI*), and cumulative repay (*CR*) have the highest standard deviations and therefore, I transform all the continuous control variables into log form.[33] The mean of the development index (*DEVI*) is 55.038.[34] The mean of operational and financial disclosure (*FDIS*), is 1.844, thus suggesting that, on average, Chinese P2P platforms publicize a moderate number (around two) of disclosure items.

Insert Table 2.2 about here

[32] The default mean of platform-observations is 0.292 (i.e., 29.2%); the default rate of platforms is 0.383 in this sample (the total number of platforms is 170 and the number of survival platforms 105). The default mean is for platform-observations and the default rate is for platforms, the range is different.
[33] Transforming these variables into log form is due to the skewed distribution of their original form.
[34] *DEVI* ranges from 0 to 100; the higher the value of *DEVI*, the better the quality of a platform is considered by WDZJ; the mean value of 55.038 lies is in the middle of the range.

2.6.2. Correlation Analysis

The correlation matrix in Table 2.3 for my sample's variables shows all correlations are less than 0.7, with most of them being less than 0.5 (results not tabulated, available on request). This means that multicollinearity is likely not an issue with my data. I also compute the VIF value in each regression; all VIF values are less than 7 and all mean VIF values are less than 3 which also demonstrates that the multicollinearity is not a concern in my study.

Table 2.3 also shows the univariate relationships between dependent variable *DEFAULT* and testing variables *DEVI* and *FDIS*, and the univariate relationships between *CC* and *DEVI* and *FDIS*, as well as other control variables. Both the *DEFAULT* and the *CC* are negatively and significantly correlated with *DEVI* and *FDIS*, indicating that rating indexes and operational and financial disclosure can help reduce default probability and average lending rate of platforms. These results are consistent with Hypothesis 1 and 2. However, these results need to be cautious since other influencing factors are not controlled in univariate analysis.

Insert Table 2.3 about here

Table 2.4 shows the correlations between all rating indexes. All correlations are less than 0.7, most of them are less than 0.3 which prove that the multicollinearity is not a concern in my data.

Insert Table 2.4 about here

2.6.3. Comparison Analysis

Table 2.5 compares the differences in testing and controlling variables between default platforms and survival platforms. All the mean differences between default and survival are statistically significant. The mean of *DEVI* for default platforms is 3.911, while the mean of *DEVI* for survival platforms is 4.027. The t-test indicates the significant difference between them. This result means the development index of survival platforms is significantly higher than the default platforms. The mean of *FDIS* for default platforms is 1.085, while the mean of *FDIS* for survival platforms is 2.156. The t-test results indicate the operational and financial disclosure score of survival platforms is significantly higher than the default platforms. This result indicates that survival platforms disclose more operational and financial information.

Insert Table 2.5 about here

Table 2.6 compares the differences in testing and controlling variables for the platforms in different locations. Half of the control variables show significant differences in different locations. The data shows there is no significant differences on default between platforms in East and West economic regions, but the significant differences on default between platforms in East or West and Central region. The default of platform gradually decreases from the East, West, and Central regions may because that the number of platforms increases from the East, West, and Central regions. T-test results indicate there are significant differences in *DEVI* and *FDIS* among different locations. The cost of capital varies a lot in different locations, *IN*, *ALT*, and *CR* all show significant differences in different locations. The significant differences in *DEVI* and *FDIS* among East, West, and Central economic region mean that the level of third-party provided information in the East economic region is higher, and operation and financial information disclosure in the East and Central economic region is much higher. However, the significant differences in interest rate among different regions show that the average lending rate is highest in the West economic region.

Insert Table 2.6 about here

Table 2.7 reports mean differences in different background platforms. Results show most variables are statistically significant. The T-test results indicate *DEVI* and *FDIS* are significantly different among different background platforms. The cost of capital varies a lot among platforms with different backgrounds, so do *IN*, *ALT*, and *CR*. There are significant differences in *DEVI* and *FDIS* among platforms held by private companies, venture capitals, listed companies, and state-owned companies. The highest level of third-party provided information and voluntarily disclosed operation and financial information is in the platforms held by venture capitals and listed companies. The default probability is relatively lower in these platforms. In contrast, platforms held by private companies disclose the least information, so the default probability of private platforms is also higher. Interest rates are also differing significantly among platforms with different backgrounds. All the data shows the platforms held by listed companies perform better in information disclosure, therefore, they have lower default probability.

Insert Table 2.7 about here

2.6.4. The Relationship between Default Probability and Sources of Disclosure of Platforms

Table 2.8 presents the results for Models (1) to (3). The signs of the coefficients for most variables in Model (1) are as expected, except the coefficients of *ALT*. Average loan time (*ALT*) is negatively related to *DEFAULT*. One of the explanations for the negative coefficient of *ALT* is that platforms with small size and low quality tend to offer more short-term loans (WDZJ, 2017), this may motivate the negative *ALT* coefficient.

With respect to the development index (*DEVI*) – the key variable of interest here - results in Panel A of Table 2.8 show that the sign of *DEVI* is negative and significant, which is consistent with H1a. When the components of that index are used separately in Model (2-2), the results in Panel A of Table 2.8 show that popularity index (*POPI*), liquidity index (*LIQI*), and transparency index (*TRANI*) are significantly positively related to *DEFAULT*; trading index (*TRADI*), leverage index (*LEVI*), dispersity index (*DISI*), and brand index (*BRAI*) are significantly negatively related to *DEFAULT*; technology index (*TECI*) and revenue_income index (*REVI*) are unrelated to *DEFAULT*. These results suggest that it is only the overall third-party provided information index and four components of it (*TRADI*, *LEVI*, *DISI*, and *BRAI*) that are useful in reducing default probability in the P2P lending market. It is possible that the third-party index helps predict a more accurate picture of the default probability in the P2P lending market, being a single gauge that synthesizes various aspects of a platform's operations and thus encompassing a wide breadth of information.

Based on several P2P lending studies (Herzenstein, et. al., 2011; Michels, 2012), information disclosed voluntarily by platforms could provide more useful information to investors. Combined with studies on the effect of financial information disclosure in corporate finance (Bostan, 1997; Sengupta, 1998), I compute operational and financial disclosure indices for each P2P lending platform (reflected via *FDIS*). The effect of operational and financial disclosure on default probability is shown in Panel B of Table 2.8. The coefficient of *FDIS* in Model (3) is negative and statistically significant. The coefficient -0.114 indicates that each additional voluntary operational and financial information disclosure helps reduce the default probability by 11.4 percentage points; these results are consistent with H1b.

To identify whether it is operational or financial information disclosure that more strongly motivates this negative effect over default probability, I classify the six types of voluntary operational and financial information disclosure into two groups, namely Operational information (*OI*) and financial information (*FI*), and estimate the effect of each on the default probability. The results in Model (3-1) show that both *FI* and *OI* bear a significantly inverse relationship to *DEFAULT*, particularly *FI*, whose coefficient is over nine times the magnitude of that of *OI*. This suggests that it is the financial aspects of voluntary information disclosure that are more important for the reduction of the default probability of P2P platforms in China. The results in Model (3-2) show each coefficient of individual operational and financial information disclosure types. The *OD* (operational data) shows significant effect in reducing the default probability, while the *OR* (operational report) does not; all the financial disclosures (*FDO* (financial data), *ARWOFI* (audit report without financial information), *AFD* (audited financial data) and *AFS* (audited financial statement)) show the strong effects on reducing *DEFAULT* (more so for *AFS*, which demonstrates the strongest negative effect over *DEFAULT*).

Insert Table 2.8 about here

Having used the Probit model to examine the effect of information disclosure on the default probability, I also use AUC to evaluate the predictive power of models 1 to 3 (Huang and Ling, 2015).[35] The results show that the AUC of the base model (model 1) is 0.7443 (which means that the base model can predict default with 74.43% accuracy), the AUC of model (2) is 0.7732 (indicating that the model can predict default with 77.32% accuracy), while the AUC of Model (3) is 0.8245 (implying that the model can predict default with 82.45% accuracy). All AUCs are higher than 0.5, thus suggesting that the predictive powers of these models are better than random guesses.

Insert Table 2.9 about here

[35] AUC is a standard metric used to assess models that predict classification probabilities and the higher its value, the better the predictive ability of the model.

2.6.5. The Relationship between Cost of Capital and Sources of Disclosure of Platforms

Table 2.10 presents the results for Model (4) to Model (6). The signs of the coefficients of most variables in Model (4) are in line with expectations, except for the risk-free rate (*RF*), investor number (*IN*), and net capital inflow (*NCI*). Surprisingly, the risk-free rate, which is proxied by the monthly SHIBOR, is negatively related to the cost of capital. One possible reason is that the shadow banking market (P2P lending market is one of the shadow banking in China) and traditional banking market are operating oppositely in China. Chen et al. (2018) state that the contractionary monetary policy (which will lead to the higher *SHIBOR*, the risk-free rate in my paper, boosts the capital into the shadow banking market (P2P lending market), the higher competition driven by increased investors reduces the return required by investors, which dampen the cost of capital of platforms. An explanation for the positive relationship between investor number (*IN*)/net capital inflow (*NCI*) and cost of capital (*CC*) of platform may be the characteristic of cost of capital in the P2P lending market, where it is not only the cost of capital of platform but also the return accepted by investors.

To assess the impact of information disclosure over cost of capital, I add the development index (*DEVI*) in Model (5). The results in Panel A of Table 2.10 show the sign of *DEVI* is negative and statistically significant, thus suggesting that third-party provided information significantly reduces the cost of capital (*CC*) of platforms, confirming hypothesis H2a. Results from Model (5-1) further indicate that technology

(*TECI*), transparency (*TRANI*), brand (*BRAI*), and revenue income (*REVI*) indices significantly reduce the average lending rate of platforms and leverage index (*LEVI*) also bear a similar, yet insignificant, effect. In contrast, the popularity index (*POPI*) and dispersity (*DISI*) are found to increase the cost of capital of P2P platforms, and trading index (*TRADI*) and liquidity index (*LIQI*) have an analogous impact, but not significantly.

Panel B of Table 2.10 shows testing results for the impact of operational and financial information disclosure on P2P platforms' cost of capital. The sign of *FDIS* in model (6-1) is negative but insignificant and, thus not consistent with H2b. When I re-estimate model (6-1) by classifying the six types of financial information disclosure into two groups (*OI* and *FI*) and present the results in model (6-2), I find that *FI* (financial information) has a significant effect on reducing the cost of capital, but *OI* (operational information) does not. This suggests that the voluntary financial information disclosure is more important than that of the operating information for investors. The results in Model (6-3) further show that the *OR* (operational report) bears a positive and significant effect over cost of capital, while the *OD* (operational data) does not. What is more, audited financial statement (*AFS*) and audited financial data (*AFD*) shows significantly strong power to reduce the cost of capital, but the *FDO* presents a weaker effect. The above suggests that the effect of the total operational and financial disclosure index (*FDIS*) is mainly rooted in financial information disclosure (*FI*), which maintains its strong and significant effect in terms of both reducing the default probability and the cost of capital in the P2P lending market of China. Within the financial information disclosure, the audited financial statement variable shows the quite high significantly negative effect on reducing the cost of capital of platforms (the coefficient -0.0555 suggests that it decreases the cost of capital by 5.55 percentage points).

Insert Table 2.10 about here

2.6.6. Effect of Government Regulation

I now turn to investigate the effect of government regulatory intervention over the default probability of P2P platforms. There are two main critical government regulations on the Chinese P2P lending market, which were promulgated in August 2016[36] and March 2018.[37]

Table 2.11 displays the results of the effect of each of the two government regulations on the default probability, both separately (Models 7-1 and 7-2) and in interaction with the disclosure variables (*DEVI*GR1*, *FDIS*GR1* in Model 7-1; *DEVI*GR2FDIS*GR2* in Model 7-2). Prior literature finds that the effect of government regulatory intervention on the default probability of firms (platforms) can be negative (Stiglitz,

[36] In August 2016, the China Banking Regulatory Commission published its 'Interim Measures for the Management of Business Activities of Internet Lending Information Intermediaries' (available at: http://www.cac.gov.cn/2016-08/25/c_1119451974.htm). This is the first regulation that include some mild restrictions, such as banning the establishment of capital pools, requiring registration management of platforms, clarifying business rules in the market, and instituting supervision and management measures.

[37] In March 2018, the China Banking Regulatory Commission - Office of the Leading Group for the Special Campaign against Internet Financial Risks published the 'Notice on Intensifying the Corrective Action on Asset Management Business through the Internet and Conducting Acceptance Work' (available at: http://www.wfgx.gov.cn/GXQXXGK/TRZZX/201804/t20180408_2759009.html). This is an enhanced regulation that include some strong restrictions, such as prohibiting platforms' fund-raising in disguised forms, collection of public deposits, issuance of securities, strictly requiring the register capital and the scale of platforms, force withdrawing those (platforms) do not meet the requirement.

1993; Kim et al., 2013; Li et al., 2017; Giamporcaro et al., 2019; Ashraf, 2020), as well as positive (Weiss, 2008; Pennathur et al., 2014; Lo et al., 2019). However, my results in Table 2.11 demonstrate that neither government regulatory intervention conferred any significant impact over the default probability of Chinese P2P platforms. In addition, the interactive results show the regulations have negatively affected the relationship between *FDIS* and *DEFAULT* (with the significantly negative coefficient of interactive terms *FDIS*GR1* and *FDIS*GR2*) which demonstrate that the effect of voluntary operational and financial information disclosure (*FDIS*) on reducing default probability strengthened with the government regulatory intervention (*GR*). The possible interpretation of these results is that the government regulation helps remove some low-quality platforms and strengthen the role of *FDIS*.

Insert Table 2.11 about here

The effects of the two government interventions over cost of capital, both separately and in interaction with the disclosure variables (*DEVI*GR1*, *FDIS*GR1* in Model 8-1; *DEVI*GR2*, *FDIS*GR2* in Model 8-2), are shown in Table 2.12. Results in Table 2.12 suggest that both regulations have negatively affected cost of capital (consistent with hypothesis 3b) which means cost of capital of P2P platforms have been reduced after regulations promulgated. Meanwhile, the moderating effect of regulation appears on both third-party provided information and operational financial information disclosure. The significantly positive interactive terms (*DEVI*GR1*, *DEVI*GR2*, *FDIS*GR1*, and *FDIS*GR2*) show that the government regulatory intervention (*GR*) could alleviate the effect of third-party provided information (*DEVI*) and voluntary operational and financial information disclosure (*FDIS*) on cost of capital on platforms. The possible explanation of these results is that the government regulations improve the market environment, thereby reducing the disclosing role played by *DEVI*/*FDIS* on cost of capital.

Insert Table 2.12 about here

2.6.7. Robustness Tests

To ascertain the robustness of my findings, I perform a battery of tests. I begin by estimating a random-effect regression specification for the subsample (105) of survived platforms. Results are presented in Table 2.13 and are qualitatively similar to those from the full sample. More specifically, similar to results in Table 2.10, the testing variables - *DEVI* (which measures the third-party provided information), retains its significantly negative effect on the cost of capital of platforms, while *FDIS* bears an insignificant effect. Similar to the results in Table 2.10, using operational information disclosure and financial information disclosure separately, I find that financial information disclosure (*FI*) shows a significant effect on reducing the cost of capital, with audited financial statements (*AFS*) being a strongly negative effect.

Insert Table 2.13 about here

To mitigate possible endogeneity concerns, I employ a dynamic panel regression model[38], using the lag of explanatory variables as the instrumental variable to deal with endogeneity. All results are reported in Tables 2.14 and are similar to the panel regression results: both third-party provided information and financial information disclosure have a significant effect in terms of reducing the cost of capital of platforms.

Insert Table 2.14 about here

2.7.Conclusion

Although P2P lending platforms are typified by issues of information asymmetry between transacting parties, the effect of information disclosure emanating from diverse sources (platforms and ratings agencies) over the P2P-industry's performance has received rather limited attention to date. I address this issue by investigating the impact of distinct sources of disclosure (voluntary operational and financial information disclosure by platforms; third-party provided information) over two aspects of P2P-platform performance (default probability; cost of capital) in the context of the Chinese P2P lending market, drawing on data from 170 P2P platforms in China for the 2015-2019 window. Unlike previous studies of the P2P market internationally, which are based on single platforms (due to the small number of platforms in most countries) and voluntary information disclosure only, my study is the first to investigate the

[38] The dynamic panel regression is one of methods to deal with endogenous problem. The basic idea of the dynamic panel regression method is to use the lags of the explanatory variable or the explained variable as the instrumental variable (IV).

relationship between information disclosure and P2P platform performance at a multi-platform level and conditioned on various types of disclosure.

My empirical results indicate that the default probability of Chinese P2P lending platforms is significantly affected (in different directions) by all information disclosure channels (third-party provided information; voluntary operational and financial information disclosure) relevant to the P2P industry; with the exception of the subset of voluntary operational information, the remaining information disclosure sources (third-party provided information; voluntary financial information disclosure) and government regulatory intervention also help reduce the cost of capital for those platforms; meanwhile, government regulatory intervention moderates both the impact of voluntary operational and financial information disclosure on the default probability, and the effect of the third-party provided information and the voluntary operational and financial information disclosure on the cost of capital of platforms. The insignificant effect of voluntary operational information disclosure on the cost of capital may be due to the fact that the operating data and report can only reveal the outside operational status of the platform (including aspects, such as e.g., operating days, borrowing and lending amount, investor and borrower numbers), without delving into inside financial data (it offers no information on financial statements) or the corporate governance of the platform.[39]

[39] This is in line with earlier literature (Serrano-Cinca et al., 2015; Wang et al., 2020), which denotes that outside operational information may help reduce the default probability, yet only weakly so, since operational information is often of lower salience for P2P investors (who may be far from familiar with the structural workings of P2P lending platforms).

These results have greatly improved the existing literature in three aspects: first, it it contributes to the emerging literature of peer-to-peer lending market (Jiang et al., 2019; Herzenstein et al., 2011; Pope and Syndor, 2011; Duarte et al., 2012; Michels, 2012; Lin et al., 2018; Jiang et al., 2019; Chen et al., 2020): to our best knowledge, our paper is one of the few studies about peer-to-peer lending platform performance rather than individual borrowers' loan performance, i.e., about the newly developing peer-to-peer lending market in China; second, it contributes to the corporate disclosure literatures (Healy et al., 1999a; Diamond and Verrecchia, 1991; Botosan, 1997; Sengupta,1998; Verrecchia, 2001; Lambert et al., 2007), in particular, investigated the effects of information disclosure, which includes third-party provided information and voluntary operational and financial information disclosure on the default probability and interest rate; third, it contributes to the literatures on information intermediaries (Gurley and Shaw,1960; Campbell and Kracaw, 1980; Diamond, 1984; Boyd and Prescott, 1986; Merton, 1989; 1993) by studying the usefulness of information provided by the third-party independent agency.

My results bear important implications for a number of parties related to the P2P lending industry, including regulators, transacting parties (borrowers/lenders) and the platforms themselves. Regulators should actively encourage the broad production and dissemination of information by both P2P platforms, as well as third parties (like rating agencies), to help enhance the industry’s performance. Since information disclosure can, however, be the product of adverse selection (the case, for example, of platforms "shopping" for positive ratings by rating agencies, which then end up publishing positive outlooks on those platforms), regulators should consider imposing rules aiming at discouraging such colluding behavior. To further empower investors in their investment choices when using these platforms, regulatory authorities could also consider launching outreach initiatives (e.g., including special education courses) geared towards improving their financial literacy. My results are also of key relevance to participants of P2P lending platforms; since the probability of default is an inverse function of the information available for a platform, it becomes necessary for platforms' participants to undertake a thorough evaluation of the information available regarding each platform before deciding which one to opt for in order to make informed investment choices. As far as platforms themselves are concerned, the evidence presented here denotes that they should strive for high transparency, in order to ensure that they are able to both attract high-quality investors and offer an environment in which these investors will be able to perform their function as borrowers or lenders without issues of asymmetric information undermining their confidence.

References

ACCA, 2016. The rise of peer-to-peer lending in China: An overview and survey case study. The Association of Chartered Certified Accountants, 1-23.

Ahmad, N., Li, Z.H., Tian, X.L., 2019. Increased firm profitability under a nationwide environmental information disclosure program? Evidence from China. Journal of Cleaner Production 230, 1176-1187.

Aikins, S., 2009. Global financial crisis and government intervention: A case for effective regulatory governance. International Public Management Review, 10(2): 23-43.

Akerlof, G., 1970. The market for 'lemons': quality uncertainty and the market mechanism. Quarterly Journal of Economics 90, 629-650.

Andrikopoulos, P., Gebka, B., Kallinterakis, V., 2021. Regulatory mood-congruence and herding: evidence from cannabis stocks. Journal of Economic Behavior and Organization 185, 842-864.

Armitage, S., Marston, C., 2008. Corporate disclosure, cost of capital and reputation: Evidence from finance directors. The British Accounting Review 40(4), 314-336.

Ashraf, B.N., 2020. Economic impact of government interventions during the COVID-19 pandemic: International evidence from financial markets. Journal of Behavioral and Experimental Finance 27, 100371

Barth, M.E., Konchitchki, Y., Landsman, W.R., 2013. Cost of capital and earnings transparency. Journal of Accounting and Economics 55(2-3), 206-224.

Berkovich, E., 2011. Search and herding effects in peer-to-peer lending: evidence from prosper.co. Ann Finance 7, 389-405.

Bohl, M.T., Putz, A., Siklos, P.L., Sulewski, C., 2020. Information transmission under increasing political tensions—Evidence from the Berlin Produce Exchange 1887–1896. Journal of Futures 41, 226-244.

Botosan, C., 1997. Disclosure level and the cost of equity capital. The Accounting Review 72, 327-349.

Boyd, J., Prescott, E.C., 1986. Financial intermediary coalitions. Journal of Economic Theory 38, 211-232.

Breuer, W., Soypak, C.K., Steininger, B.I., 2020. Magnitude effects in lending and borrowing: empirical evidence from a P2P platform. The European Journal of Finance 26 (9), 854-873.

Campbell, T.S., Kracaw, W.A. 1980. Information production, market signalling, and the theory of financial intermediation. Journal of Finance 35, 863-882.

Carhart, M.M., 1997. On persistence in mutual fund performance. Journal of Finance 52, 57-82.

Chava, S., Purnanandam, A., 2010. Is default risk negatively related to stock returns? The Review of Financial Studies 23(6), 2523-2559.

Chen, H.Y., Tsai, C.H., 2017. Changing regulations of peer-to-peer lending in China. Banking & Financial Services Policy Report 36, 13-25.

Chen, K.J., Ren, J., Zha, T., 2018. The Nexus of Monetary Policy and Shadow Banking in China. American Economic Review 108(12), 3891-3936.

Chen, X.C., Jin, F.J., Zhang, Q., Li, Y. 2016. Are investors rational or perceptual in P2P lending? Information Systems and e-Business Management 14, 921–944.

Chen T., Karathanasopoulos A., Ko, S.I.M., Lo, C.C., 2020. Lucky lots and unlucky investors. Review of Quantitative Finance and Accounting 54, 735–751.

Cheynel, E., 2013. A theory of voluntary disclosure and cost of capital. Review of Accounting Studies 18(4), 987-1020.

Clinch, G., Verrecchia, R.E., 2015. Voluntary disclosure and the cost of capital. Australian Journal of Management 40(2), 201-223.

CreditEase Research Institute, 2020. The world's first P2P online lending platform Zopa obtains a full UK banking license. Available at: https://www.keyike.com/article/123676.

Deer, L., Mi, J., Yuxin, Y., 2015. The rise of peer-to-peer lending in China: An overview and survey case study. Association of Chartered Certified Accountants.

Diamond, D., 1984. Financial intermediation and delegated monitoring. Review of Economic Studies 51, 393-414.

Diamond, D., Verrecchia, R., 1991. Disclosure, liquidity, and the cost of capital. Journal of Finance 66, 1325-1355.

Duarte, J., Siegel, S., Young, L., 2012. Trust and credit: the role of appearance in peer-to-peer lending. Review of Financial Studies 25, 2455-2484.

Dutta, S., Nezlobin, A., 2017. Information disclosure, firm growth, and the cost of capital. Journal of Financial Economics 123(2), 415-431.

Easley, D., O'hara, M., 2004. Information and the cost of capital. Journal of Finance 59(4), 1553-1583.

Editorial department, 2020. The development of credit system in China. Cover Story. Available at: https://wenku.baidu.com/view/638323051cb91a37f111f18583d049649a660e7b.html?fr=search-1-wk_user_nor-income3&fixfr=qds6ZbkNrMQpUziMfY3f2w%3D%3D

Fama, E.F., French, K.R., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3-56.

Fama, E.F., French, K.R., 1996. Multifactor explanations of asset pricing anomalies. Journal of Finance 51, 55-84.

Feinman, J.N., 1993. Reserve Requirements: History, Current Practice, and Potential Reform. 79 Fed. Res. Bull., 569.

Fledstein, M., Eckstein, O., 1970. The fundamental determinants of the interest rate. The Review of Economics and Statistics 52, 363-375.

Francis, J., Nanda, D., Olsson, P., 2008. Voluntary disclosure, earnings quality, and cost of capital. Journal of Accounting Research 46(1), 53-99.

Freedman, S., Jin, Z.G., 2008. Do social networks solve information problems for peer-to-peer lending? Evidence from prosper.com. Available at SSRN: https://papers.ssrn.com/s013/papers.cfm?abstract_id=1936057.

Fung, D.W.H., Lee, W.Y., Yeh, J.J.H, Yuen, F.L., 2020. Friend or foe: The divergent effects of FinTech on financial stability. Emerging Markets Review 45, 100727.

Ge, R., Feng, J., Zhang, P.Z., 2017, Predicting and deterring default with social media information in peer-to-peer lending. Journal of Management Information Systems 34, 401-424.
Gerding, E.F., 2007. Laws Against Bubbles: An experimental-asset-market approach to analyzing financial regulation. Wisconsin Law Review, 5. Available at SSRN: https://ssrn.com/abstract=1088474
Giamporcaro, S., Gond, J. P., O'Sullivan, N., 2019. How Governments Orchestrate Corporate Social Responsibility Interventions through Financial Markets. In Academy of Management Proceedings 1, 19380. Briarcliff Manor, NY 10510: Academy of Management.
Gilchrist, S., Zakrajšek, E. 2007. Investment and the cost of capital: New evidence from the corporate bond market. Available at: https://www.nber.org/papers/w13174
Goldstein, I., Yang, L., 2017. Information disclosure in financial markets. Annual Review of Financial Economics 9, 101-125.
Gurley, J.R., Shaw, E.S., 1960. Money in a theory of finance. Brookings Institution, Washington, D. C.
Healy, P., Hutton, A., Palepu, K., 1999. Stock performance and intermediation changes surrounding sustained increases in disclosure. Contemporary Accounting Research 16, 485-520.
Herzenstein, M., Sonenshein, S., Dholakia, M.U., 2011. Tell me a good story and I may lend you money: the role of narratives in peer-to-peer lending decisions. Journal of marketing research XLVIII, 138-149.
Hirshleifer, D. 2008. Psychological bias as a driver of financial regulation. European Financial Management 14 (5), 856–874.
Huang, J., Ling, C.X., 2015. Using AUC and accuracy in evaluating learning algorithms. IEE Transactions on Knowledge and Data Engineering 17, 299-310.
Hussain, H.I., Ghani, E.K., Razimi, M. S.A., 2019. Systematic risk and determinants of cost of capital: an empirical analysis of selected case studies. Journal of Security & Sustainability Issues, 9(1).
Indjejikian, R.J., 2007. Discussion of accounting information, disclosure, and the cost of capital. Journal of Accounting Research 45(2), 421-426.
Jensen, M., Meckling, W., 1976. Theory of the firm: managerial behaviour, agency costs and ownership structure. Journal of Financial Economics 28, 51-82.
Jiang, J., Wang, Z., Zhang, X., 2019. Government affiliation and fintech industry: The peer-to-peer lending platforms in China. PBC School of Finance, Tsinghua University July 7, 2019.
Ke W.C., Chen, H., Lin, H.W.W., Liu, Y.C., 2017. The impact of numerical superstition on the final digit of stock price. North American Journal of Economics and Finance 39, 145-157.
Khan, S., Goswami, A., Kumar, V., 2020. Peer to peer lending market by business model (alternate marketplace lending and traditional lending), type (consumer lending and business lending), and end user (consumer credit loans, small business loans, student loans, and real estate loans): global opportunity analysis and industry forecast, 2020-2027. Allied Market Research, 3P-118-BI-A01618, Available at:

2. *Disclosure Sources, Regulatory Changes and Market Performance: Evidence from the Chinese Peer-to-Peer Lending Market*
https://www.alliedmarketresearch.com/peer-to-peer-lending-market

Kim, T., Koo, B., Park, M., 2013. Role of financial regulation and innovation in the financial crisis. Journal of Financial Stability 9, 662-672.

Krokida, S., Makrychoriti, P., Spyrou, S., 2020. Monetary policy and herd behavior: international evidence. Journal of Economic Behavior & Organization 170, 386–417.

Lambert, R., Leuz, C., Verrcchia, R., 2007. Accounting information, disclosure, and the cost of capital. Journal of Accounting Research 45, 385-420.

Li, D., Cao, C., Zhang, L., Chen, X., Ren, S., Zhao, Y., 2017. Effects of corporate environmental responsibility on financial performance: The moderating role of government regulation and organizational slack. Journal of Cleaner Production 166, 1323-1334.

Li, E., Liao, L., Wang, Z., Xiang, H., 2020. Venture capital certification and customer response: Evidence from P2P lending platforms. Journal of Corporate Finance 60, 101533.

Lin, M., Prabhala, P.N., Viswanathan, S., 2018. Judging borrowers by the company they keep: friendship networks and information asymmetry in online peer-to-peer lending. Management Science 59, 17-35.

Lo, K.L., Mi, J.J., Yang, M., Zhang, S., 2019. Do financial regulations have impacts on ownership structure of P2P firms? Applied Economics Letters, DOI: 10.1080/13504851.2019.1675859.

Lufax, 2014, P2P lending market in China. Available at: www.lufax.com.

Lyons, A.C., Kass-Hanna, J., Fava, A., 2021. Fintech development and savings, borrowing, and remittances: A comparative study of emerging economies. Emerging Markets Review 19, 100842.

Mao, J., Lv, B.Y., Ma, G.R., 2015. Transfer payment and government expansion: a study based on "price effect". Management World 7(187), 29-41. Available at: http://www.cqvip.com/qk/95499x/201507/665320875.html

Merton, R.C., 1989, On the application of the continuous-time theory of finance to financial intermediation and insurance. Geneva Papers on Risk and Insurance Theory 14, 225-261.

Merton, R.C., 1993, Operation and regulation in financial intermediation: a functional perspective, In: England, P. (Ed.). Operation and Regulation of Financial Markets, The Economic Council, Stockholm.

Michels, J., 2012, Do unverifiable disclosure matter? evidence from peer-to-peer lending. The Accounting Review 87, 1385-1413.

Newzoo, 2021. Introduction to the Metaverse Report. Newzoo Platform, free version. Available at: https://newzoo.com/insights/trend-reports/newzoo-intro-to-the-metaverse-report-2021-free-version/

Omran, M., Pointon, J., 2004. The determinants of the cost of capital by industry within an emerging economy: evidence from Egypt. Available at SSRN 549382.

Pennathur, A., Smith, D., Subrahmanyam, V., 2014. The stock market impact of government interventions on financial services industry groups: Evidence from the 2007–2009 crisis. Journal of Economics and Business 71, 22-44

Pope, D.G., Sydnor, J.R., 2011. What's in a picture? evidence of discrimination from prosper.com. Journal of Human Resources 46, 53-92.

Schwert, G.W., 1981. Using financial data to measure effects of regulation. Journal of Law and Economics 24(1), 121-158.

Serrano-Cinca, C., Gutierrez-Nieto, B., Lopez-Palacios, L., 2015. Determinants of default in P2P lending. PloS ONE 10: e0139427. doi: 10.1371/journal.pone.0139427.

Sengupta, P., 1998. Corporate disclosure quality and the cost of debt. The Accounting Review 73, 459-474.

Smith, C., Warner, J., 1979. On financial contracting: an analysis of bond covenants. Journal of Financial Economics 23, 249-283.

Stiglitz, J.E., 1993. The role of the state in financial markets. The World Bank Economic Review 7, 19-52.

Tian, G., Wang, X., Wu, W., 2021. Borrow low, lend high: Credit arbitrage by sophisticated investors. Pacific-Basin Finance Journal 67, 101544.

Vassalou, M., Xing, Y., 2004. Default risk in equity returns. The Journal of Finance 59(2), 831-868.

Verrecchia, E.R., 2001. Essays on disclosure. Journal of Accounting and Economics 32, 97-180.

Wang, Q., Si, Z., Chen, X., 2020. Information disclosure and the default risk of online peer-to-peer lending platform. Finance Research Letters, 38(C).

Wang, T., Kang, Y., Pan, Y., Management, S.O., University, X.P., 2016. Comparative analysis of Chinese and American P2P internet lending platform model. Journal of Xi'an University of Posts and Telecommunications 21(5), 80-87. DOI: 10.13682/j.issn. 2095-6533.2016.05.016.

WDZJ., 2017. Comparison of platform models of yiren dai, ppdai, and hexin dai. WDZJ Report, 17 Nov, 2017. Available at: http://www.360doc.com/content/17/1117/07/30963157_704529765.shtml

Weiss, N.E., 2008. Government interventions in financial markets: economic and historic analysis of subprime mortgage options. CSR report for Congress. Congressional Research Service, RL34423.

Wei, W., Gaofeng, J., 2004. Information Disclosure, Transparency and the Cost of Capital [J]. Economic Research Journal 7, 107-114.

Xiang, H., Wang, Z., Jiang, J., Liao, L., 2019. Pie or trap: what is represented by interest rate in peer-to-peer lending platform? China Financial Research Conference, July 7, 2019.

Zhang, W., Zhang, J., Li, Y., Xiong, X., 2019. Excess return and moderation effect of voluntary information disclosure in peer-to-peer lending market. China Financial Research Conference, July 7, 2019.

Zhao, H., 2019. Analysis on the current situation and problems of developing personal credit system in China. Market Bserver, 2019-01. Available at: https://wenku.baidu.com/view/f6b53cf882c4bb4cf7ec4afe04a1b0717fd5b3b6.html?fr=search-1-wk_user_nor-income1&fixfr=0DyDgcrPa66r5F1YXGi7SA%3D%3D

Zhi, F., 2016, Who Owns the Power of Credit Rating of P2P Lending? China Finance 95, 97 (Feb. 2016).

Zhou, X., Chen, S., 2021. FinTech innovation regulation based on reputation theory with the participation of new media. Pacific-Basin Finance Journal 67, 101565.

Zhou, Z., Zhou, H., Zeng, H., Chen, X., 2018. The impact of water information disclosure on the cost of capital: An empirical study of China's capital market. Corporate Social Responsibility and Environmental Management 25(6), 1332-1349.

Tables

Table 2.1. Sample Selection

	No. Obs.
Platforms listed on CSMAR	8,767
Months covered in the sample	52
Observations on CSMAR	252,513
Platforms listed on rating index dataset published by WDZJ	170
Months	52
Less: platforms with missing data	2,222
Observations in rating index dataset	4,813
Platform disclosure	
Observations without disclosure	729
Observations with disclosure	4,084
Observations disclose operational information (OI)	3,842
Observations disclose operational data (OD) only	1,046
Observations disclose operational report (OR) only	1,756
Observations disclose operational data (OD) and operational report (OR)	1,040
Observations disclose financial information (FI)	2,384
Observations disclose audit report without financial information (ARWOFI)	653
Observations disclose financial data only (FDO)	52
Observations disclose audit report with financial data (AFD)	1,004
Observations disclose audited financial data and financial statement (AFS)	2,282

Notes: WDZJ is a third-party dataset of Chinese P2P lending platforms. wangdaizhijia.com.
All financial disclosure information is collected at the end of June, 2020.

Table 2.2. Sample Descriptive

Variable	Obs.	Mean	Std. Dev.	Min	Max
DEFAULT	4,813	0.292	0.455	0	1
CC	4,555	2.299	0.690	1.539	2.906
RF	4,813	1.196	0.189	0.958	1.596
CPI	4,813	4.616	0.012	4.600	4.649
L	4,813	1.122	0.423	1	3
BD	4,813	0.399	0.490	0	1
B	4,813	2.369	1.166	1	4
DEAR	4,813	0.150	0.408	0	1
IN	4,555	7.176	3.257	0.692	12.320
ALT	4,555	1.863	0.879	0.104	3.603
CR	4,559	11.764	1.563	7.578	16.129
NCI	4,555	-0.0002	1.000	-1.376	1.755
DEVI	3,876	3.945	0.175	3.703	4.423
FDIS	4,813	1.397	1.181	0	4

Note: all variables are standard data, not raw data. And the *CC*, *RF*, *CPI*, *IN*, *ALT*, *CR*, *NCI*, *DEVI* have been taken log and winsorized in the following regressions. The raw mean of *CC* is 9.466, and the raw mean of *RF* is 3.368.

Table 2.3. Correlation Matrix

Variables	DEFAULT	CC	RF	CPI	IN	NCI	ALT	CR	BD	DEAR	DEVI	FDIS
DEFAULT	1											
CC	0.2262*	1										
RF	0.0961*	-0.0777*	1									
CPI	-0.1524*	-0.0625*	-0.1919*	1								
IN	0.1039*	0.0497*	0.1560*	-0.5472*	1							
NCI	-0.1069*	0.1204*	0.0634*	-0.3998*	0.2348*	1						
ALT	-0.2009*	0.1909*	0.0321*	0.1670*	0.0822*	-0.0434*	1					
CR	-0.0672*	-0.1662*	0.1375*	-0.0332*	0.5515*	-0.0025	0.3852*	1				
BD	-0.1729*	-0.0795*	0.2603*	0.1594*	-0.0482*	-0.1552*	0.1277*	0.0825*	1			
DEAR	-0.1754*	-0.0201	-0.0347*	0.02	0.1375*	-0.0405*	0.1908*	0.1992*	0.0362*	1		
DEVI	-0.2943*	-0.2156*	0.1308*	0.5458*	0.0828*	-0.3014*	0.4418*	0.6368*	0.3915*	0.2561*	1	
FDIS	-0.4120*	-0.1426*	0.0047	0.2977*	-0.0685*	-0.2011*	0.1107*	0.1353*	0.1148*	0.1255*	0.4267*	1

Notes: *p<0.05

Table 2.4. Correlation Matrix (Rating Indexes)

Variables	DEVI	TRADI	POPI	TECI	LEVI	LIQI	DISI	TRANI	BRAI	REVI
DEVI	1									
TRADI	0.501	1								
POPI	0.379	0.654	1							
TECI	0.399	0.341	0.229	1						
LEVI	-0.098	-0.268	-0.332	-0.086	1					
LIQI	-0.143	-0.105	0.015	-0.018	0.002	1				
DISI	0.656	0.198	0.268	0.181	-0.201	-0.198	1			
TRANI	0.6	0.053	0.064	0.156	0.017	-0.085	0.357	1		
BRAI	0.595	0.446	0.205	0.318	-0.026	-0.15	0.112	0.259	1	
REVI	0.358	0.132	0.08	0.08	-0.027	-0.089	0.241	0.235	0.198	1

Notes: *$p<0.05$

Table 2.5. Comparison between Platforms that Default and Survival

	Default		Survival		Difference in Means	
	Obs.	Mean	Obs.	Mean	t-statistics	Prob.
Control Variables						
CC	3188	2.370	1367	2.135	10.65	***
IN	3188	6.941	1367	7.725	-7.50	***
NCI	3410	-0.069	1403	0.167	-7.46	***
ALT	3188	1.909	1367	1.756	5.40	***
CR	3192	11.822	1367	11.627	3.85	***
BD	3410	0.454	1403	0.268	2.20	**
DEAR	3410	0.104	1403	0.262	-12.35	***
Rating Indexes						
DEVI	2738	3.911	1138	4.027	-19.15	***
Voluntary Disclosures						
FDIS	3410	1.085	1403	2.156	-31.36	***

Notes: ***p<0.01, **p<0.05, *p<0.1
All the variables are standard, not raw data.

Table 2.6. Comparison between Platforms in Different Locations

	L1	L2	L3	Difference in Means	
Obs.	4398	243	172		
	Mean	Mean	Mean	t-statistics	Prob.
Dependent Variables					
DEFAULT	0.2981	0.2757		0.7428	
		0.2757	0.1453	3.1804	***
	0.2981		0.1453	4.3284	***
CC	2.2091	2.2172		-0.1811	
		2.2172	2.1038	1.4852	
	2.2091		2.1038	1.9626	*
Control Variables					
IN	7.2771	6.6149		3.0897	***
		6.6149	5.5273	3.6898	***
	7.2771		5.5273	6.8967	***
NCI	-0.0144	0.0939		-1.6437	*
		0.0939	0.2359	-1.4822	
	-0.0144		0.2359	-3.2175	***
ALT	1.8718	2.0017		-2.2344	**
		2.0017	1.4468	7.4153	***
	1.8718		1.4468	6.2013	***
CR	11.8280	11.6547		1.6969	*
		11.6547	10.3675	12.2581	***
	11.8280		10.3675	11.9620	***
BD	0.4111	0.2963		3.5527	***
		0.2963	0.2442	1.1707	
	0.4111		0.2442	4.3831	***
DEAR	0.2299	0.1152		4.1808	***
		0.1152	0.0000	4.7214	***
	0.2299		0.0000	7.1637	***
Rating Indexes					

DEVI	3.9993	3.9186		5.9809	***
		3.9186	3.8922	1.8215	*
	3.9993		3.8922	6.2184	***
Voluntary Disclosures					
FDIS	1.8507	1.5744		3.5344	***
		1.5744	2.0349	-4.5900	***
	1.8507		2.0349	-1.9545	*

Notes: ***p<0.01, **p<0.05, *p<0.1

L1-L3 represents LOCATION1-LOCATION3.

RF and *CPI* are dropped in this table because they don't change with the platforms.

All the variables are standard, not raw data.

Table 2.7. Comparison between platforms in different backgrounds

	B1	B2	B3	B4	Difference in Means	
Obs.	1561	907	1148	1105		
	Mean	Mean	Mean	Mean	t-statistics	Prob.
Dependent Variables						
DEFAULT	0.3344	0.3212			0.6807	
	0.3344		0.2229		6.4546	***
	0.3344			0.2769	3.1791	***
		0.3212	0.2229		5.0973	***
		0.3212		0.2769	2.1811	**
			0.2229	0.2769	-2.9835	***
CC	2.2527	2.2959			-1.5944	
	2.2527		2.1242		4.4183	***
	2.2527			2.1455	3.9454	***
		2.2959	2.1242		5.4249	***
		2.2959		2.1455	5.2851	***
			2.1242	2.1455	-0.6632	
Control Variables						
IN	6.9379	8.0056			-7.9313	***
	6.9379		7.4027		-3.4708	***
	6.9379			6.6371	2.4739	**
		8.0056	7.4027		3.8319	***
		8.0056		6.6371	9.9126	***
			7.4027	6.6371	5.3820	***
NCI	0.0085	0.0234			-0.3667	
	0.0085		-0.0612		1.8160	*
	0.0085			0.3280	-0.6281	
		0.0234	-0.0612		1.9080	*
		0.0234		0.3280	-0.2105	
			-0.0612	0.3280	-2.2205	**
ALT	1.8560	1.9995			-3.8591	***

	1.8560		1.8650		-0.2514	
	1.8560			1.7612	2.8716	***
		1.9995	1.8650		3.1416	***
		1.9995		1.7612	6.2315	***
			1.8650	1.7612	2.7346	***
CR	11.4660	12.0587			-8.9736	***
	11.4660		12.3662		-14.0133	***
	11.4660			11.3632	1.9218	***
		12.0587	12.3662		-3.9370	***
		12.0587		11.3632	11.2960	***
			12.3662	11.3632	15.9351	***
BD	0.2595	0.4925			-12.2466	***
	0.2595		0.4441		-10.3436	***
	0.2595			0.4760	-11.9227	***
		0.4925	0.4441		2.2151	***
		0.4925		0.4760	0.7420	
			0.4441	0.4760	-1.5289	
DEAR	0.1684	0.3405			-10.0976	***
	0.1684		0.2647		-6.2003	***
	0.1684			0.1276	2.9140	***
		0.3405	0.2647		3.7844	***
		0.3405		0.1276	11.8496	***
			0.2647	0.1276	8.3230	***
Rating Indexes						
DEVI	3.9032	4.0474			-19.3489	***
	3.9032		4.0678		-23.4394	***
	3.9032			3.9562	-8.4294	***
		4.0474	4.0678		-2.3557	**
		4.0474		3.9562	11.2899	***
			4.0678	3.9562	14.6298	***
Voluntary Disclosures						
FDIS	1.6291	2.0463			-8.3426	***

	1.6291		1.8502		-4.8622	***
	1.6291			1.9719	-6.9421	***
		2.0463	1.8502		4.1070	***
		2.0463		1.9719	1.3879	
			1.8502	1.9719	-2.4871	**

Notes: ***p<0.01, **p<0.05, *p<0.1
B1-B4 represents BACKGROUND1-BACKGROUND4.
RF and *CPI* are dropped in this table because they don't change with the platforms.
All the variables are standard, not raw data.

Table 2.8. Probit Regression Results for the Relationship between Default Probability and Sources of Disclosure

Panel A			
DEFAULT	(1)	(2-1)	(2-2)
CC	0.671***	0.651***	0.491***
	(0.0326)	(0.0356)	(0.0387)
IN	-0.0142***	-0.0175***	-0.0161***
	(0.0027)	(0.0032)	(0.0038)
NCI	0.0108	-0.0031	-0.0044
	(0.0067)	(0.0076)	(0.0077)
ALT	-0.161***	-0.139***	-0.00645
	(0.0103)	(0.0118)	(0.0146)
CR	0.0458***	0.0608***	0.0647***
	(0.0062)	(0.0080)	(0.0125)
BD	-0.0988***	-0.0255	-0.0397**
	(0.0139)	(0.0171)	(0.0170)
DEAR	-0.186***	-0.209***	-0.224***
	(0.0182)	(0.0199)	(0.0190)
DEVI		-0.424***	
		(0.0726)	
TRADI			-0.0079***
			(0.0009)
POPI			0.0001***
			(0.0001)
TECI			-0.0001
			(0.0001)
LEVI			-0.0001***
			(0.0001)
TRANI			0.0001***
			(0.0001)
BRAI			-0.0001***
			(0.0001)
LIQI			0.0037***
			(0.0005)
DISI			-0.0052***
			(0.0005)
REVI			-0.0002
			(0.0003)
L	Yes	Yes	Yes
B	Yes	Yes	Yes
Constant	-5.377***	-0.236	-6.104***
	(0.374)	(0.877)	(0.568)
Prob > chi2	0.0001	0.0001	0.0001
Pseudo R2	0.1490	0.1765	0.2386
Observations	4,373	3,534	3,446
No. Platforms	170	170	170

Notes: Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
The dependent variable is *DEFAULT*.
The marginal effect has been calculated and reported in the table.

Panel B			
DEFAULT	(3-1)	(3-2)	(3-3)
CC	0.618***	0.562***	0.233***
	(0.0340)	(0.0340)	(0.0262)
IN	-0.0157***	-0.0169***	0.0022
	(0.0030)	(0.0029)	(0.0032)
NCI	-0.0115	-0.0154**	-0.0103
	(0.0073)	(0.0072)	(0.0071)
ALT	-0.154***	-0.139***	-0.131***
	(0.0110)	(0.0111)	(0.0111)
CR	0.0569***	0.0565***	0.0323***
	(0.0074)	(0.0074)	(0.0075)
BD	-0.0188	-0.0144	-0.0134
	(0.0158)	(0.0158)	(0.0158)
DEAR	-0.166***	-0.155***	-0.134***
	(0.0187)	(0.0187)	(0.0181)
DEVI	-0.136**	-0.184***	-0.112*
	(0.0673)	(0.0675)	0.233***
FDIS	-0.114***		
	(0.0061)		
OI		-0.0213*	
		(0.0119)	
OD			-0.0605***
			(0.0153)
OR			0.0161
			(0.0145)
FI		-0.198***	
		(0.0104)	
ARWOFI			-0.0840***
			(0.0167)
AFD			-0.109**
			(0.0430)
FDO			-0.129***
			(0.0257)
AFS			-0.314***
			(0.0140)
L	Yes	Yes	Yes
B	Yes	Yes	Yes
Constant	-3.710***	-3.584***	-4.143***
	(0.941)	(1.047)	(1.016)
Prob > chi2	0.0001	0.0001	0.0001
Pseudo R2	0.2407	0.2585	0.2719
Observations	3,534	3,534	3,534
No. Platforms	170	170	170

Notes: Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
The dependent variable is *DEFAULT*.
The marginal effect has been calculated and reported in the table.
AUC is 0.743 for the Model 1 (benchmark); 0.7732 for the Model (2) and 0.8245 for Model (3).

Table 2.9. AUCs of Models

Model	(1)	(2)	(3)
AUC	0.7743	0.7732	0.8245

Notes: Model (1) is the base model which is the benchmark, model (2) is the model includes third-party provided information, and the voluntary operational and financial information disclosure is added in model (3).

Table 2.10. Random-Effect Regression Results for the Relationship between Cost of Capital Interest Rate and Sources of Disclosure

Panel A			
CC	(4)	(5-1)	(5-2)
RF	-0.129***	-0.138***	-0.145***
	(0.0213)	(0.0273)	(0.0236)
CPI	0.0110	0.0267**	0.0249**
	(0.0077)	(0.0111)	(0.0105)
IN	0.0081***	0.0058**	0.0015
	(0.0026)	(0.0028)	(0.0026)
NCI	0.0138***	0.0086***	0.0073***
	(0.0030)	(0.0024)	(0.0023)
ALT	0.0780***	0.0905***	0.101***
	(0.0127)	(0.0158)	(0.0155)
CR	-0.0168**	-0.0122	-0.0164***
	(0.0078)	(0.0078)	(0.0062)
BD	-0.0191	-0.0040	0.0032
	(0.0125)	(0.0125)	(0.0120)
DEAR	-0.0113	-0.0521*	-0.0536**
	(0.0361)	(0.0283)	(0.0262)
DEVI		-0.214***	
		(0.0548)	
TRADI			0.0001
			(0.0001)
POPI			0.0001**
			(0.0001)
TECI			-0.0001*
			(0.0001)
LEVI			-0.0001
			(0.0001)
TRANI			-0.0001***
			(0.0001)
BRAI			-0.0001***
			(0.0001)
LIQI			0.0011
			(0.0007)
DISI			0.0010*
			(0.0005)
REVI			-0.0003**
			(0.0001)
L	Yes	Yes	Yes
B	Yes	Yes	Yes
Constant	2.599***	3.394***	2.552***
	(0.0868)	(0.219)	(0.118)
Prob > chi2	0.0001	0.0001	0.0001
R-sq	0.1276	0.1662	0.1916
Observations	4,373	3,534	3,446
No. Platforms	170	170	170

Notes: Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The dependent variable is *CC*, which is the cost of capital of platforms.

The Hausman test result indicates that the GLS (Random-effect regression) is more suitable than Fixed-effect regression. Meanwhile, the two-way Fixed-effect regression results are same as the Random-effect.

Panel B			
CC	(6-1)	(6-2)	(6-3)
RF	-0.136***	-0.134***	-0.115***
	(0.0276)	(0.0269)	(0.0265)
CPI	0.0274**	0.0259**	0.0262**
	(0.0112)	(0.0106)	(0.0105)
IN	0.0058**	0.0052*	0.0074***
	(0.0027)	(0.0028)	(0.0029)
NCI	0.0081***	0.0077***	0.0075***
	(0.0022)	(0.0022)	(0.0022)
ALT	0.0916***	0.0924***	0.0864***
	(0.0149)	(0.0151)	(0.0147)
CR	-0.0125*	-0.0116	-0.0137*
	(0.0075)	(0.0073)	(0.0071)
BD	-0.0042	-0.0075	-0.0026
	(0.0127)	(0.0124)	(0.0123)
DEAR	-0.0498*	-0.0435	-0.0411
	(0.0291)	(0.0333)	(0.0300)
DEVI	-0.206***	-0.200***	-0.244***
	(0.0570)	(0.0555)	(0.0589)
FDIS	-0.0043		
	(0.0094)		
OI		0.0240	
		(0.0159)	
OD			0.0057
			(0.0237)
OR			0.0384**
			(0.0166)
FI		-0.0278**	
		(0.0123)	
ARWOFI			-0.0402***
			(0.0143)
FDO			0.0250
			(0.0190)
AFD			-0.0602**
			(0.0280)
AFS			-0.0555***
			(0.0203)
L	Yes	Yes	Yes
B	Yes	Yes	Yes
Constant	3.366***	3.324***	3.504***
	(0.233)	(0.226)	(0.237)
Prob > chi2	0.0001	0.0001	0.0001
R-sq	0.1669	0.1786	0.2096
Observations	3,534	3,534	3,534
No. Platforms	170	170	170

Notes: Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The dependent variable is *CC*, which is the average cost of capital of platforms.

The Hausman test result indicates that the GLS (Random-effect regression) is more suitable than Fixed-effect regression. Meanwhile, the two-way Fixed-effect regression results are same as the Random-effect.

Table 2.11. Probit Regression Results – The Impact of Government Regulation on the Relationship between Default Probability and Sources of Disclosure

DEFAULT	(7-1)	(7-2)
CC	0.646***	0.610***
	(0.0337)	(0.0338)
IN	-0.0166***	-0.0176***
	(0.0030)	(0.0030)
NCI	-0.0032	-0.0150**
	(0.0073)	(0.0074)
ALT	-0.156***	-0.155***
	(0.0109)	(0.0110)
CR	0.0592***	0.0544***
	(0.0074)	(0.0075)
BD	-0.0653***	-0.0248
	(0.0165)	(0.0160)
DEAR	-0.144***	-0.169***
	(0.0184)	(0.0186)
DEVI	-0.242**	-0.0342*
	(0.0989)	(0.0693)
FDIS	-0.0797***	-0.107***
	(0.0109)	(0.0064)
GR1	0.165	
	(0.404)	
DEVIGR1	0.0154	
	(0.104)	
FDISGR1	-0.0657***	
	(0.0141)	
GR2		0.916
		(1.695)
DEVIGR2		-0.222
		(0.418)
FDISGR2		-0.0773**
		(0.0333)
L	Yes	Yes
B	Yes	Yes
Constant	-0.492	-4.641***
	(1.575)	(0.971)
Prob > chi2	0.0001	0.0001
Pseudo R2	0.2605	0.2471
Observations	3,534	3,534
No. Platforms	170	170

Notes: Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Dependent variable is *DEFAULT*.
Time variable hasn't controlled in this model because *GR1* and *GR2* are time-series variables.

Table 2.12. Random-Effect Regression Results – The Impact of Government Regulation on the Relationship between Cost of Capital Interest Rate and Sources of Disclosure

CC	(8-1)	(8-2)
RF	-0.0792***	-0.127***
	(0.0231)	(0.0240)
CPI	0.0295***	0.0307***
	(0.0100)	(0.0112)
IN	0.0079***	0.0059**
	(0.0026)	(0.0026)
NCI	0.0048**	0.0078***
	(0.0022)	(0.0021)
ALT	0.0927***	0.0979***
	(0.0139)	(0.0133)
CR	-0.0010	-0.0133*
	(0.0067)	(0.0072)
BD	0.0044	-0.0006
	(0.0114)	(0.0119)
DEAR	-0.0460	-0.0491
	(0.0282)	(0.0301)
DEVI	-0.311***	-0.242***
	(0.0874)	(0.0508)
FDIS	-0.0138	-0.0100
	(0.0114)	(0.0084)
GR1	-0.921***	
	(0.291)	
DEVIGR1	0.208***	
	(0.0737)	
FDISGR1	0.0222**	
	(0.0109)	
GR2		-2.142***
		(0.703)
DEVIGR2		0.501***
		(0.170)
FDISGR2		0.0265*
		(0.0135)
L	Yes	Yes
B	Yes	Yes
Constant	-0.775	-0.562
	(2.883)	(2.567)
Prob > chi2	0.0001	0.0001
R-sq	0.1712	0.1720
Observations	3,534	3,534
No. Platforms	170	170

Notes: Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Dependent variable is *CC*, which is the average cost of capital of platforms.
Time variable hasn't controlled in this model because *GR1* and *GR2* are time-series variables.

Table 2.13. Subsample Random-Effect Regression Results

Panel A			
CC	(4)	(5-1)	(5-2)
RF	-0.184***	-0.145***	-0.199***
	(0.0522)	(0.0536)	(0.0510)
CPI	6.680***	9.347***	9.312***
	(1.202)	(0.991)	(1.091)
IN	0.0450	0.00798	-0.0142
	(0.0100)	(0.0088)	(0.0088)
NCI	0.142***	0.112***	0.113***
	(0.0088)	(0.0104)	(0.0097)
ALT	0.493***	0.391***	0.419***
	(0.0279)	(0.0246)	(0.0266)
BD	0.0138	0.00217	-0.0352
	(0.0311)	(0.0291)	(0.0318)
DEAR	-0.0961**	-0.0631**	-0.0798*
	(0.0658)	(0.0494)	(0.0416)
DEVI		-0.363**	
		(0.164)	
TRADI			-0.298
			(0.0775)
POPI			0.0376**
			(0.0149)
TECI			-0.0265**
			(0.0194)
LEVI			-0.0121*
			(0.0068)
LIQI			0.269***
			(0.0725)
DISI			-0.0540
			(0.0469)
TRANI			-0.00394***
			(0.0148)
BRAI			-0.0557***
			(0.0178)
REVI			-0.0096***
			(0.0074)
Time	Yes	Yes	Yes
L	Yes	Yes	Yes
B	Yes	Yes	Yes
Constant	-29.43***	-39.96***	-40.94***
	(5.535)	(4.627)	(5.046)
Observations	3,188	2,523	2,414
No. Platforms	105	105	105
Prob>chi2	0.0000	0.0000	0.0000
R-sq	0.5308	0.6117	0.6577

Notes: Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The dependent variable is *CC*, which is the average cost of capital of platforms.

In subsample regression, only survival platforms data are kept.

The Hausman test result indicates that the GLS (Random-effect regression) is more suitable than Fixed-effect regression. Meanwhile, the two-way Fixed-effect regression results are same as the Random-effect.

Panel B			
CC	(6-1)	(6-2)	(6-3)
RF	-0.158***	-0.129*	-0.141**
	(0.0602)	(0.0684)	(0.0578)
CPI	9.091***	7.096***	9.086***
	(1.024)	(1.202)	(1.044)
IN	-0.0086	0.0022	-0.0097
	(0.0090)	(0.0098)	(0.0090)
NCI	0.113***	0.0975***	0.115***
	(0.0109)	(0.0102)	(0.0107)
ALT	0.389***	0.337***	0.387***
	(0.0247)	(0.0304)	(0.0246)
BD	0.0023	-0.0018	0.0038
	(0.0289)	(0.0291)	(0.0288)
DEAR	-0.0663**	-0.0419**	-0.0586*
	(0.0488)	(0.0421)	(0.0505)
DEVI	-0.373**	-0.627***	-0.363**
	(0.161)	(0.164)	(0.153)
FDIS	0.0129		
	(0.0206)		
OI		0.0491	
		(0.0356)	
OD			0.0348
			(0.0422)
OR			0.0408
			(0.0499)
FI		-0.0021**	
		(0.0254)	
ARWOFI			-0.0124*
			(0.0468)
FDO			-0.0125
			(0.150)
AFD			-0.0509
			(0.0494)
AFS			-0.0606**
			(0.0352)
Time	Yes	Yes	Yes
L	Yes	Yes	Yes
B	Yes	Yes	Yes
Constant	-38.75***	-28.64***	-38.78***
	(4.762)	(5.720)	(4.857)
Observations	2,523	2,105	2,523
No. Platforms	105	105	105

Notes: Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The dependent variable is *CC*, which is the average cost of capital of platforms.

In subsample regression, only survival platforms data are kept.

The Hausman test result indicates that the GLS (Random-effect regression) is more suitable than Fixed-effect regression. Meanwhile, the two-way Fixed-effect regression results are same as the Random-effect.

Table 2.14. Random-Effect Regression Results -- Subsample

CC	(5-3)	(5-3)	(6-4)	(6-4)
RF	-0.133***	-0.179***	-0.118***	-0.166***
	(0.0267)	(0.0473)	(0.0278)	(0.0477)
CPI	0.768*	9.731***	0.714*	9.756***
	(0.553)	(0.896)	(0.544)	(0.898)
IN	0.00416	-0.0143**	0.00498	-0.0140**
	(0.00671)	(0.00684)	(0.00661)	(0.00682)
NCI	0.0108***	0.119***	0.00924***	0.117***
	(0.00236)	(0.00999)	(0.00214)	(0.0103)
ALT	0.113***	0.395***	0.112***	0.397***
	(0.0229)	(0.0231)	(0.0227)	(0.0225)
BD	0.00568	-0.0153	0.00417	-0.0130
	(0.0138)	(0.0236)	(0.0135)	(0.0240)
DEAR	-0.100***	-0.0402	-0.0875***	-0.0298
	(0.0340)	(0.0494)	(0.0333)	(0.0492)
LDEVI	-0.317***	-0.243*	-0.319***	-0.220*
	(0.0587)	(0.132)	(0.0609)	(0.132)
LAFS			-0.0566***	-0.0577*
			(0.0209)	(0.0304)
L	Yes	Yes	Yes	Yes
B	Yes	Yes	Yes	Yes
Constant	9.918***	-42.34***	0.321	-42.54***
	(2.398)	(4.271)	(2.552)	(4.272)
Observations	3,672	3,424	3,672	3,424
No. Platforms	170	161	170	161
Instrumented		DEVI		AFS
Instruments		LDEVI		LAFS

Notes: Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The dependent variable is *CC*, which is the average cost of capital of platforms.

LDEVI and *LAFS* represent the one lag of *DEVI* and *AFS*.

The Housman Test result shows the Random-Effect is more suitable.

Appendixes

Appendix 2.1. Variable Explanation

Variables	Variable Explanation
DEFAULT	default probability of platforms; dummy variable: 1 means platform default, 0 means platform survival
CC	cost of capital; average return provided and accepted to investors
RF	risk free rate; monthly SHIBOR: Shanghai Interbank Offered Rate; unit: %
CPI	Consumer Price Index (last month=100)
IN	Investor numbers; monthly total investor numbers of platform
NCI	Net capital inflow; monthly net capital inflow of platform
ALT	average loan maturity monthly average loan period of platform (month)
CR	cumulative repay; monthly cumulative outstanding loans of platform (yuan)
BD	banking deposits; dummy variable: 1 if the capital custody in banks is implemented (the capital of the platform has been put into a banking account); 0 otherwise
DEAR	disclosed external assessment report[a]; dummy variable: 1 if external assessment report given, 0 otherwise
L	platform geographical location, dummy variable: L1 if platform located in Eastern economic area, 0 otherwise, L2 if platform located in Western economic area, 0 otherwise; L3 if platform located in Central economic area; 0 otherwise; L4 if platform located in Northeastern economic area, 0 otherwise
B	the background of platform, dummy variable: B1 if platform is held by private company, 0 otherwise; B2 if platform is held by venture capital, 0 otherwise; B3 if platform is held by listed company, 0 otherwise; 4 if platform is held by state-owned company or bank; 0 otherwise
DEVI	development index published by WDZJ; it is calculated by weighted average[b] of following 9 indexes
TRADI	trading index published by WDZJ
POPI	popularity index published by WDZJ
TECI	technology index published by WDZJ
LEVI	leverage index published by WDZJ
LIQI	liquidity index published by WDZJ
DISI	dispersity index published by WDZJ
TRANI	transparency index published by WDZJ
BRAI	brand index published by WDZJ
REVI	revenue income index published by WDZJ
FDIS	a quality measure of financial disclosure; Sum (OD OR ARWOFI FDO AFD AFS)
OI[c]	a dummy measure of operational information disclosure; 1 if OD or OR disclosed
OD[d]	dummy variable: 1 if operational data given, 0 otherwise
OR[e]	dummy variable: 1 if operational report given, 0 otherwise
FI[f]	a dummy measure of financial information disclosure; 1 if ARWOFI, FDO, AFD, or AFS disclosed
ARWOFI[g]	dummy variable: 1 if audit report without financial information given, 0 otherwise
FDO[h i]	dummy variable: 1 if financial data (non-audited financial data) given, 0 otherwise
AFD[j]	dummy variable: 1 if audited financial data given, 0 otherwise
AFS[k]	dummy variable: 1 if audited financial statement given, 0 otherwise
GR	Dummy variable: 1 if government regulatory intervention happened, 0

	otherwise

Notes: all continuous variables have been taken ln and winsorized.

WDZJ: wangdaizhijia.com, a third-party dataset which publish data of Chinese Peer-to-Peer Platforms. Although the data published in WDZJ is no longer public, we have downloaded and saved all rating indexes data.

[a] external assessment report: an external assessment report that legally prescribed by Chinese government, it should be published by legal firm to confirm the compliance of platform.

[b] the weights calculated and published by WDZJ. DEVI = TRADI*12% + POPI*11% + TECI *5% + LEVI*6% + LIQI*12% + DISI*5% + TRANI*11% + BRAI*20% + REVI *18%

[c] OI represents operational information, which includes trading volume, investor number, loan number, cumulative repay, average loan time, loan completion time…

[d] OD represents operational data, which include trading volume, investor number, loan number, cumulative repay, average loan period, loan completion time… It is an informal operational information that couldn't be traced.

[e] OR represents operational report, which include trading volume, investor number, loan number, cumulative repay, average loan period, loan completion time… It is a formal operational information that could be traced.

[f] FI represents financial information, which includes cash, receivable, payable, capital...

[g] ARWOFI means the platform discloses audit report but doesn't disclose financial data or financial statement.

[h] FDO represents the platform discloses financial data only, but doesn’t disclose audit report.

[i] FD means financial data, which includes cash, accounts receivable, payable, capital…It is an informal financial information that couldn't be traced, while FS represents financial statement, which includes balance sheet, income statement and cash flow statement. It is a formal financial information that could be traced.

[j] AFD means the platform discloses audit report with informal financial data.

[k] AFS means the platform discloses audit report with formal financial statement.

Appendix 2.2. The Endogenous Problem

The endogenous problem is a common issue during the social science research. Based on the “Introductory Econometrics: A Modern Approach” (Jeffrey M. Wooldridge, 2015[40]), in the multiple regression model, I have a strict exogenous assumption, that is, "when the explanatory variable X in all periods is given, the mean value of the random interference term in each period is 0, which can be expressed by the following equation:

$$\mathrm{Y_t} = \beta_0 + \beta_1 X_t + \varepsilon_t$$
$$E(\varepsilon \mid X) = 0$$

The strict exogenous assumption is usually hard to be satisfied, therefore, only concurrent exogenous are required which is the weak exogenous assumption. The conditional mean form of the weak exogenous hypothesis is:

$$E(\varepsilon_t \mid X_t) = 0$$

However, the weak exogenous assumption cannot be satisfied in many datasets, which means:

$$E(\varepsilon_t \mid X_t) \neq 0$$

If the weak exogenous assumption is not satisfied, which means the disturbance term and the explanatory variable are not the weak exogenous, the model has an endogenous problem, and the explanatory variable related to the disturbance term is called an endogenous variable.

Generally, there are four types endogenous problem: omission of explanatory variables; the explanatory variable X and explained variable Y are mutually causal,

[40] Wooldridge, J. M., 2015. Introductory econometrics: A modern approach. Cengage learning.

which is the reverse causality problem; self-selection problem; the measurement error problem.

There are four solutions to endogenous problems:

The first one is the natural experiment method. The natural experiment is the occurrence of certain external emergencies, which makes the research subjects seem to be randomly divided into experimental groups or control groups. This is the most recommended method, but natural experiments need to find an event that only affects the explanatory variable but not the explained variable. Fuchs-Schündeln and Hassan (2016)[41] write a paper that introduce and analyze the natural experiments method in detail.

The second one is the Difference-in-Difference method (DID). The DID method should be used to study the net effect of the event shock when there is an external event shock and this shock only affects part of the sample. The basic idea is to make a difference between the treated group which is the group that affected by the event shock and the control group which is the group selected from the unaffected samples according to certain standards. Actually, the DID method is a variant of fixed effects, and the process of difference in DID is a process of eliminating fixed effects. Chen and Wu (2015)[42] state the DID method comprehensive in the article "The Research Status and Potential Problems of the Domestic Double Difference Method" published in the "Quantitative Economics and Technical Economics Research" in the seventh issue of

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[41] Fuchs-Schündeln, N., Hassan, T. A., 2016. Natural experiments in macroeconomics. In Handbook of macroeconomics (Vol. 2, pp. 923-1012). Elsevier.

[42] Chen, L., Wu, H., 2015. Research status and potential problems of differences-in-differences method in China. The Journal of Quantitative & Technical Economics, 7, 133-148.

2015.

The third one is the instrumental variable method (IV). This is a classic method of dealing with endogenous problems, which is to find a variable that is related to the endogenous explanatory variable, but not related to the random disturbance term. Under the framework of OLS, there are multiple instrumental variables (IV) at the same time, these instrumental variables are called two-stage least squares (2SLS) estimator. Campante and Do (2014)[43] used the IV method to deal with the endogenous problem.

The last one is the dynamic panel regression method. The basic idea of the dynamic panel regression method is to use the lags of the explanatory variable or the explained variable as the instrumental variable (IV) (Mao et al., 2015[44]).

Jayaraman and Milbourn (2012)[45] used three methods (IV, Natural experiment method, and DID) to solve the endogenous problem and gave a good example to deal with the endogeneity.

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43 Campante, F. R., & Do, Q. A., 2014. Isolated capital cities, accountability, and corruption: Evidence from US states. American Economic Review, 104(8), 2456-81.

44 Mao, J., Lv, B.Y., Ma, G.R., 2015. Transfer payment and government expansion: a study based on "price effect". Management World, 7,29-41,187. Available at: http://www.cqvip.com/qk/95499x/201507/665320875.html

45 Jayaraman, S., Milbourn, T. T., 2012. The role of stock liquidity in executive compensation. The Accounting Review, 87(2), 537-563.

3. The Effect of Media News and Social Media Information on the Default Probability and Cost of Capital: Evidence from Chinese Peer-to-Peer Lending Market

Abstract

The main purpose of this paper is to examine the effect of media and social media sentiments on default probability[46] and cost of capital of peer-to-peer (P2P) lending platforms in China (2015-2019). Using media news and social media information data from the Chinese peer-to-peer lending market for sentiment analysis with Python, I find that both media sentiment and social media sentiment have a significantly negative effect on the platform's default probability. Even though the results indicate both media sentiment and social media sentiment have an insignificant effect on the platform's cost of capital, I find the asymmetry effect between positive change on sentiment and negative change on sentiment of news on default probability and cost of capital of platforms. The results show that only positive change on sentiment of news has a significant impact on reducing default probability and cost of capital of platforms.

Keywords: Media Sentiment; Social Media Sentiment; Information Asymmetry; Default Probability; Cost of Capital; Peer-to-peer Lending Market

JEL classification: G11, G21, G28

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[46] Default probability: this is a dummy variable with a value of 1 if the platform defaults, and 0 otherwise. The default data was published on WDZJ.COM, which is a third-party information intermediary in Chinese peer-to-peer lending market.

3. *The Effect of Media News and Social Media Information on The Default Probability and Cost of Capital: Evidence from Chinese Peer-to-Peer Lending Market*

3.1. Introduction

Business presses and media news agencies play an important role as information intermediaries to disseminate information and alleviate information asymmetry in financial markets (Cahan et al., 2015). Broadly speaking, media can be classified into two separate types: traditional mass media[47] and new media (i.e., digital interactive media), or say, social media[48], both of which are the important channels for investors to acquire 'private', or say 'inside', information (Fang and Peress, 2009; Da et al., 2011).

Existing literature has extensively examined the impacts of media news and social media information on financial markets. Many studies state that media information has a significant effect on the firm's performance or valuation: i.e., to increase stock returns & firm values, to predict the future earnings, and to decrease the cost of capital (Barber and Loeffler, 1993; Albert and Smaby, 1996; Tetlock et al., 2008; Cahan et al., 2015 and many others). However, other research papers find only a weak effect of media coverage (Wang and Ye, 2015; Fang and Peress, 2009). Similarly, the relationship between social media information and financial market performance has also been a hot research topic in recent years. Some studies indicate that the effect of social media information on investors' behavior and/or stock market activities is weak (Tumarkin and Whitelaw, 2001; Dewally, 2003). However, other studies state that the effect of

[47] Media news is the news published by traditional media or mass media, such as the Wall Street Journal, China Daily.
[48] Social media information is the news or information published by social media or new media, such as Twitter, Facebook, Weibo.

social media information can significantly increase the stock returns, predict the market volatility, and enhance the stock market performance (Antweiler and Frank, 2004; Das and Chen, 2007; Da et al., 2011; Bollen et al., 2011; Ge et al., 2017, etc.).

Even though the body of empirical studies examining the effect of media news and social media posts is relatively mature in the stock and bond markets, for the newly innovative financial market, like peer-to-peer (P2P) online lending market, such an effect has not yet been fully studied. The innovative P2P lending, also referred to as alternative lending, is an online-based marketplace lending, which uses technology (e.g., disruptive innovation) and connects individual lenders and borrowers directly. The rapid development of new media in recent years creates a research opportunity to examine to what extent traditional media news (coverage) and new media information could affect loan investors' online lending behavior in the context of the peer-to-peer lending market. As an innovative market, the serious information asymmetry exists in peer-to-peer lending market which has resulted in the greater significance of information in the peer-to-peer lending market (Verrecchia, 2001). Therefore, I fill in the gap to add another piece of empirical evidence to the literature, by examining the effect of media news and social media information on default probability and cost of capital of China's peer-to-peer online lending platforms. Importantly, I go further to explore the issue of why media news and social media information could have an effect on platforms' (firms') performance. According to prior literatures (Luo and Li, 2014; Gao and Yang, 2018; Kim and Ryu, 2021; Chiang and Lin, 2019), one of the reasons is that the sentiment has an effect on investors' behavior. The improving sentiment could enhance investors' confidence and investors' participation; therefore, such reports will help to decrease default probability and cost of capital of platforms.

In this research, I examine the effect of media and social media sentiments on default probability and cost of capital of China's peer-to-peer lending platforms (2015-2019). The results show a significantly negative effect of both media and social media sentiments on default probability, but a weak effect of media sentiment and social media sentiment on cost of capital. Moreover, the asymmetry effect between positive change of sentiment and negative change of sentiment on cost of capital has been proved after using the PSM method. The results prove that only positive change on media and social media sentiment could help reduce the default probability and cost of capital. I also find a significant and positive effect of media/social media sentiments and positive change on media/social media sentiment on investor number, which is consistent with my argument that the sentiment has an effect on investors' participation.

My study contributes to the existing literature in several ways. First, this paper contributes to the emerging literature on the peer-to-peer lending market. It has been widely presented in prior literature that there can be an issue of information asymmetry between online borrowers and investors in the peer-to-peer lending market (Freedman and Jin, 2008; Berkovich, 2011; Herzenstein et al., 2011; Michels, 2012; Duarte et al., 2012; Liao et al., 2017; Chen et al., 2018; Lin et al., 2018). I argue that the sentiments on media news and the social media posts can effectively alleviate the information asymmetry in the Chinese peer-to-peer lending market. I am interested in examining China's P2P lending market, for two main reasons: (1) the Chinese peer-to-peer lending market is the most innovative market in the last decade and the largest internet lending market in the world, with a cumulative number of over 6,000 platforms; meanwhile, compared with other countries, Chinese peer-to-peer lending market has some different characteristics (Wang et al., 2016); (2) It has gone through a complete life cycle of different development stages (start-up, sharply increase, then decline) which could help to explore the determinants of online lending platforms' failures dynamically. Second, my paper contributes to the media news literature (Barber and Loeffler, 1993; Albert and Smaby, 1996; Tetlock et al., 2008; Fang and Peress, 2009; Cahan et al., 2015; etc.), by extending the media sentiment effect to the context of the peer-to-peer lending market in China. Third, this paper contributes to the social media information literature (Antweiler and Frank, 2004; Das and Chen, 2007; Da et al., 2011; Bollen et al., 2011; Ge et al., 2017, etc.), by extending the social media sentiment effect to the context of the peer-to-peer lending market in China. Importantly, this paper finds the different asymmetry effect between positive change on sentiment and negative change on sentiment. Last, this paper goes further to provide an explanation why such an effect of media news and social media information on the alternative lending market exists.

The paper is structured as follows. Section 3.2 provides a literature review and hypothesis development, Section 3.3 provides an introduction of data and variables, Section 3.4 presents the sentiment analysis in my paper, Section 3.5 presents my methods and research models, Section 3.6 shows results and analysis, and the conclusions are provided in Section 3.7.

3.2.Literature Review and Hypothesis Development

Behavioral finance literature has extensively documented the effect of social mood on financial decisions, such as: firm valuation; capital budgeting; IPO and/or M&A activities and so on (Nofsinger, 2005). Empirical studies related to the effect of media news and the social media information effect on the financial market are becoming more frequent since the fast development of machine learning technology (Cahan, et al., 2015; Joseph, et al.,2017). The sentiment analysis based on texts and images makes quantifying language of news possible. There are many papers focusing on this effect (e.g., Barber and Loeffler, 1993; Albert and Smaby, 1996; Tetlock et al., 2008; Fang and Peress, 2009; Cahan et al., 2015), and most of the papers study the effect on stock markets. Different from these papers, my paper focuses on the effects of media news and social media information on the peer-to-peer lending market and concentrates on the simultaneous effect of both media news and social media posts.

3.2.1. The Effect of Media News

Media news effect on financial markets, especially on stock markets, has been studied extensively (Barber and Loeffler, 1993; Albert and Smaby, 1996; Tetlock et al., 2008;

Fang and Peress, 2009, Joseph, et al., 2017, etc.). Some papers state that there is a significant effect of media news on market performance.

Barber and Loeffler (1993) use second-hand information to investigate the news' effect on a security's price and trading volume and find that the price pressure induced by investor attention, leads to the positive abnormal return. Albert and Smaby (1996) argue that even though previous research has shown a significant positive effect of the news on abnormal returns, the effect is then followed by a partial price reversal, suggesting that the initial reaction was partly due to price pressure. Therefore, they use the estimated period after the event rather than before the event, and find that the significant reversal disappeared. Based on these two studies, researchers further investigate the impact of mass media on stock market performance from the view of the price pressure and the information diffusion (Ferreira and Smith, 1999; Kerl and Walter, 2007). All the results are consistent with prior studies that favorable news and recommendations have a positive effect on stock return and trading volume. Ferreira and Smith (1999) also find that non-repeated positive news have a significantly larger effect on average return of stocks than repeated positive news. Tetlok et al. (2008) state that negative words in financial news predict low firm earnings and negative words about firm fundamentals could be used to predict the low firm earnings and stock returns. Engelberg and Parsons (2011) first propose the causal relationship between media events and market reactions. They examine different levels of regional media coverage with regard to the same information event, and find that local media coverage could predict local trading volume. Dougal et al. (2012) show that news from the Wall Street Journal can predict the return of the Dow Jones Industrial Average for the next day. Peress (2014) investigates the causal effect of mass media on the stock market by investigating the strike of national newspapers in several countries, and reveals that after the closure of newspaper media, the ability of media information to predict trading volume and earnings has been weakened, especially for the stocks of small companies that are controlled by retail investors. Then, Ozik et al. (2013) find that different types of media news have different effects on hedge fund returns. The funds covered by corporate communications coverage outperformed the funds covered by general newspapers coverage by around 11%, however, the abnormal returns reveal that the investors do not react to media coverage and they ignore this important effect. Cahan et al. (2015) state that firms with good CSR (Corporate Social Responsibility) and favorable media coverage receive a higher firm value and a lower cost of capital.

Other papers hold some different opinions and state that media news may not work for all the firms' performance in the financial market. Wang and Ye (2015) find that firms receiving more neutral media coverage about their controlling shareholders enjoy higher valuation, whereas negative media coverage on controlling shareholders imposes adverse effects on firm valuation. Interestingly, favorable media coverage on their controlling shareholders does not necessarily enhance firm valuation as a whole, and the media news effect only works for those firms with lower non-controlling shareholder ownership and firms hiring small audit firms. Fang and Peress (2009) find that stocks with no media coverage have significant cross-section return premiums than stocks with high media coverage, even after controlling for major risk factors. Meanwhile, they state that the reason of the phenomenon is due to the positive relationship between media coverage and analyst forecast dispersion[49]/idiosyncratic volatility [50], and the negative relationship between analyst forecast dispersion/idiosyncratic volatility and stock return. Therefore, the stocks with high media coverage also earn lower returns.

Even though there are many papers above studying the effect of media coverage on firm's market activities, most of these studies focus on the effect of media news on the stock market and fund market, and there is less research on the effect of media news on the peer-to-peer lending market. Prior literature only focuses on the study about textual information of loan requests, for example, Gao and Lin (2015) state that investors indeed consider text descriptions when investing based on the data from Prosper.com, and the loan descriptive text features can explain and predict loan default. At the same time, investors could correctly interpret the information content of the loan descriptive texts. However, Gao and Lin (2015) do not conduct any text analysis on media news. Meanwhile, most studies research the effect of media news on firm value, trading volume, return in the stock market, but few papers study the effect on business bankruptcy and default probability, not to mention in less developed markets, such as peer-to-peer lending market.

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[49] Analyst forecast dispersion: the dispersion of analyst forecast.
[50] Idiosyncratic volatility: an indication of the speed at which firm-specific information is incorporated into prices.

As an innovative and less developed market, such as peer-to-peer lending market, information asymmetry is generally considered to be a serious issue. The graver information asymmetry made the peer-to-peer lending market an inefficient market, which promotes the effect of public information in the peer-to-peer lending market. Therefore, I expect the media news sentiment negatively affects the default probability of platforms, and my first hypothesis is stated as follows:

H1: Media news significantly affects the performance of peer-to-peer lending platforms.

H1a: Positive (negative) media news has a significant impact on decreasing (increasing) the default probability of platforms.

H1b: Positive (negative) media news has a significant impact on decreasing (increasing) the cost of capital of platforms.

3.2.2. The Effect of Social Media Information

The economy is a complex system of human interactions (Nofsinger, 2005). Unlike traditional mass media (i.e., one-way communication in nature), new media, conveying information and stimulating interactions and spreading emotions from one to the other, affects how people feel and drive how people will act. With the increasing popularity of social media platform, like Twitter and Weibo, social media information plays a more important role in media fields. Gathering empirical research regarding the impact of social media on the financial market and their economic consequences has become an increasingly popular focus for scholars.

Some papers state there is a significant correlation between social media postings and the financial market performance. Antweiler and Frank (2004) collect posts from Yahoo Finance and find that social media postings help to predict the market volatility, so as to have a significant effect on stock returns, but have a less significant effect on trading volume.[51] Das and Chen (2007) use the postings from Yahoo Finance to construct a proxy for the investors' sentiment and find that this constructed proxy is significantly correlated to the trading volume and the volatility. Da et al. (2011) use the search frequency in Google as a direct proxy for investor attention and show that this proxy can predict the stocks' prices in the next 2 weeks. Zhang et al. (2013) employ the search frequency of stock name in Baidu Index to explore the relationship between the search frequency and the asset price, and find a significant relationship. Zhang et al. (2014) employ the frequency of news that appeared in Baidu News as a proxy for information appearance and show that this proxy can explain the volatility persistence of the SME price index returns. Bollen et al. (2011) construct the collective mood proxy based on Twitter and find a significant predictive ability of the mood for the closing price of the Dow Jones Industrial Average. Zhang et al. (2016) employ the daily happiness index extracted from Twitter to investigate the impact of the sentiment on the stock market performance and find the positive relationship between them. Shen et al. (2016) construct a proxy for internet information flow by using the news appearing in Baidu

[51] They use the Dow Jones Internet index and the Dow Jones Industrial Average to calculate the market volatility and return.

News and find that the contemporary information can effectively reduce the volatility. Both the lead information and the aggregate information have some power to explain stock market behavior. Sul et al. (2016) find that the lower the number of followers (lower than 171) of a firm's users, the more significant effect of their sentiment on firm's future stock return.

On the other hand, some papers hold different opinions and find there is a weak relationship between social media postings and the stock performance. By using the postings in internet-based financial forums, Tumarkin and Whitelaw (2001) show that changes in investor opinions on days that published unusually active news are correlated with abnormal industry-adjusted returns. But the postings could not predict industry-adjusted earnings or abnormal trading volumes. This is consistent with a market efficiency hypothesis, stating that all the information has already been included in the recent stock price. Meanwhile, Dewally (2003) find that online postings related to stock recommendations are overwhelmingly positive, with a ratio of buy advice to sell advice greater than 7:1, which means the posts that recommend to buy a stock are 7 times the posts that recommend to sell. Moreover, most recommend postings follow a momentum strategy: recommend to buy the stock after the stock price increases. In addition, however, the stock market does not react to these internet-based recommendations. Dewally states that the postings on the internet do not affect the stock price and have no informational content.

A few researchers have studied peer-to-peer lending market as well. Ge et al. (2017) state that borrowers' social media account information disclosure could help reduce borrowers' default probability in China. Meanwhile, they find that the more messages borrowers posted on social media sites, the lower default probability of borrowers. In their research, they collect all the loan listings in one Chinese peer-to-peer platform (Renren Dai) from 2011 to 2013, and the borrowers' Weibo account messages, which uses a famous social media site (Weibo.com) in China, and use the logistic and PSM models to test the social media information effect on individual borrowers' default probability.

These findings inspire me that the social media information has impact on individuals' behavior in peer-to-peer lending market. Therefore, it could also affect the platforms' performance because most transactions in peer-to-peer lending market appears between individuals. In addition, the information asymmetry also promotes the power of social media information. Hence, I focus on the effect of social media information on default probability and cost of capital at the platforms' level in the peer-to-peer lending market, and my second hypothesis is stated as follow:

H2: Social media information significantly affects the performance of peer-to-peer lending platforms.

H2a: Positive (negative) social media information has a significant impact on decreasing (increasing) the default probability of platforms.

H2b: Positive (negative) social media information has a significant impact on decreasing (increasing) the cost of capital of platforms.

3.2.3. The Investors' Behavior

Even though there are many papers investigating the media news and social media information effect on financial markets, few papers studied the reasons behind the effect. One of the reasons I find that could help to explain this effect is the news sentiment motivate investors' participation which may due to the herding effect or the increase investor recognition.

According to prior studies (Luo and Li, 2014; Gao and Yang, 2018; Kim and Ryu, 2021; Chiang and Lin, 2019; Hudson et al., 2020), investor sentiment has significant effect on investors' behavior. Luo and Li (2014) find that futures market sentiment has significant impact on foreign investors' behavior, when the futures market sentiment is bullish (bearish), foreign investors are net buyers (net sellers). Gao and Yang (2018) state that investor sentiment help on explaining the investors' trading behavior and stock return. Kim and Ryu (2021) find the sentiment is the important determinant of investors' behavior, the sentiment shock will change investors' net positions. In addition, they find that government regulatory intervention will weaken the degree of the herding effect. Chiang and Lin (2019) state the significant effect of market sentiment on analysts' behavior. Furthermore, the effect of market sentiment on analysts' herding behavior mainly occurs for recommendations on hard-to-value firms, large firms, as well as firms with high institutional ownership, high book-to-market ratio and low coverage by analysts. Hudson et al. (2020) document a unidirectional investor sentiment effect on the herding of UK mutual fund managers.

In P2P lending market, the improving sentiment may increase the investors' recognition[52] (Agmon and Lessard, 1977; Merton, 1987; Bodnaruk and Ostberg, 2009; Foerster and Karolyi, 2002; Green and Jame, 2013; Jacobs et al., 2016) and brings herding effect[53] (Nofsinger and Sias, 1999; Sias, 2004; Blasco and Ferreruela, 2008; Chen, 2017; Chong et al., 2017; Jiang et al., 2018), which will attract more P2P investors or attract investors invest more. The survival likelihood of peer-to-peer lending platforms relies heavily on the numbers of active investors and lenders. The herding effect could attract more investors when the investor sentiments are positive while losing more investors when the sentiments are negative (Chen, 2017; Chong et al., 2017; Jiang et al., 2018; Choi and Yoon, 2020; etc.). Meanwhile, the emergence of a large number of active investors and trading volume is likely to reduce the platform's probability of default and to decrease the cost of capital of the platform, while the loss of a large number of investors and trading volume can increase the probability of default and reduce the average return cost of capital. And since the media and social media sentiments could enhance investor confidence and investor recognition, therefore, such reports will help to decrease default probability and cost of capital of platforms (Agmon

[52] Investors will only invest in the securities they know. If a company is known by more investors, it will reduce information asymmetry (Merton, 1987).

[53] Herding behavior occurs when a group of investors intentionally follows the actions or reactions of other investors who they consider to be better informed, instead of following their own beliefs and using their own information when they made the decisions (Chen, 2017).

and Lessard, 1977; Merton, 1987; Bodnaruk and Ostberg, 2009; Foerster and Karolyi, 2002; Green and Jame, 2013; Jacobs et al., 2016).

To test whether the media and social media sentiment have the impact on the investors' participation in the peer-to-peer lending platforms, my third hypothesis is stated as follow:

H3a: Positive (negative) media news has significant impact on the increasing (decreasing) investors' participation in the peer-to-peer lending market.

H3b: Positive (negative) social media information (post) has significant impact on the increasing (decreasing) investors' participation in the peer-to-peer lending market.

3.2.4. The Peer-to-peer Lending Market

Studies in the peer-to-peer lending market arise from 2008. Most of the earlier studies investigate the individual level by including the borrowers' or lenders' behavior (Freedman and Jin, 2008; Berkovich, 2011; Liao et al.,2017; Chen et al., 2018; Chen et al., 2020, etc.), the effect of borrowers' voluntary information disclosure (Herzenstein et al., 2011; Michels, 2012; Duarte et al., 2012; Lin et al., 2018, etc.), and the operational mechanism between the borrower and lender (Wei and Lin, 2017). Some studies examine the platform level research on the excess return, background, and location. (Zhang et al., 2019; Xiang et al., 2019; Li et al., 2020; etc.)

Some of the papers study the participators' behavior in the peer-to-peer lending market; Freedman and Jin (2008) find that adverse selection exists in the peer-to-peer lending market. Berkovich (2011) states that herding effects exist among investors of peer-to-peer platforms. Liao et al. (2017) find that unexperienced lenders in peer-to-peer platforms invest in loans with high-interest rates and high default rates hastily. Chen et al. (2018) find that peer-to-peer loans invested by female investors have higher default probability and lower loan returns. However, Chen et al. (2020) state that the female borrowers have lower default probability in the peer-to-peer lending market.

Other papers research borrowers' self-voluntary information disclosure effect on the peer-to-peer lending market. Herzenstein et al. (2011) and Michels (2012) find that borrowers' voluntary information disclosure could affect the lending rate and default probabilities. Duarte et al. (2012) find that borrower's appearance has the effect on the loan's default probabilities and interest rates. Lin et al. (2018) state that online friendships of borrowers could affect the lending rate and default probabilities.

Few papers study the mechanism in the peer-to-peer lending market: Wei and Lin (2017) find that loans with posted interest rate mechanism[54] have a higher probability and faster speed to be funded compared with auction mechanism in the peer-to-peer lending market.

[54] Posted prices means the contract interest rate is set by platform, while auctions mean the contract interest rate is determined through an auction process.

There are also some papers that focus on the platform-level research: Zhang et al. (2019) find that the excess return exists in the peer-to-peer lending market; Xiang et al. (2019) state that interest rate of platforms is significantly positively related to risk of platforms; Li et al. (2020) finds that the platforms which have VC-background are less likely to default.

3.3.Sample Selection

My sample consists of peer-to-peer lending platforms from September 2015 to May 2019[55] which are included in CSMAR database. All the basic data have been collected from CSMAR. All media news and social media information are collected, by using python programming, from WDZJ and P2PEYE[56], which are the two most famous peer-to-peer lending information intermediaries in China.[57] All media news is published on News Forum by all news agencies, while all social media posts are published on Community Forum by all participants which include investors, lenders, and potential investors or lenders on these two peer-to-peer lending information intermediaries.

As shown in Table 3.1, my final sample includes the monthly data of 971 peer-to-peer

[55] The time sample is from the September 2015 to May 2019 because the CSMAR only published the P2P platforms data since September 2015, and there are few media news and social media information updated in WDZJ and P2PEYE after the May 2019.

[56] WDZJ and P2PEYE are two most popular and largest information intermediaries in Chinese Peer-to-Peer lending market. Although the data published in WDZJ is no longer public, we have downloaded and saved all media news and social media posts.

[57] I collect the media news and the social media posts from WDZJ and P2PEYE rather than Baidu, which is the largest search engine, and Weibo, which is the largest social media platform, for three reasons: 1. Most of the media news in Baidu comes from WDZJ and P2PEYE; 2. There are few posts and little Peer-to-peer lending platforms information in Weibo, while most of investors publish posts on WDZJ and P2PEYE communities; 3. Baidu has the anti-python mechanism which may lead to some illegal act.

lending platforms between September 2015 and May 2019. 686 platforms are survival while the 285 platforms are in default. The total observations are 19,861. My study starts from September 2015 because that is when CSMAR began to publish information about peer-to-peer lending platforms.

Insert Table 3.1 about here

To evaluate the effect of media coverage on the default probability and the cost of capital at the platform level, I use Python to collect all media news on WDZJ and P2PEYE from September 2015 to May 2019. There are 6,380 news items published on WDZJ and 3,923 news items published on P2PEYE, therefore, the total news items that I collected are 10,303 items.

To evaluate the effect of social media postings on the default probability and the cost of capital at the platform level, I also use Python to collect all social media postings on WDZJ and P2PEYE forums from September 2015 to May 2019. There are 24,746 postings published on WDZJ and 156,518 posts published on P2PEYE, therefore, the total posts that I collected are 181,264.

3.4.Sentiment Analysis

One of the important parts in this paper is to conduct sentiment analysis of media news and social media posts. To examine the media and social media sentiment tendencies, I use two different methods: Naive Bayes[58] in traditional machine learning[59] and BP (Back Propagation)[60] which is a widely used neural network.[61]

For the Naive Bayes, I first clear the data by filtering the data through the Chinese dictionaries in Snownlp, splitting the words, dropping the low-related words, and keeping the high-related words which means the machine needs to clear the common nouns and prepositions. Then, I choose positive feature words and negative feature words though 1000 random sample, and put these feature words[62] into the model in Snownlp to train. Snownlp is a popular nature language process with generalizing class libraries that was written by Python, which used to deal with Chinese text sentiment analysis. Snownlp brings some trained dictionaries that cover most of Chinese text, and it can be used in different scenes and areas, especially comments and opinions. Many studies use it to run the text analysis, like Chen et al. (2018), Zhao et al. (2018), Jia and Li (2020), Song et al. (2020), and Zhang et al. (2020). Meanwhile, it can also be used to train your own models with putting specific feature words into the sentiment analysis processing libraries and therefore be trained. After the training, the model can judge each news item automatically in python. It will output the probability of the news,

[58] Naive Bayes method is a classification method based on Bayes theorem and independent hypothesis of feature conditions. Naive Bayesian algorithm is widely used in text recognition, text classification, and image recognition. It can classify unknown text or image according to its existing classification rules, and finally achieve the purpose of classification.

[59] Machine learning studies how computers simulate or implement human learning behavior in order to acquire new knowledge or skills and reorganize the existing knowledge structure so as to continuously improve its own performance. The research directions of traditional machine learning mainly include decision tree, random forest, artificial neural network and Bayesian learning.

[60] BP (back propagation) neural network is a multi-layer feedforward neural network trained according to the error reverse propagation algorithm, and it is currently the most widely used neural network.

[61] Neural network algorithm is composed of a large number of neurons connected by adjustable connection weights, with the characteristics of large-scale parallel processing, distributed information storage, good self-organization and self-learning ability. It is widely used in deep learning research area.

[62] The feature words have been listed in Appendix 3.2.

which range from 0 to 1. If the news probability is not higher than 0.33[63], I judge it as news with negative sentiment tendency and use -1 to represent it; if the news probability is not higher than 0.66, I judge it as news with neutral sentiment tendency and use 0 to represent it; and if not, the news then should have a positive sentiment tendency and use 1 to represent it. Many people think that the news title should have more weight compared with other sentences in a news item or post. So, based on Piotroski et al. (2017), I put 30% weight to the title and 70% weight to other content of all news and posts. At last, since I use monthly data to examine the effect of the media news and social media posts, following the method of Cahan et al. (2015), I calculate the monthly media sentiment of each platform by using the aggregated number of positive sentiment news minus the aggregated number of negative sentiment news and then divided by the total amount of news in each month, the function is as follows:

$$MF_{it} = \frac{N.POS_{it} - N.NEG_{it}}{N.TOL_{it}}$$

Where, *MF* represents monthly news sentiment for each platform, *i* represents platform, *t* represents time (month). *N.POS* (*N.NEG*) represents number of positive (negative) news based on the sentiment that we calculate by the above method; *N.TOL* represents number of total news.

For the neural network, I just use the models that are trained by Baidu API which is a Chinese Text Analytics created by Baidu company. Baidu API uses the specific three-layer back-propagation neutral network that is being trained using thousands of human

[63] The 0.33 and 0.66 are set in the Python and the Snownlp, based on the paper of Piotroski et al. (2017), the 0.33 and 0.66 should be used when I coding the sentiment analysis.

labelled news and accurate feature words. Because of the byte limitation[64] since August 2019 in Baidu API, the results may not be reproduced; therefore, I just use these results to do the robustness check. Another reason for using Naive Bayes in Snownlp in my main model rather than the Back-Propagation Neutral Network in Baidu API is that there is no need to consider the word order in the news, I only need to analyze the key words and get the classified result. Therefore, the Naive Bayes is more suitable, so, I used the results from the Snownlp in my main model, while the results from the Baidu API in the robustness check. Finally, all the programming and coding are based on Python.

3.5.Methods

3.5.1. Descriptive Statistics

The descriptive statistical analysis for all variables is reported in Table 3.2.[65] *DEFAULT* represents default probability of platforms, which is measured as 1 if the platform has defaulted, and 0 if the platform has survived. *CC* represents cost of capital of platform, which is also the average return provided and accepted to investors. *IN* represents investor number of platform, which is the monthly total investor numbers of platform. *NCI* represents net capital inflow of platform, which is the monthly net capital inflow of platform. *ALT* represents average loan maturity of platform, which is the

[64] Baidu API has the byte limitation that could only deal with the sentiment analysis within 2048 bytes since August 2019.

[65] And the definitions of all variables are shown in Appendix 3.1.

monthly average loan period of platform. *CR* represents cumulative repay of platform, which is the monthly cumulative outstanding loans of platform. *L* represents platform geographical location and *B* represents the background of platform. *RF* represents risk free rate, which is the monthly SHIBOR (Shanghai Interbank Offered Rate). As the results, the mean of default is 0.2962, which implies most of the platforms are survival. The mean of the cost of capital of the platform is 10.499%, and the median is 10.62%. The mean of risk-free rate is 3.4513, and the median is 3.3059% which are lower than the cost of capital of the peer-to-peer lending platform. All the continuous variables in the basic model are winsorized at the top and bottom at 1%.

The range of *MCMF* (media news sentiment) is -1 to 1, the mean of *MCMF* is 0.0804, and the median is 0, which means that the media sentiment is slightly positive in total. The mean of *SMMF* (social posts sentiment) is 0.1283 and the median is 0, which means that the social media sentiment is also slightly positive in total. The testing variables which include *MCMF* and *SMMF* display significant variations, the dependent variables *DEFAULT* (default probability) and *CC* (cost of capital) also display significant variations, though other control variables have relatively low variations.

Insert Table 3.2 about here

3.5.2. Unit Root Test

All the p-value are less than 0.05 which means that all the continuous variables in my basic model are stationary at least in 1 lag. I use the Fisher unit root test because of the unbalanced panel data sample.

3.5.3. Correlation Analysis

Table 3.3 show the correlations between all variables in the models. *DEFAULT* and *CC* are dependent variables, the *MCMF* and *SMMF* are testing variables. Except these four variables, the *CR* (cumulative repay), *ALT* (average lending time), *NCI* (net capital inflow), *L* (Location), and *B* (business background) are control variables. Meanwhile, the *CR*, *ALT*, and *NCI* change with time and platforms, while the *B* (business background) and *L* (location) only change with platforms.

The results show that *CC* and *CR* are positively correlated to *DEFAULT*, the two testing variables: *MCMF* and *SMMF* have impact on reducing *DEFAULT*; *ALT* (*NCI*) is positively (negatively) correlated to *CC*, but both of testing variables have positive (*MCMF* and *SMMF*) show less effect on *CC*. However, these results should be re-tested by the multi-regressions.

Insert Table 3.3 about here

3.5.4. Logistic Regression

The Logistic regression[66] has been chosen to test the effect of media and social media

[66] The Logistic regression is usually used for regression where the dependent variable is dichotomous. The

sentiment on default probability. According to the study of Carlos et al. (2015) and Xiang et al. (2018), return or interest rate will significantly increase the default probability. According to the study of Jiang et al. (2018), state-owned platforms have lower default probability, therefore, different backgrounds have different effect on default probability of platforms. Based on the report published by Lufax (2014), different locations represented different levels of economic development conditions for peer-to-peer lending platforms, therefore, different locations have various effects on default probability of platforms. Prior studies find that the size and lending time of platforms have impact on default probability (Carlos et al., 2015; Jiang et al., 2018; Wang et al., 2020). Meanwhile, CSMAR publishes the *TV*, *CR*, *ALT*, and *NCI*. However, the *TV* is dropped because of multicollinearity. Therefore, *CR* (cumulative repay), *ALT* (average lending time), *NCI* (net capital inflow), *B* (background), *L* (location) are control variables in my model. Therefore, my Base1[67] is as follow:

$$DEFAULT_{it} = \alpha_{it} + \beta_1 CC_{it} + \beta_2 CR_{it} + \beta_3 ALT_{it} + \beta_4 NCI_{it} + \beta_5 \sum_{n=1}^{4} L_{it} + \beta_6 \sum_{n=1}^{4} B_{it} + \varepsilon_{it} \quad \text{(Base1)}$$

Prior literature (Barber and Loeffler, 1993; Albert and Smaby, 1996; Antweiler and Frank, 2004; Das and Chen, 2007; Tetlock et al., 2008; Fang and Peress, 2009, Bollen et al., 2011; Da et al., 2011; Zhang et al., 2014, Zhang et al., 2016; Shen et al., 2016; Zhang et al., 2016; Ge, et al., 2017; Joseph, et al., 2017; etc.) study the media news and

dependent variable in the Logistic model can be of the class of binary nonlinear difference equations or multi classification, but the binary classification is more commonly used and easier to explain.

[67] The constant term represents the long-standing (non-random) part that is not explained by the independent variable, that is, the information residue. The random error is the error between the predicted value and the actual value without the constant term in the independent variable interpretation space.

social media posts effect on firms' behavior (firms' valuation) and investors' behavior (stocks' earning, volatility) and find some significant results.

To test the effect of media news and social media posts effect on the default probability at platform level, the media sentiment and social media sentiment are added on the basis of the Base1 model. Follow the above theories, the models are as follows:

$$DEFAULT_{it} = \alpha_{it} + \beta_1 MCMF_{it} + \beta_2 SMMF_{it} + \sum_{n=3}^{n} \beta_n Controls_{it} + \varepsilon_{it} \quad (1)$$

$$DEFAULT_{it} = \alpha_{it} + \beta_1 MCMF_{it-1} + \beta_2 SMMF_{it-1} + \sum_{n=3}^{n} \beta_n Controls_{it} + \varepsilon_{it} \quad (2)$$

$$DEFAULT_{it} = \alpha_{it} + \beta_1 (MCMF_{it} - MCMF_{it-1}) + \beta_2 (SMMF_{it} - SMMF_{it-1}) + \sum_{n=3}^{n} \beta_n Controls_{it} + \varepsilon_{it} \quad (3)$$

Model (1) to model (3) are used to test the effect of media news and social media posts on default probability. Model (1) is level model: Default is affected by level of sentiment (include all positive, natural and negative sentiment). In the model (1), *DEFAULT* is dependent variable, *MCMF* (media sentiment) and *SMMF* (social media sentiment) are testing variables successively, control variables are: *CC* (cost of capital), *CR*, *ALT*, *NCI*, *B*, and *L*. I expect the higher *CC* (cost of capital), the higher *DEFAULT* (default probability) since the higher return, the higher risk based on CAPM theory (Sharpe, 1964); the higher *CR* (cumulative repay), the higher *DEFAULT* because the higher *CR* means the weaker solvency; the higher *ALT* (average lending time), the higher *DEFAULT* because the time will increase the risk; the higher *NCI* (net capital inflow), the lower *DEFAULT* because *NCI* could measure the liquidity of platform, the higher liquidity, the lower risk (Fama and French, 1993,1996).

Model (2) is lagged level model which is used to test the effect of the lag of media news and the lag of social media posts on default probability. The $MCMF_{it-1}$ is the one lag of media sentiment and the $SMMF_{it-1}$ is the one lag of social media sentiment.

Model (3) is used to examine the effect of the change of media sentiment and social media sentiment (include positive change, negative change and no change) on default probability. The ($MCMF_{it}$ - $MCMF_{it-1}$) is the change of media sentiment and the ($SMMF_{it}$ - $SMMF_{it-1}$) is the change of social media sentiment.

Based on a review of the literature (Barber and Loeffler, 1993; Albert and Smaby, 1996; Tetlock et al., 2008; Da et al., 2011; Ge, et al., 2017; Joseph, et al., 2017; Shen et al., 2016; etc.) and hypothesis 1, news and sentiment have the significant effect on the firms' performance (trading volume and return) because they contain some inside information and market (investor) expectations. Therefore, as a market whose performance is extremely affected by investors' behavior, I expect that the sentiment and the change in sentiment have the power on reducing the default probability.

3.5.5. Multi-Regression Analysis – Cost of capital

The Random-Effect regression (GLS) has been chosen to test the effect of media and social media sentiment on cost of capital follow the results of Hausman Test. But we then also control the time variable to run the Two-Way Fixed-Effect model to deal with the endogenous problem. Based on Fledstein and Eckstein's (1970) paper, the risk-free rate is positively related to return. According to the study of Jiang et al. (2018) and the report published by Lufax (2014), different backgrounds and locations have various effect on platforms' cost of capital. Meanwhile, prior literature states that the size and lending time could affect the cost of capital (Carlos et al., 2015). Therefore, *RF*, *CR*, *ALT*, *NCI*, *B* (background), *L* (location) are control variables in my model.

Prior literature (Barber and Loeffler, 1993; Albert and Smaby, 1996; Antweiler and Frank, 2004; Tetlock et al., 2008; Das and Chen, 2007; Fang and Peress, 2009; Bollen et al., 2011; Da et al., 2011; Zhang et al., 2014, Zhang et al., 2016; Shen et al., 2016; Zhang et al., 2016; Ge, et al., 2017; Joseph, et al., 2017; etc.) studied the media news and social media posts effect on return (cost of capital) and find various results. Therefore, my Base2 is as follow:

$$\begin{aligned} CC_{it} &= \alpha_{it} + \beta_1 RF_{it} + \beta_2 CR_{it} + \beta_3 ALT_{it} + \beta_4 NCI_{it} \\ &+ \beta_5 \sum_{n=1}^{4} L_{it} + \beta_6 \sum_{n=1}^{4} B_{it} + \varepsilon_{it} \quad \text{(Base2)} \end{aligned}$$

To test the effect of media news and social media information effect on the cost of capital at platform level, I use the Two-Way Fixed-Effect[68] analysis. The models are as follows:

$$CC_{it} = \alpha_{it} + \beta_1 MCMF_{it} + \beta_2 SMMF_{it} + \sum_{n=3}^{n} \beta_n Controls_{it} + \varepsilon_{it} \quad (4)$$

$$CC_{it} = \alpha_{it} + \beta_1 MCMF_{it-1} + \beta_2 SMMF_{it-1} + \sum_{n=3}^{n} \beta_n Controls_{it} + \varepsilon_{it} \quad (5)$$

$$CC_{it} = \alpha_{it} + \beta_1 (MCMF_{it} - MCMF_{it-1}) + \beta_2 (SMMF_{it} - SMMF_{it-1}) + \sum_{n=3}^{n} \beta_n Controls_{it} + \varepsilon_{it} \quad (6)$$

Model (4) to model (6) are used to test the effect of media news and social media posts on cost of capital. In the model (4) to model (6), *CC* (cost of capital) is dependent variable, *MCMF* (media coverage sentiment), and *SMMF* (social media sentiment) are testing variables in sequence, control variables are: *RF*, *CR*, *ALT*, *NCI*, *B*, and *L*. I expect the higher *RF* (risk-free rate), the higher *CC*[69] (Feldstein and Eckstein, 1970); the higher *CR* (cumulative repay), the lower *CC* because the higher *CR* means the larger size of platform and weaker solvency of platform for investors; the higher *ALT* (average lending time), the higher *CC* because the time value of money (longer period, the less value of money); the higher *NCI* (net capital inflow), the lower *CC* because *NCI* could measure the liquidity of platform, the higher liquidity, the lower risk (Fama and French, 1993,1996) which will lead to the lower return and cost of capital of platforms.

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[68] Follow the results of Hausman Test, the Random-Effect regression (GLS) is more suitable than Fixed-Effect regression (FGLS). But we then also control the time variable to run the Two-Way Fixed-Effect model to deal with the endogenous problem.

[69] The *CC* (cost of capital) here also represents the return from investors' perspective.

Model (4) is level model: Cost of Capital (*CC*) is affected by level of sentiment (include all positive, natural and negative sentiment).

Model (5) is lagged level model which is used to test the effect of the lag of media news and the lag of social media posts on cost of capital. The $MCMF_{it-1}$ is the one lag of media sentiment and the $SMMF_{it-1}$ is the one lag of social media sentiment.

Model (6) is used to examine the effect of the change of media sentiment and social media sentiment on cost of capital. The ($MCMF_{it}$ - $MCMF_{it-1}$) is the change of media sentiment and the ($SMMF_{it}$ - $SMMF_{it-1}$) is the change of social media sentiment.

Based on literature (Barber and Loeffler, 1993; Albert and Smaby, 1996; Tetlock et al., 2008; Da et al., 2011; Ge, et al., 2017; Joseph, et al., 2017; Shen et al., 2016; etc.) and hypothesis 2, news and sentiment contains inside information and market (investor) expectations which help on affecting firms' performance (trading volume and return). Since the cost of capital also represents the average return of platform from investors' perspective, I expect that the sentiment and the change on sentiment could decrease the cost of capital.

3.5.6. Multi-Regression Analysis – Investors' Behavior

As I stated in the literature review, one of the reasonable explanations for why the media sentiment and social media sentiment could affect default probability and firm's value is that the sentiment could affect investors' participation. To test whether the media news and social media information have effect on the investors' behavior, I use the Two-Way Fixed-Effect Regression[70] analysis again. The *IN* (investor number) and is chosen to test the effect because it could measure the investors' participation in the whole market of each platform. As the models in 3.5.5., the testing models are as follows:

$$IN_{it} = \alpha_{it} + \beta_1 MCMF_{it} + \beta_2 SMMF_{it} + \sum_{n=3}^{n} \beta_n Controls_{it} + \varepsilon_{it} \quad (7)$$

$$IN_{it} = \alpha_{it} + \beta_1 MCMF_{it-1} + \beta_2 SMMF_{it-1} + \sum_{n=3}^{n} \beta_n Controls_{it} + \varepsilon_{it} \quad (8)$$

$$IN_{it} = \alpha_{it} + \beta_1 (MCMF_{it} - MCMF_{it-1}) + \beta_2 (SMMF_{it} - SMMF_{it-1}) + \sum_{n=3}^{n} \beta_n Controls_{it} + \varepsilon_{it} \quad (9)$$

Model (7) to model (9) are used to test the effect of media news and social media posts on investor number (*IN*). The *MCMF* is the measure of media sentiment and the *SMMF* is the measure of social media sentiment. As the models in 3.5.4. and 3.5.5., I examine the effect of media and social media sentiment ($MCMF_{it}$ and $SMMF_{it}$), one lag of them ($MCMF_{it-1}$ and $SMMF_{it-1}$), change of them ($MCMF_{it} - MCMF_{it-1}$ and $SMMF_{it} - SMMF_{it-1}$) in sequence.

Based on literature (Luo and Li, 2014; Gao and Yang, 2018; Kim and Ryu, 2021; Chiang and Lin, 2019; Hudson et al., 2020) and hypothesis 3, sentiment has significant

[70] I controlled the time variable in the Panel Random-Effect Regression to run the Two-Way Fixed-Effect Regression.

impact on investors' behavior in futures market and stock market, and positive sentiment could attract investors (or attract investors invest more), I expect that *MCMF* and *SMMF* are significantly positive related to *IN* (investor number).

3.6.Empirical Results and Analysis

3.6.1. Default Probability of Platform

Table 3.4 represent the results of *MCMF* and *SMMF* effect on default probability. All the results of control variables are consistent with my expectation (the higher the Cost of Capital (*CC*), the higher Cumulated Repay (*CR*), the lower Net Cash Inflow (*NCI*), the higher Default (*DEFAULT*) except the Average Lending Time (*ALT*). I expect the higher Average Lending Time (*ALT*), the higher *DEFAULT*, but the results show the reverse effect. One of the possible reasons is platforms with small size and low quality tend to offer more short-term loans (WDZJ, 2017), which may motivate the negative *ALT* coefficient. Panel A of Table 3.4 represents the results of media sentiment (*MCMF*) and social media sentiment (*SMMF*) effect on default probability, the results show that both media sentiment (*MCMF*) and social media sentiment (*SMMF*) have a significantly negative effect on default probability. The coefficient -0.0490 (-0.0520) indicates that the media sentiment (social media sentiment) helps reduce the default probability at 4.90 (5.20) percentage points.

Panel B of Table 3.4 shows the impact of one lag of media sentiment (*MCMF*) and one lag of social media sentiment (*SMMF*) on default probability. Based on the results, both the $MCMF_{t-1}$ and the $SMMF_{t-1}$ have significantly negative effects on default probability. The coefficient -0.0361 (-0.0452) indicates that one lag of media sentiment (one lag of social media sentiment) helps reduce the default probability at 3.61 (4.52) percentage points.

The results of media sentiment (*MCMF*) and social media sentiment (*SMMF*) are consistent with the literature and hypothesis 1. The higher media sentiment and social media sentiment, is the lower default probability.

Since I used the logistic model to examine the effect of media sentiment (*MCMF*) and social media sentiment (*SMMF*) on default probability, I need to evaluate the prediction power with the area under the receiver operational characteristic (ROC) curve (AUC). AUC is a standard metric used to assess models that predict classification probabilities (Huang and Ling, 2015). Table 3.5 displays the AUCs of each model I used in the testing of default probability of platforms. The AUC of Base model is 0.6988, which is also the benchmark. After adding the *MCMF* and *SMMF* separately in the model (1) and model (2), the AUC increased to 0.7122 and 0.7138, then, the AUC improved to the larger value in the model (3) which is the model with both *MCMF* and *SMMF*, and reach 0.7577. All the results demonstrate the increasingly significant effect of media sentiment (*MCMF*) and social media sentiment (*SMMF*) on default probability of platforms.

Insert Table 3.4 about here

Insert Table 3.5 about here

3.6.2. Cost of Capital of Platform

Table 3.6 represents the results of media sentiment (*MCMF*) and social media sentiment (*SMMF*) effect on cost of capital. Almost all the results of control variables are consistent with my expectation (the higher Risk-Free Rate (*RF*), lower Cumulated Repay (*CR*), the higher Average Lending Time (*ALT*), the lower Net Cash Inflow (*NCI*), the higher cost of capital). Panel A of Table 3.6 represents the results of media sentiment (*MCMF*) and social media sentiment (*SMMF*) effect on cost of capital, the results show that both media sentiment (*MCMF*) and social media sentiment (*SMMF*) have weak effect on cost of capital. Meanwhile, Panel B of Table 3.6 shows the results of predictive power of media sentiment (*MCMF*) and social media sentiment (*SMMF*) on cost of capital. The insignificant coefficients on one lag of media sentiment (*MCMF*) and social media sentiment (*SMMF*) reveal that none of them have been significantly related to cost of capital.

Insert Table 3.6 about here

Even though all these results are consistent with some prior studies that the news has a weak effect on cost of capital, these attract my deep study on this question. I consider that both the current sentiments and one lag of them cannot reflect the change on the sentiment which could be the crucial factor affecting the default probability and cost of capital of platforms. Therefore, the change of media sentiment (*DMCMF*) and social media sentiment (*DSMMF*) are examined in Panel C of Table 3.6. However, the results still show less effect of media and social media sentiment. In addition, I also test the effect of the change of media sentiment (*DMCMF*) and social media sentiment (*DSMMF*) on the default probability, the results in Panel C of Table 3.4 still display the insignificance of change in media sentiment (*DMCMF*) and social media sentiment (*DSMMF*).

3.6.3. PSM Results - Default Probability

Prior studies prove the asymmetry effect between goods news and bad news on stock volatility[71] (Engle and Ng, 1993; Braun et al., 1995; Malik, 2011) and return[72] (Bae and Karolyi, 1994; Depken, 2001; Nasseri et al., 2016). Therefore, I use the PSM model to test the different effects of positive sentiment and negative sentiment. In Model (3-2), I compare the observations with positive change on media sentiment to the observations with no change on media sentiment; in Model (3-3), I compare the observations with negative change on media sentiment to the observations with 0 change on media sentiment; similarly, in Mode (3-4) and (3-5), I compare the observations with positive and negative change on social media sentiment to the

[71] Engle and NG (1993), Braun et al. (1995), and Malik (2011) find the negative news have more effects on stock volatility than positive news.
[72] Bae and Karolyi (1994) and Depken (2001) state the asymmetry effect of good and bad news on stock return; Nasseri et al. (2016) prove that the news sentiment effect is stronger and more sensitive in bull market.

observations with no change on social media sentiment. All the samples after matching have passed the balance test.

Results in Table 3.7 show that only positive DMCMF and positive DSMMF have significant effects on decreasing default of platforms. In model (3-2), the significant coefficient of *PSM-DM* (positive *DMCMF*) is -0.0215, which means each increase in media sentiment (*MCMF*) could help to reduce the default probability at 2.15%. In model (3-4), the significant coefficient of *PSM-DS* (positive *DSMMF*) is -0.0478, which indicates that each increase in social media sentiment (*SMMF*) reduces the default probability at 4.78%. In model (3-3) and (3-5), the insignificant *PSM-DM* (negative *DMCMF*) and *PSM-DS* (negative *DSMMF*) show the lower effect of the negative change in media sentiment (*MCMF*) and social media sentiment (*SMMF*) on default probability.

Insert Table 3.7 about here

These results indicate that only positive change of media/social media sentiment have a significant impact on decreasing default which proves that only the improving sentiments (both media and social media) could help to reduce the default probability of platforms. The possible explanation is the increasing media/social media sentiment has been interpreted as good indicator by investors who are subsequently willing to invest more capital into platforms, but even the deteriorating media/ social media sentiment has been interpreted as bad signal by investors, it will not persuade investors to leave immediately because all the bids and products in peer-to-peer lending market cannot be sold or withdrawn in a short period of time once the investment is completed. These results prove that the asymmetry effect between positive sentiment and negative sentiment still exists in the peer-to-peer lending market.

3.6.4. PSM Results - Cost of Capital

As I discussed in 3.6.3., the PSM model is also used to test the effect of the change of media/social media sentiment on cost of capital again. In Model (6-2) and Model (6-3), the observations with positive and negative change on media sentiment is compared with the observations with no change on media sentiment; in Mode (3-4) and (3-5), the observations with positive and negative change on social media sentiment to the observations with no change on social media sentiment. All the samples after matching have passed the balance test.

Table 3.8 shows the PSM results of cost of capital. In model (6-2), the significant coefficient of *PSM-RM* (positive *DMCMF*) is -0.0335, which means each increase in *MCMF* could help to reduce the cost of capital at 3.35%. In model (6-4), the significant coefficient of *PSM-RS* (positive *DSMMF*) is -0.0482, which indicates that each increase in *SMMF* reduces the cost of capital at 4.82%. In model (6-3) and (6-5), the insignificant *PSM-RM* (negative *DMCMF*) and *PSM-RS* (negative *DSMMF*) show the lower effect of the negative change in *MCMF* and *SMMF* on cost of capital.

Insert Table 3.8 about here

The results indicate that only positive change of media/social media sentiment have significant impacts on decreasing cost of capital which proves that only the increasing sentiments (both media and social media) have the negative impact on cost of capital of platforms. As I stated in 3.6.3., the asymmetry effect between positive change of sentiment and negative change of sentiment in peer-to-peer lending market is one possible reason. Only the improving sentiments (both media and social media) could attract investors which could increase the demand for bids or products of platforms in the lending market and reduce the cost of capital of platforms. Another reasonable theory is the investor recognition (Agmon and Lessard, 1977; Merton, 1987; Bodnaruk and Ostberg, 2009; Foerster and Karolyi, 2002; Green and Jame, 2013; Jacobs et al., 2016): investor confidence and recognition increases with the improving sentiment which will also raise the capital supply in the peer-to-peer lending market which could decrease the cost of capital of platforms.

3.6.5. Investors' Behavior

In order to confirm my above conjecture about the reasons of the effect of media and social media sentiment, I examine the effect of sentiments on investors' participation in peer-to-peer lending market. Table 3.9 indicates the effect of *MCMF* and *SMMF* on investor number (*IN*). The results in Panel A of Table 3.9 are consistent with hypothesis

3, both the *MCMF* and *SMMF* have significant positive effects on investor number (*IN*). The coefficient 0.221 (0.0884) indicates that *MCMF* (*SMMF*) help increase the *IN* at 22.1 (8.84) percentage points. Meanwhile, results in Panel B of Table 3.9 still reveal the strong effect of one lag of *MCMF* (*SMMF*) on investor number (*IN*). All these results are consistent with prior literature and theories (Luo and Li, 2014; Gao and Yang, 2018; Kim and Ryu, 2021).

Similar as default and cost of capital, I also investigate the effect of change (first difference) of media/ social media sentiment on investor number. However, the results in Panel C of Table 3.9 show less effect of change of media and social media sentiment.

Insert Table 3.9 about here

3.6.6. PSM Results - Investor Number

Because of the weak effect of the change (first difference) of media/social media sentiment on investor number, I still use the PSM model to study these effects by separating the positive and negative change (first difference) of media and social media sentiment. Table 3.10 displays the PSM results between the positive/negative change of media sentiment and the zero change of media sentiment (list in (9-2)/ (9-3)); and the results between positive/negative change of social media sentiment and zero change of social media sentiment (list in PSM (9-4)/ (9-5). In model (9-2), the significant coefficient of *PSM-IM* (positive *DMCMF*) is 0.192, which means each increase in

MCMF could help on increase investor number at 19.2%. In model (9-4), the significant coefficient of *PSM-IS* (positive *DSMMF*) is 0.216, which indicates that each increase in *SMMF* raises investor number at 21.6%. In model (9-3) and (9-5), the insignificant *PSM-IM* (negative *DMCMF*) and *PSM-IS* (negative *DSMMF*) show the less effect of the negative change in *MCMF* and *SMMF* on investor number. These results prove that only positive change of media and social media sentiment has significant effect on investor number.

Insert Table 3.10 about here

In summary, these results in Table 3.10 are consistent with my supposition (in 3.6.3. and 3.6.4.) that only increasing (positive change of) sentiments (both media and social media) could attract more investors and enhance investor confidence, which help to reduce default probability and cost of capital of platforms.

3.6.7. Robustness Check

I use Baidu API a Chinese Text sentiment analysis tool to recalculate scores of media sentiment (*MCMFR*) and social media sentiment (*SMMFR*). Then, I replace the *MCMF* and *SMMF* in my default models and the cost of capital models to run the robustness check. Results in Table 3.11 indicate the significant impact of media and social media sentiment on reducing default probability; results in Table 3.13 show the less effect of media and social media sentiment on cost of capital; and results in Table 3.14 suggest the significant positive effect of media and social media sentiment on the investor number. All the results are similar as previous results, which means that my results are robust.

Insert Table 3.11 about here

Insert Table 3.12 about here

Insert Table 3.13 about here

Insert Table 3.14 about here

3.7.Conclusion

This study investigates the effects of media sentiment and social media sentiment on default probability and cost of capital in the Chinese peer-to-peer lending market. Using the unique media news and social media posts dataset that was collected by python and analyzed by Snownlp, a sentiment analysis instrument, I find that both the media sentiment and social media sentiment could affect the default probability. However, both media sentiment and social media sentiment have less of an effect on the cost of capital of platforms in the peer-to-peer lending market. Meanwhile, only the positive change on the media and social media sentiment could reduce the default probability and cost of capital, while the negative change on sentiments has less of an effect. Furthermore, the sentiment could affect the investors' participation and investors' behavior in the P2P lending market because both the sentiment and the positive change on sentiment have significant positive relations on investor number.

My study contributes to the existing literatures from several aspects. Firstly, I find the significant effect of media sentiment and social media sentiment on the loan default, cost of loan, and the investors' behavior. These results significant contribute to media news literature and social media information literature ((Barber and Loeffler, 1993; Albert and Smaby, 1996; Tetlock et al., 2008; Fang and Peress, 2009; Cahan et al., 2015; Antweiler and Frank, 2004; Das and Chen, 2007; Da et al., 2011; Bollen et al., 2011; Ge et al., 2017) by extending the social media sentiment effect to the context of the peer-to-peer lending market in China. Secondly, I find that the media news sentiment and the social media information sentiment could alleviate the information asymmetry in the P2P market, which extend the existing studies in peer-to-peer lending market (Freedman and Jin, 2008; Berkovich, 2011; Herzenstein et al., 2011; Michels, 2012; Duarte et al., 2012; Liao et al., 2017; Chen et al., 2018; Lin et al., 2018). Thirdly, I find the asymmetry effect between positive change on sentiment and negative change on sentiment on default probability and cost of capital of platforms, which gives inspirations for future studies. Fourthly, I explain the feasible and potential reason and mechanism of the effect of media news and social media information, which contributes to behavior finance literature (Nofsinger and Sias, 1999; Sias, 2004; Blasco and Ferreruela, 2008; Green and Jame, 2013; Jacobs et al., 2016; Luo and Li, 2014; Gao and Yang, 2018; Chiang and Lin, 2019; Hudson et al., 2020; Kim and Ryu, 2021).

This study has some implications to participators in the peer-to-peer lending market.

For policymakers, the government should focus on the effect of media news and social media posts in the innovation market by monitoring the media sentiment and social media sentiment in the market. This will help on improving the government regulation on the newly financial market. For investors, they need to pay more attention on the platforms with improving media and social media sentiment because they will help on reducing default probability and cost of capital (which is also return for investors).

References

Abdi, H., Williams, L.J., 2010, Principal component analysis, Wiley Interdisciplinary: Reviews Computational Statistics 2(4), 433-459.

Agmon, T., Lessard, D.R., 1977. Investor recognition of corporate international diversification. The Journal of Finance, 32(4), 1049–1055.

Akerlof, G.A., 1970. The market for «lemons»: quality uncertainty and the market mechanism in Quarterly Journal of Economics, 84.

Albert, R.L., Smaby, T.R., 1996, Market response to analyst recommendations in the ‘‘dartboard’’ column: the information and price-pressure effects, Review of Financial Economics 5, 59–74.

Antweiler, W., Frank, M.Z., 2004, Is all that talk just noise? The information content of Internet stock message boards, Journal of Finance 59, 1259–1294.

Bae, K.H., Karolyi, G.A., 1994. Good news, bad news and international spillovers of stock return volatility between Japan and the U.S. Pacific-Basin Finance Journal 2 (4), 405-438.

Barber, B.M., Loeffler, D., 1993, The ‘‘dartboard’’ column: Second-hand information and price pressure, Journal of Financial Quantities Analysis 28, 273–284.

Berkovich, E., 2011. Search and herding effects in peer-to-peer lending: evidence from prosper.co. Ann Finance 7, 389-405.

Blasco, N., Ferreruela, S., 2008. Testing intentional herding in familiar stocks: an experiment in an international context. The Journal of Behavioral Finance 9(2), 72-84.

Bodnaruk, A., Ostberg, P., 2009. Does investor recognition predict returns? Journal of Financial Economics 91(2), 208-226.

Bollen, J., Mao, H.N., Zeng, X.J., 2011, Twitter mood predicts the stock market, Journal of Computer Science 2, 1–8.

Braun, P.A., Nelson, D.B., Sunier, A.M., 1995. Good News, bad News, volatility, and betas. Journal of Finance L (5), 1575-1603.

Cahan, F.S., Chen, C., Chen, L., Nguyen, H.N., 2015. Corporate social responsibility and media coverage. Journal of Banking and Finance 59, 409-422.

Carlos, S.C., Begoña G.N., Luz L.P., 2015, Determinants of Default in P2P Lending, PLoS ONE 10, e0139427.

Carrasco, P.G., Michelon, G., 2017, The power of stakeholders’ voice: The effects of social media activism on stock markets, Business Strategy and the Environment 26, 855-872.

Chen, C., Chen, J., Shi, C., 2018. Research on credit evaluation model of online store based on SnowNLP. 2018 3rd International Conference on Advances in Energy and Environment Research (ICAEER 2018), 53, Available at: https://www.e3s-conferences.org/articles/e3sconf/abs/2018/28/e3sconf_icaeer2018_03039/e3sconf_icaeer2018_03039.html

Chen, J., Jiang, J., Liu, Y., 2018. Financial literacy and gender difference in loan performance, Journal of Empirical Finance 48, 307-320.

Chen, T. 2017. Investor attention and global stock returns. Journal of Behavioral Finance 18 (3): 358–382.

Chen, X., Huang, B., Ye, D., 2020. Gender gap in peer-to-peer lending: evidence from China. Journal of Banking & Finance 112, 105633

Choi, K.H., Yoon, S.M., 2020. Investor sentiment and herding behavior in the Korean stock market. International Journal of Financial Studies 8(2):34. https://doi.org/10.3390/ijfs8020034

Chong, T., Liu, X., Zhu, C., 2017. What explains herd behavior in the Chinese stock market? Journal Behavioral Finance 18 (4), 448-456.

Da, Z., Engelberg, J., Gao, P., 2011, In search of attention, Journal of Finance 66(5), 1461-1499.

Das, S.R., Chen, M.Y., 2007, Yahoo! for Amazon: Sentiment extraction from small talk on the web, Management Science 53, 1375–1388.

Depken, G.A., 2001. Good news, bad news and GARCH effects in stock return data. Journal of Applied Economics IV (2), 313-327

Dewally, M., 2003. Internet investment advice: Investing with a rock of salt. Financial Analysts Journal 59(4): 65–77.

Dougal, C., Engelberg, J., García, D., Parsons, C.A., 2012, Journalists and the stock market, Review of Financial Studies 25, 639–679.

Duarte, J., Siegel, S., Young, L., 2012. Trust and credit: the role of appearance in peer-to-peer lending. Review of Financial Studies 25, 2455-2484.

Engle, R.F., Ng, V.K., 1993. Measuring and testing the impact of news on volatility. Journal of Finance 48 (5), 1749-1778.

Engelberg, J.E., Parsons, C.A., 2011, The causal impact of media in financial markets, Journal of Finance 66, 67–97.

Fama, E.F., 1970, Efficient capital markets: A review of theory and empirical work, Journal of Finance 25, 383–417.

Fama, F.E., French, K.R., 1993. Common risk factors in the returns on stocks and bonds, Journal of Financial Economics 33, 3-56.

Fama, F.E., French, K.R., 1996. Multifactor explanations of asset pricing anomalies. Journal of Finance 51, 55-84.

Fang, L., Peress, J., 2009. Media coverage and the cross-section of stock returns. Journal of Finance 64, 2023-2052.

Ferreira, E.J., Smith, S.D., 1999, Stock price reactions to recommendations in the Wall Street Journal ‘‘Small Stock Focus’’ column. Quarterly Review of Economics and Finance 39, 379–389.

Fledstein, M., Eckstein, O., 1970. The fundamental determinants of the interest rate. The Review of Economics and Statistics 52, 363-375.

Foerster, S.R., Karolyi, G.A., 2002. The effects of market segmentation and investor recognition on asset prices: Evidence from foreign stocks listing in the United States. Journal of Finance 54(3), 981-1013.

Freedman, S., Jin, Z.G., 2008. Do social networks solve information problems for peer-to-peer lending? Evidence from prosper.com. Available at SSRN: https://papers.ssrn.com/s013/papers.cfm?abstract_id=1936057.

Ge, R., Feng, J., Gu, B., Zhang, P., 2017. Predicting and deterring default with social media information in Peer-to-Peer lending. Journal of Management Information Systems 34, 401–424.

Gao, B., Yang, C., 2018. Investor trading behavior and sentiment in futures markets. Emerging Markets Finance and Trade 54(3), 707-720.

Gao, Q., Lin, M., 2015, Lemon or cherry? The value of texts in debt crowdfunding. Center for Analytical Finance, University of California, Santa Cruz, Working Paper No. 18

Chiang, M.T., Lin, M.C., 2019. Market sentiment and herding in analysts' stock recommendations. The North American Journal of Economics and Finance 48, 48-64.

Goh, K. Y., Heng, C. S., Lin, Z. J., 2013. Social media brand community and consumer behavior: quantifying the relative impact of user- and marketer-generated content. Information System Research 24, 88-107.

Green, T.C., Jame, R., 2013. Company name fluency, investor recognition, and firm value. Journal of Financial Economics 109(3), 813-834.

Herzenstein, M., Sonenshein, S., Dholakia, M.U., 2011. Tell me a good story and I may lend you money: the role of narratives in peer-to-peer lending decisions. Journal of marketing research XLVIII, 138-149.

Hildebrand, C., Herrmann, G.A., Landwehr, J. R., 2013, When social media can be bad for you: Community feedback stifles consumer creativity reduces satisfaction with self-designed products. Information System Research 24, 14-29.

Huang, J., Ling, C. X., 2015, Using AUC and accuracy in evaluating learning algorithms, IEE Transactions on Knowledge and Data Engineering 17, 299-310.

Hudson, Y., Yan, M., Zhang, D., 2020. Herd behavior & investor sentiment: Evidence from UK mutual funds. International Review of Financial Analysis 71, 101494.

Jacobs, H., Hillert, A., Bias, A., 2016. Investor recognition, and trading behavior. Review of Finance 20(2), Pages 693–723.

Jia, L., Li, Z., 2020. Emotional analysis on the public sentiment of students returning to University under COVID-19. IEEE Xplore. Available at: https://ieeexplore.ieee.org/abstract/document/9407471

Jiang, J., Wang, Z., Zhang, X., 2019. Government affiliation and fintech industry: The peer-to-peer lending platforms in China. PBC School of Finance, Tsinghua University, July 7 (2019).

Jiang, Y., Ho, Y.C., Yan, X., Tan, Y., 2018. Investor platform choice: Herding, platform attributes, and regulations. Journal of Management Information Systems 35 (1), 86–116.

John, J.A., Draper, N.R., 1980. An alternative family of transformations. Applied Statistics 29, 190-197.

Joseph, N., Kar, A.K., Ilavarasan, P.V., Ganesh, S., 2017. Review of discussions on Internet of things (IoT): Insights from Twitter Analytics. Journal of Global Information Management 25(2), 1-14.

Kerl, A.G., Walter, A., 2007. Market responses to buy recommendations issued by personal finance magazines: Effects of information, price-pressure, and company

characteristics Review of Finance, 117–141.
Kim, K., Ryu, D., 2021. Does sentiment determine investor trading behavior?. Applied Economics Letters 28(10), 811-816.
Li, E., Liao, L., Wang, Z., Xiang, H., 2020. Venture capital certification and customer response: Evidence from P2P lending platforms. Journal of Corporate Finance 60, 101533.
Liao, L., Wang, Z., Xiang, J., Yang, J., 2017. Thinking fast, not slow: Evidence from peer-to-peer lending. Kelley School of Business Research Paper, 16-64.
Lin, M., Prabhala, P.N., Viswanathan, S., 2018. Judging borrowers by the company they keep: friendship networks and information asymmetry in online peer-to-peer lending. Management Science 59, 17-35.
Lin, M.C., 2018. The impact of aggregate uncertainty on herding in analysts' stock recommendations. International Review of Financial Analysis 57, 90-105.
Lufax, 2014. P2P Lending Market in China. www.lufax.com.
Luo, J. S., Li, C. A., 2008. Futures market sentiment and institutional investor behavior in the spot market: The emerging market in Taiwan. Emerging Markets Finance and Trade 44(2), 70-86.
Malik, F., 2011. Estimating the impact of good news on stock market volatility. Applied Financial Economics 21 (8), 545-554.
Merton, R.C., 1987. A simple model of capital market equilibrium with incomplete information. The Journal of Finance 42(3), 483-510.
Michels, J., 2012, Do unverifiable disclosure matter? evidence from peer-to-peer lending. The Accounting Review 87, 1385-1413.
Nasseri, A., Ali, F.M., Tucker, A., 2016. Good news and bad news: Do online investor sentiments reaction to return news asymmetric? [C]//MIDAS@ PKDD/ECML, 55-66.
Nofsinger, J.R., 2005. Social mood and financial economics, Journal of Behavioral Finance 6, 144–160.
Nofsinger, J.R., Sias, R., 1999. Herding and feedback trading by institutional and individual investors. Journal of Finance 54, 2263 – 2295
Ozik, G., Sadka, R., 2013, Media coverage and hedge fund returns, Financial Analysts Journal 69, 57-75.
Peress, J., 2014, The media and the diffusion of information in financial markets: Evidence from newspaper strikes, Journal of Finance 69 2007–2043.
Piotroski, D.J., Wong, J.T., Zhang, T., 2017. Political bias in corporate news: The role of conglomeration reform in China. Journal of Law and Economics 60, 173-207.
Sharpe, W.F. (1964) Capital asset prices: A theory of market of market equilibrium under conditions of risk. Journal of Finance 19, 425-442.
Shen, D.H., Zhang, W., Xiong, X., Li, X., Zhang, Y.J., 2016. Trading and non-trading period internet information flow and intraday return volatility. Physica A 451, 519–524.
Sias, R.W., 2004. Institutional herding. The Review of Financial Studies 17(1), 165-206.
Song, W., Qin, A., Xu, T., 2020. Sentiment analysis based on product review data of

Chinese commerce website of JD. In 3rd International Conference on Advances in Management Science and Engineering (IC-AMSE 2020), Atlantis Press, 67-71.

Sul, H.K., Dennis, A.R., Yuan, L., 2016. Trading on Twitter: Using social media sentiment to predict stock returns, Journal of the Decision Science Institute 48, 454-488.

Tetlock, P.C., Tsechshansky, M.S., Macskassy, S., 2008. More than words: Quantifying language to measure firm' fundamentals, Journal of Finance 3, 1437-1467.

Tumarkin, R., Whitelaw, R.F., 2001. News or noise? Internet postings and stock prices, Financial Analysts Journal 57, 41.

Verrecchia, E.R., 2001. Essays on disclosure. Journal of Accounting and Economics 32, 97-180.

Vieira, E. F. S., Pereira, M. S. V., 2015. Herding behaviour and sentiment: Evidence in a small European market. Revista de Contabilidad 18(1), 78-86.

Wang, J., Ye, K., 2015. Media coverage and firm valuation: Evidence from China, Journal of Business Ethics 127, 510-511.

Wang, Q., Si, Z., Chen, X. 2020. Information disclosure and the default risk of online peer-to-peer lending platform. Finance Research Letters, 38(C).

Wang, T., Kang, Y., Pan, Y., Management, S.O., University, X.P., 2016. Comparative analysis of Chinese and American P2P internet lending platform model. Journal of Xi'an University of Posts and Telecommunications 21(5), 80-87. DOI: 10.13682/j.issn. 2095-6533.2016.05.016.

WDZJ, 2017. Comparison of platform models of yiren dai, ppdai, and hexin dai. WDZJ Report, 17 Nov, 2017. Available at: http://www.360doc.com/content/17/1117/07/30963157_704529765.shtml

Wei, Z., Lin, M., 2017. Market mechanisms in online peer-to-peer lending. Management Science 63(12), 4236-4257.

Xiang, H., Wang, Z., Jiang, J., Liao, L., 2018, Pie or trap: what is represented by interest rate in Peer-to-Peer lending platform? China Financial Research Conference, July 7, 2018.

Zhao, Z.S., Jin, X.S., Wen, T.T., Liang, J.H., 2018. News comment data analysis based on Python-Snownlp. Public Communication of Science & Technology 10(18):104-105. Avaliable at: https://www.cnki.com.cn/Article/CJFDTotal-KJCB201818057.htm

Zeng, Z.W., Diao, M.G., Wang, X.P., He, B.H., 2020. Analysis of User Sentiment Trend and Concern Based on Mask Review Data. Microprocessors 41(6), 58-62. Avaliable at: https://d.wanfangdata.com.cn/periodical/jsjxtyy202012036

Zhang, P.W., Jia, Y.F., Shao, X.Q., Bainaer, M., Zhao, Y.F., 2020. Analysis of user sentiment trend and concern based on mask review Data. Microprocessors 41(6), 58-62.

Zhang, Y.J., Feng, L.N., Jin, X., Shen, D.H., Xiong, X., Zhang, W., 2014. Internet information arrival and volatility of SME PRICE INDEX. Journals & Books, Physica A 399, 70–74.

Zhang, W., Li, X., Shen, D.H., Teglio, A., 2016. Daily happiness and stock returns: Some international evidence, Physica A 460, 201–209.

Zhang, W., Shen, D.H., Zhang, Y.J., Xiong, X., 2013. Open source information, investor attention, and asset pricing, Economic Modelling 33, 613–619.

Zhang, W., Zhang, J., Li, Y., Xiong, X., 2019. Excess return and moderation effect of voluntary information disclosure in peer-to-peer lending market. China Financial Research Conference, July 7, 2019.

Tables

Table 3.1. Sample Selection

	No. Obs.
Platform data	
Platforms listed on CSMAR	971
Survival platforms	686
Default platforms	285
Months	45
Monthly observations on CSMAR	19,861
News data	
Media coverage news	10,303
Media coverage news on WDZJ	6,380
Media coverage news on P2PEYE	3,923
Social media postings	181,264
Social media postings on WDZJ	24,746
Social media postings on P2PEYE	156,518
Final data	
Total sample	
Platforms	971
Monthly observations	19,861

Notes: WDZJ and P2PEYE are two most popular information intermediaries in Chinese Peer-to-Peer lending market.

All media coverage news and social media postings are collected at the end of June 2019.

Table 3.2. Sample Descriptive

Variables	Mean	Median	Std. Dev.	Min	Max	No. Obs.
DEFAULT	0.2962	0	0.4566	0	1	19,861
CC	10.499	10.62	4.6215	0.12	46.6	19,861
IN	5.7357	5.9940	2.8629	1	11.6592	19,861
RF	3.4513	3.3059	0.6596	2.689	4.9352	19,861
L	1.3655	1	0.7418	0	4	19,861
B	1.3891	1	1.1109	0	4	19,861
CR	9.8651	9.6090	1.9937	4.9367	14.4025	19,861
ALT	1.6598	1.6677	0.8950	0.0296	3.5228	19,861
NCI	-0.3233	-1.9678	5.5017	-9.1908	10.5354	19,861
MCMF	0.0804	0	0.3005	-1	1	19,861
SMMF	0.1283	0	0.3253	-1	1	19,861
MCMFR	0.0803	0	0.3001	-1	1	19,861
SMMFR	0.1011	0	0.3328	-1	1	19,861

Note: All continuous variables in this table expect *CC* and *RF* have been winsorized and taken std. B and L are categorical control variables. Range of *B*: (0,4). Range of *L*: (0,4)

Table 3.3. Correlation matrix

	DEFAULT	CC	RF	CR	ALT	NCI	MCMF	SMMF
DEFAULT	1							
CC	0.1501*	1						
RF	0.0545*	0.0799*	1					
CR	0.0974*	0.0061	0.1174*	1				
ALT	0.0106	0.5633*	0.1310*	0.4551*	1			
NCI	0.0128	-0.1792*	-0.1119*	0.0131	0.1628*	1		
MCMF	-0.0055*	0.0256	0.0425*	0.2957*	0.1758*	0.0076	1	
SMMF	-0.0310*	0.0115	0.0278*	0.0333*	0.0195*	-0.0046	0.0663*	1

Notes: *p<0.05

Table 3.4. Logistic Regression Results – News Effect on Default

Panel A				
DEFAULT	(Base1)	(1-1)	(1-2)	(1-3)
CC	0.181***	0.181***	0.181***	0.181***
	(0.0084)	(0.0084)	(0.0084)	(0.0084)
CR	0.0472***	0.0493***	0.0474***	0.0494***
	(0.0020)	(0.0021)	(0.0020)	(0.0021)
ALT	-0.135***	-0.134***	-0.135***	-0.134***
	(0.0059)	(0.0059)	(0.0059)	(0.0059)
NCI	-0.0004	-0.0004	-0.0004	-0.0004
	(0.0006)	(0.0006)	(0.0006)	(0.0006)
MCMF		-0.0521***		-0.0490***
		(0.0111)		(0.0111)
SMMF			-0.0543***	-0.0520***
			(0.0101)	(0.0101)
T	YES	YES	YES	YES
B	YES	YES	YES	YES
L	YES	YES	YES	YES
Constant	-6.4491***	-6.5569***	-6.4673***	-6.5683***
	(0.3937)	(0.3939)	(0.3936)	(0.3939)
Prob>chi2	0.0001	0.0001	0.0001	0.0001
Pseudo R2	0.0725	0.0735	0.0739	0.0748
Observations	19,798	19,798	19,798	19,798
No. Platforms	971	971	971	971

Notes: Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

The dependent variable is *DEFAULT*.

Panel B			
DEFAULT	(2-1)	(2-2)	(2-3)
CC	0.183***	0.184***	0.184***
	(0.0085)	(0.0085)	(0.0085)
CR	0.0501***	0.0487***	0.0502***
	(0.0021)	(0.0020)	(0.0021)
ALT	-0.137***	-0.138***	-0.137***
	(0.0060)	(0.0060)	(0.0060)
NCI	-0.0003	-0.0004	-0.0004
	(0.0006)	(0.0006)	(0.0006)
LMCMF	-0.0383***		-0.0361***
	(0.0113)		(0.0113)
LSMMF		-0.0465***	-0.0452***
		(0.0104)	(0.0104)
T	YES	YES	YES
B	YES	YES	YES
L	YES	YES	YES
Constant	-6.9111***	-6.8502***	-6.9249***
	(0.4625)	(0.4622)	(0.4625)
Prob>chi2	0.0001	0.0001	0.0001
Pseudo R2	0.0752	0.0757	0.0762
Observations	18,690	18,690	18,690
No. Platforms	945	945	945

Notes: Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The dependent variable is *DEFAULT*.

LMCMF and *LSMMF* represent one lag of *MCMF* and *SMMF*.

Panel C	
DEFAULT	(3-1)
CC	0.183***
	(0.0085)
CR	0.0485***
	(0.0020)
ALT	-0.138***
	(0.0060)
NCI	-0.0004
	(0.0006)
DMCMF	-0.0121
	(0.0092)
DSMMF	-0.0055
	(0.0075)
T	YES
B	YES
L	YES
Constant	-6.8333***
	(0.4622)
Prob > chi2	0.0000
Pseudo R2	0.0748
Observations	18,690
No. Platforms	945

Notes: Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The dependent variable is *DEFAULT*.

DMCMF (*DSMMF*) is the first difference of *MCMF* (*SMMF*).

Table 3.5. AUCs of Models

MODELS	(Base1)	(1-1)	(1-2)	(1-3)
No. Obs.	19,798	19,798	19,798	19,798
AUCs	0.6988	0.7122	0.7138	0.7577

Notes: Model (Base1) is the basic default model, so, the AUC of Model (Base) is the benchmark. Model (1-1) to (1-3) are the models include *MCMF*, *SMMF* and both.

Table 3.6. Two-way Fixed-Effect Regression Results – News Effect on Cost of Capital

Panel A				
CC	(Base2)	(4-1)	(4-2)	(4-3)
RF	11.19***	11.19***	11.19***	11.19***
	(0.58)	(0.58)	(0.58)	(0.58)
CR	-0.0388***	-0.0388***	-0.0390***	-0.0391***
	(0.0081)	(0.0081)	(0.0080)	(0.0080)
ALT	0.785***	0.785***	0.785***	0.785***
	(0.0168)	(0.0168)	(0.0168)	(0.0168)
NCI	-0.0024***	-0.0024***	-0.0024***	-0.0024***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)
MCMF		0.0060		0.00957
		(0.0103)		(0.0109)
SMMF			-0.0046	-0.0100
			(0.0130)	(0.0138)
T	YES	YES	YES	YES
B	YES	YES	YES	YES
L	YES	YES	YES	YES
Constant	-5.046	-5.762	-4.740	-5.557
	(197.2)	(197.3)	(197.2)	(197.2)
Prob>chi2	0.0001	0.0001	0.0001	0.0001
R2	0.5352	0.5352	0.5353	0.5354
Observations	19,855	19,855	19,855	19,855
No. Platforms	971	971	971	971

Notes: Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The dependent variable is *CC*.

Panel B			
CC	(5-1)	(5-2)	(5-3)
RF	64.86***	64.84***	64.88***
	(5.939)	(5.94)	(5.941)
CR	-0.0431***	-0.0430***	-0.0433***
	(0.0083)	(0.0083)	(0.0083)
ALT	0.795***	0.795***	0.795***
	(0.0170)	(0.0170)	(0.0170)
NCI	-0.0025***	-0.0025***	-0.0025***
	(0.0007)	(0.0007)	(0.0007)
LMCMF	0.0029		0.0025
	(0.0106)		(0.0119)
LSMMF		0.0025	0.0010
		(0.0133)	(0.0148)
T	YES	YES	YES
B	YES	YES	YES
L	YES	YES	YES
Constant	3.371	3.370	3.371
	(2.149)	(2.149)	(2.149)
Prob>chi2	0.0001	0.0001	0.0001
R2	0.5469	0.5468	0.5470
Observations	18,741	18,741	18,741
No. Platforms	945	945	945

Notes: Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

The dependent variable is *CC*.

LMCMF and *LSMMF* represent one lag of *MCMF* and *SMMF*.

Panel C	
CC	(6-1)
RF	1.719***
	(0.208)
CR	-0.0433***
	(0.0039)
ALT	0.795***
	(0.0052)
NCI	-0.0025***
	(0.0006)
DMCMF	0.0026
	(0.0074)
DSMMF	-0.0067
	(0.0094)
T	YES
B	YES
L	YES
Constant	1.236***
	(0.398)
Prob>chi2	0.0000
R2	0.5470
Observations	18,741
No. Platforms	945

Notes: Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The dependent variable is *CC*.

DMCMF (*DSMMF*) is the first difference of *MCMF* (*SMMF*).

Table 3.7. PSM Results – News Effect on Default

DEFAULT	(3-2)	(3-3)	(3-4)	(3-5)
PSM-DM	-0.0215***	0.0049		
	(0.0080)	(0.0093)		
PSM-DS			-0.0478**	-0.0337
			(0.0189)	(0.0217)
CC	0.182***	0.167***	0.127***	0.193***
	(0.0141)	(0.0175)	(0.0266)	(0.0323)
CR	0.0367***	0.0465***	0.0179***	0.0037
	(0.0044)	(0.0075)	(0.0062)	(0.0095)
ALT	-0.148***	-0.138***	-0.0927***	-0.0990***
	(0.0123)	(0.0181)	(0.0238)	(0.0261)
NCI	0.0003	-0.0013	-0.0028	-0.0035*
	(0.0012)	(0.0017)	(0.0020)	(0.0021)
T	YES	YES	YES	YES
B	YES	YES	YES	YES
L	YES	YES	YES	YES
Constant	-4.8052***	-3.3804***	-3.1227***	-2.1745***
	(0.6750)	(0.3824)	(0.4986)	(0.6130)
Observations	4,331	2,433	1,251	1,061
No. Platforms	970	541	252	231
LR chi2	244.66	117.53	67.87	81.78
Prob > chi2	0.0000	0.0000	0.0000	0.0000
Pseudo R2	0.0436	0.0363	0.0444	0.0617
Log likelihood	-2684.94	-1560.03	-730.85	-622.30

Notes: Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The dependent variable is *DEFAULT*.

Model (3-3) compares the positive *DMCMF* (set as 1 in *PSM-DM*) and 0 *DMCMF* (set as 0 in *PSM-DM*); and model (3-4) compares the negative *DMCMF* (set as 1 in *PSM-DM*) and 0 *DMCMF* (set as 0 in *PSM-DM*); Model (3-5) compares the positive *DSMMF* (set as 1 in *PSM-DS*) and 0 *DSMMF* (set as 0 in *PSM-DS*); and model (3-6) compares the negative *DSMMF* (set as 1 in *PSM-DS*) and 0 *DSMMF* (set as 0 in *PSM-DS*). The results show that only positive *DMCMF* and positive *DSMMF* have significant effects on decreasing default of platforms.

Table 3.8. PSM Results – News Effect on Cost of Capital

CC	(6-2)	(6-3)	(6-4)	(6-5)
PSM-RM	-0.0335**	0.0174		
	(0.0136)	(0.0127)		
PSM-RS			-0.0482***	-0.0179
			(0.0145)	(0.0231)
RF	9.211***	1.746***	9.416***	2.065***
	(0.641)	(0.236)	(0.663)	(0.453)
CR	-0.0589***	-0.0617***	-0.0615***	-0.0815***
	(0.0053)	(0.0055)	(0.0055)	(0.0094)
ALT	0.570***	0.899***	0.568***	0.640***
	(0.0104)	(0.0071)	(0.0108)	(0.0139)
NCI	-0.0026**	-0.0019**	-0.0023*	-0.0029*
	(0.0011)	(0.0009)	(0.0012)	(0.0017)
T	YES	YES	YES	YES
B	YES	YES	YES	YES
L	YES	YES	YES	YES
Constant	-8.320***	-8.311***	-8.489***	-8.467***
	(0.749)	(0.747)	(0.770)	(0.766)
Prob>chi2	0.0000	0.0000	0.0000	0.0000
R-squared	0.4315	0.6688	0.4401	0.4752
Observations	4,407	9,800	3,864	2,041
No. Platforms	970	919	971	541

Notes: Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The dependent variable is *CC*.

Model (6-3) compares the positive *DMCMF* (set as 1 in *PSM-RM*) and 0 *DMCMF* (set as 0 in *PSM-RM*); and model (6-4) compares the negative *DMCMF* (set as 1 in *PSM-RM*) and 0 *DMCMF* (set as 0 in *PSM-RM*); Model (6-5) compares the positive *DSMMF* (set as 1 in *PSM-RS*) and 0 *DSMMF* (set as 0 in *PSM-RS*); and model (6-6) compares the negative *DSMMF* (set as 1 in *PSM-RS*) and 0 *DSMMF* (set as 0 in *PSM-RS*). The results show that only positive *DMCMF* and positive *DSMMF* have significant effect on decreasing cost of capital of platforms.

Table 3.9. Two-Way Fixed-Effect Regression Results – Investors' Behavior

Panel A			
IN	(7-1)	(7-2)	(7-3)
CC	1.147***	1.148***	1.146***
	(0.0479)	(0.0483)	(0.0479)
CR	0.563***	0.567***	0.563***
	(0.0304)	(0.0299)	(0.0298)
ALT	0.0977*	0.1000*	0.0965*
	(0.0581)	(0.0588)	(0.0581)
NCI	0.0246***	0.0245***	0.0247***
	(0.0023)	(0.0023)	(0.0023)
MCMF	0.242***		0.221***
	(0.0424)		(0.0448)
SMMF		0.104***	0.0884***
		(0.0294)	(0.0308)
T	YES	YES	YES
B	YES	YES	YES
L	YES	YES	YES
Constant	4.812	5.795	5.369
	(5.057)	(5.005)	(5.001)
Prob>chi2	0.0001	0.0001	0.0001
R2	0.7768	0.7756	0.7773
Observations	19,855	19,855	19,855
No. Platforms	971	971	971

Notes: Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The dependent variable is *IN*.

LMCMF and *LSMMF* represent one lag of *MCMF* and *SMMF*.

Panel B			
IN	(8-1)	(8-2)	(8-3)
CC	1.126***	1.125***	1.125***
	(0.0488)	(0.0193)	(0.0193)
CR	0.579***	0.583***	0.579***
	(0.0327)	(0.0102)	(0.0102)
ALT	0.108*	0.111***	0.108***
	(0.0596)	(0.0205)	(0.0205)
NCI	0.0246***	0.0246***	0.0246***
	(0.0023)	(0.0015)	(0.0015)
LMCMF	0.173***		0.157***
	(0.0427)		(0.0273)
LSMMF		0.0752***	0.0620***
		(0.0154)	(0.0156)
T	YES	YES	YES
B	YES	YES	YES
L	YES	YES	YES
Constant	10.154***	10.192***	10.210***
	(5.370)	(4.850)	(4.848)
Prob>chi2	0.0001	0.0001	0.0001
R2	0.7919	0.7912	0.7922
Observations	18,741	18,741	18,741
No. Platforms	945	945	945

Notes: Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The dependent variable is *IN*.

LMCMF and *LSMMF* represent one lag of *MCMF* and *SMMF*.

Panel C	
IN	(9-1)
CC	1.125***
	(0.0193)
CR	0.582***
	(0.0103)
ALT	0.112***
	(0.0205)
NCI	0.0247***
	(0.0015)
DMCMF	0.0362*
	(0.0201)
DSMMF	0.0171
	(0.0115)
T	YES
B	YES
L	YES
Constant	-3.079***
	(0.562)
Prob>chi2	0.0000
R-squared	0.7907
Observations	18,741
No. Platforms	945

Notes: Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The dependent variable is *IN*.

DMCMF (*DSMMF*) is the first difference of *MCMF* (*SMMF*).

Table 3.10. PSM Results – Investors' Behavior

IN	(9-2)	(9-3)	(9-4)	(9-5)
PSM-IM	0.192***	0.0783		
	(0.0426)	(0.0611)		
PSM-IS			0.216***	0.0686
			(0.0493)	(0.0736)
CC	1.488***	1.436***	1.519***	1.450***
	(0.0480)	(0.0694)	(0.0539)	(0.0834)
CR	0.691***	0.549***	0.709***	0.462***
	(0.0165)	(0.0214)	(0.0176)	(0.0236)
ALT	-0.00489	0.240***	-0.0457	0.436***
	(0.0438)	(0.0612)	(0.0481)	(0.0713)
NCI	0.0331***	0.0268***	0.0309***	0.0368***
	(0.0037)	(0.0051)	(0.0042)	(0.0059)
T	YES	YES	YES	YES
B	YES	YES	YES	YES
L	YES	YES	YES	YES
Constant	-5.398***	-2.957***	-5.548***	-2.942**
	(0.614)	(1.045)	(0.635)	(1.189)
Prob>chi2	0.0000	0.0000	0.0000	0.0000
R-squared	0.7460	0.7691	0.7320	0.7648
Observations	4,275	2,328	3,576	1,653
No. Platforms	970	553	969	464

Notes: Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Model (9-2) compares the positive *DMCMF* (set as 1 in *PSM-IM*) and 0 *DMCMF* (set as 0 in *PSM-IM*); and model (9-3) compares the negative *DMCMF* (set as 1 in *PSM-IM*) and 0 *DMCMF* (set as 0 in *PSM-IM*); Model (9-4) compares the positive *DSMMF* (set as 1 in *PSM-IS*) and 0 *DSMMF* (set as 0 in *PSM-IS*); and model (9-5) compares the negative *DSMMF* (set as 1 in *PSM-IS*) and 0 *DSMMF* (set as 0 in *PSM-IS*). The results show that only positive *DMCMF* and positive *DSMMF* have significant effect on increasing investor number of platforms.

Table 3.11. Logistic Regression Results – News Effect on Default (Robustness Check)

Panel A				
DEFAULT	(Base1)	(1-1)	(1-2)	(1-3)
CC	0.181***	0.181***	0.181***	0.181***
	(0.0084)	(0.0084)	(0.0084)	(0.0084)
CR	0.0472***	0.0493***	0.0474***	0.0493***
	(0.0020)	(0.0021)	(0.0020)	(0.0021)
ALT	-0.135***	-0.134***	-0.135***	-0.134***
	(0.0059)	(0.0059)	(0.0059)	(0.0059)
NCI	-0.0004	-0.0004	-0.0004	-0.0004
	(0.0006)	(0.0006)	(0.0006)	(0.0006)
MCMFR		-0.0515***		-0.0485***
		(0.0112)		(0.0112)
SMMFR			-0.0515***	-0.0494***
			(0.0098)	(0.0099)
T	YES	YES	YES	YES
B	YES	YES	YES	YES
L	YES	YES	YES	YES
Constant	-6.4491***	-6.5554***	-6.4621***	-6.5620***
	(0.3937)	(0.3939)	(0.3937)	(0.3939)
Prob>chi2	0.0001	0.0001	0.0001	0.0001
Pseudo R2	0.0725	0.0735	0.0738	0.0747
Observations	19,798	19,798	19,798	19,798
No. Platforms	971	971	971	971

Notes: Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The dependent variable is *DEFAULT*.

Panel B			
DEFAULT	(2-1)	(2-2)	(2-3)
CC	0.183***	0.183***	0.184***
	(0.0085)	(0.0085)	(0.0085)
CR	0.0501***	0.0486***	0.0501***
	(0.0021)	(0.0020)	(0.0021)
ALT	-0.137***	-0.138***	-0.137***
	(0.0060)	(0.0060)	(0.0060)
NCI	-0.0003	-0.0004	-0.0004
	(0.0006)	(0.0006)	(0.0006)
LMCMFR	-0.0378***		-0.0355***
	(0.0113)		(0.0114)
LSMMFR		-0.0442***	-0.0429***
		(0.0101)	(0.0101)
T	YES	YES	YES
B	YES	YES	YES
L	YES	YES	YES
Constant	-6.9105***	-6.8449***	-6.9188***
	(0.4625)	(0.4622)	(0.4626)
Prob>chi2	0.0001	0.0001	0.0001
Pseudo R2	0.0752	0.0757	0.0761
Observations	18,690	18,690	18,690
No. Platforms	945	945	945

Notes: Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The dependent variable is *DEFAULT*.

Table 3.12. AUCs of Models (Robustness Check)

MODELS	(Base1)	(1-1)	(1-2)	(1-3)
No. Obs.	19,798	19,798	19,798	19,798
AUCs	0.6988	0.6992	0.6995	0.6998

Notes: Model (Base) is the basic default model, so, the AUC of Model (1-1) is the benchmark. Model (1-1) to (1-3) are the models include *MCMF*, *SMMF* and both.

Table 3.13. Two-Way Fixed-Effect Regression Results – News Effect on Cost of Capital (Robustness Check)

Panel A				
CC	(Base2)	(4-1)	(4-2)	(4-3)
RF	11.19***	11.20***	11.19***	11.19***
	(0.58)	(0.58)	(0.58)	(0.58)
CR	-0.0388***	-0.0392***	-0.0388***	-0.0391***
	(0.0081)	(0.0081)	(0.0081)	(0.0081)
ALT	0.785***	0.784***	0.785***	0.784***
	(0.0168)	(0.0168)	(0.0168)	(0.0168)
NCI	-0.0024***	-0.0024***	-0.0024***	-0.0024***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)
MCMFR		0.0182		0.0181
		(0.0118)		(0.0118)
SMMFR			0.0060	0.0058
			(0.0103)	(0.0103)
T	YES	YES	YES	YES
B	YES	YES	YES	YES
L	YES	YES	YES	YES
Constant	-5.046	-7.611	-5.762	-8.274
	(197.2)	(197.2)	(197.3)	(197.3)
Prob>chi2	0.0001	0.0001	0.0001	0.0001
R2	0.5352	0.5350	0.5352	0.5350
Observations	19,855	19,855	19,855	19,855
No. Platforms	971	971	971	971

Notes: Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The dependent variable is *CC*.

Panel B			
CC	(5-1)	(5-2)	(5-3)
RF	64.84***	64.86***	64.87***
	(5.939)	(5.939)	(5.941)
CR	-0.0430***	-0.0431***	-0.0432***
	(0.0083)	(0.0083)	(0.0083)
ALT	0.795***	0.795***	0.795***
	(0.0170)	(0.0170)	(0.0170)
NCI	-0.00252***	-0.00252***	-0.00252***
	(0.0007)	(0.0007)	(0.0007)
LMCMFR	0.0009		0.0008
	(0.0108)		(0.0108)
LSMMFR		0.0029	0.0029
		(0.0106)	(0.0106)
T	YES	YES	YES
B	YES	YES	YES
L	YES	YES	YES
Constant	3.370***	3.371***	3.371***
	(214.9)	(214.9)	(214.9)
Prob>chi2	0.0001	0.0001	0.0001
R2	0.5468	0.5469	0.5469
Observations	18,741	18,741	18,741
No. Platforms	945	945	945

Notes: Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The dependent variable is *CC*.

LMCMFR and *LSMMFR* represent one lag of *MCMFR* and *SMMFR*.

Table 3.14. Two-Way Fixed-Effect Regression Results – Investors' Behavior (Robustness Check)

Panel A			
IN	(7-1)	(7-2)	(7-3)
CC	1.147***	1.150***	1.148***
	(0.0479)	(0.0195)	(0.0195)
CR	0.563***	0.567***	0.563***
	(0.0304)	(0.0100)	(0.0100)
ALT	0.0978*	0.0986***	0.0964***
	(0.0581)	(0.0206)	(0.0206)
NCI	0.0246***	0.0246***	0.0247***
	(0.0023)	(0.0015)	(0.0015)
MCMFR	0.239***		0.220***
	(0.0414)		(0.0280)
SMMFR		0.0323***	0.0189***
		(0.0067)	(0.0069)
T	YES	YES	YES
B	YES	YES	YES
L	YES	YES	YES
Constant	4.833	5.174	4.859
	(5.056)	(4.702)	(4.696)
Prob>chi2	0.0001	0.0001	0.0001
R2	0.7768	0.7756	0.7771
Observations	19,855	19,855	19,855
No. Platforms	971	971	971

Notes: Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The dependent variable is *IN*.

Panel B			
IN	(8-1)	(8-2)	(8-3)
CC	1.125***	1.127***	1.127***
	(0.0488)	(0.0486)	(0.0193)
CR	0.579***	0.582***	0.579***
	(0.0327)	(0.0320)	(0.0102)
ALT	0.108*	0.108*	0.106***
	(0.0597)	(0.0585)	(0.0205)
NCI	0.0246***	0.0247***	0.0247***
	(0.0023)	(0.0023)	(0.0015)
LMCMFR	0.173***		0.136***
	(0.0406)		(0.0282)
LSMMFR		0.0437**	0.0336***
		(0.0215)	(0.0074)
T	YES	YES	YES
B	YES	YES	YES
L	YES	YES	YES
Constant	10.154***	10.212***	10.217***
	(5.370)	(5.332)	(4.847)
Prob>chi2	0.0001	0.0001	0.0001
R2	0.7920	0.7917	0.7925
Observations	18,741	18,741	18,741
No. Platforms	945	945	945

Notes: Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The dependent variable is *IN*.

LMCMFR and *LSMMFR* represent one lag of *MCMFR* and *SMMFR*.

Appendixes

Appendix 3.1. Variable Explanation

Variables	Variable Explanation
DEFAULT	dummy variable: 1 means platform default, 0 means platform survival
CC	average cost of capital; monthly average cost of capital of platform; also represents the average return of platform from investors' perspective
IN	investor number; monthly total investor number of platform
RF	risk free rate; monthly SHIBOR: Shanghai Interbank Offered Rate; unit: %
location	platform geographical location
location1	dummy variable: 1 if platform located in East economic area, 0 otherwise
location2	dummy variable: 1 if platform located in West economic area, 0 otherwise
location3	dummy variable: 1 if platform located in Central economic area, 0 otherwise
location4	dummy variable: 1 if platform located in North-East economic area, 0 otherwise
background	the background of platform
background1	dummy variable: 1 if platform is controlled by private company, 0 otherwise
background2	dummy variable: 1 if platform is controlled by venture capital, 0 otherwise
background3	dummy variable: 1 if platform is controlled by listed company, 0 otherwise
background4	dummy variable: 1 if platform is controlled by state-owned company or banking 0 otherwise
ALT	average loan time; monthly average loan period of platform (month)
CR	cumulative repay; monthly cumulative outstanding loans of platform (10,000yuan)
NCI	net capital inflow; monthly net capital inflow of platform (10,000yuan)
MCMF[a]	media coverage news sentiment; monthly media sentiment calculated by monthly number of positive sentiment news minus negative sentiment news, and then, divided by monthly total number of news
SMMF[a]	Social media posts sentiment; monthly media sentiment calculated by monthly number of positive sentiment posts minus negative sentiment posts, and then, divided by monthly total number of posts.
MCMFR[b]	Similar as MCMF; used in robustness test
SMMFR[b]	Similar as SMMF; used in robustness test

Notes: all continuous variables have been winsored and taken std.

[a] Both MCMF and SMMF are measured from the sentiment analysis results in Snownlp.

[b] Both MCMFR and SMMFR are measured from the sentiment analysis results in BaiduAPI.

Appendix 3.2. Feature Words

Sentiment Feature Words	
Positive	Negative
合规	被捕
共赢	冻结
备案完成	冻结银行账户
完成备案	涉嫌
成功	非法
创新	刑事
发展	强制措施
科技	扣押
高效	查封
适合	查扣
平稳	吸收公众存款
良好	案
创新力	案件
技术	案情
智能风控	诉讼
从不	民事诉讼
防风险	刑事诉讼
高标准	报案
严要求	协查
安全	调查
资金安全	侦查
稳健	投案
稳健运营	立案
超过	非吸
合规化	涉案
数据化	资金池风险
多样化	资金池
高科技化	垫付
普惠金融	风险
更好的	不符合
更	违法
智能	关闭
智能风控系统	期限错配
保障	流动性风险
成熟	虚假标的
降低风险	矛盾
风险低	自相矛盾
低风险	不规范
收益	大相径庭
跟踪	合规线外

信息安全	无法
加密	无法解决
监管	开庭
信息系统安全	宣判
认证	逾期
银行资金存管	清收
银行存管	艰难
存管	困难
确保	离职
前列	亏损
首批	不良资产
信心	不当
加快	未披露
积极	困境
重塑	忧虑
公信力	回调
预期	跌
稳	跌幅
前	退出
前十名	劝退
透明度积分	担忧
合规积分	暗淡
保护措施	叫停
积极推进	停止
规范经营	投诉
普惠	强制
资质	暴跌
突出	下跌
未来	再跌
顺利	冲击
快速	乱象
盈利	不利
前景	不利影响
促进	清退
崛起	清盘
上市	延期
增加	辞职
大增	下调
营收增长	悲观
新增	撤退
金融科技	失效
达到	收跌
同比上升	约谈

上升	下架
增长	过度
同比增长	高估
齐全	坏账
涨幅	不能
上涨	不得
升级	集资
并购	非法集资
投资	打击
增资	严肃
整合	处理
收购	严肃处理
低估	惩处
牛市	查处
扩张	不确定
好	索赔
优化	大额索赔
信用	起诉
便捷	虚假
个性化	裁定
专业	未
优质	判决
完成	审理
符合	受挫
大涨	限额
股价大涨	催收
领跑	暴露
反弹	警惕
新高	模糊
最大	诈骗
改善	失败
有效	自首
迅速	出事
发展迅速	破产
突破	倒霉
融资	悲剧
合作	极差
领先	诱惑
领先者	陷阱
革新	骗子
卓越	跑路
复合	倒闭
培养	高发

融合	担心
加入	负面
兴起	减仓
涉足	亏
进入	造假
直投	寒冬
改造	骗局
上线	提现困难
标杆	经侦介入
联手	网站关闭
资金存管	兑付困难
率先	雷
规范	暴雷
互补	举报
鼓励	忽悠
头部	晚
晋升	太慢
分散	无法登录
坚持	延期兑付
控制	提现失败
完善	爆
风向标	整顿
复苏	雷潮
共同	损失
繁荣	惨重
立足	恐慌
健康	无法兑付
稳定	上当
良性	痛苦
推动	
顺应	
公布	
公开	
发布	
较好	
较高	
有望	
提高	
决心	
实缴	
增强	
提升	
反欺诈	

理性	
回暖	
坏账率下降	
逾期下降	
逾期率下降	
推进	
及时	
点赞	
秒到	
正能量	
快速到账	
稳心	
背景	
强大	
流畅	
可投	
正面	
正向	
重仓	
龙头	
靠谱	
划算	
到账	
安心	
复投	
再接再厉	
不错	
头部平台	
满	
满标	
满仓	
厉害	
抢标	
简洁	
愉快	
很快	
返利	
准时	
快	
非常快	
值得	
信赖	
保险	

稳当	
看好	
好的	
加仓	
赚	
靠前	
正常	
很久	
出手	
上车	
追加	

4. The Effect of the Central Government Monetary Policy and the Local Government Financing Demand on the Scale of the Shadow Banking: Evidence from P2P Lending Market

Abstract

Shadow banking in China has grown rapidly since 2010. However, the large scale of shadow banking may lead to more economic bubbles which could harm the healthy development of China's economy. Using Chinese core shadow banking and P2P lending market data, I provide the evidence that the scale of core shadow banking had a significant effect on the sharply increasing scale of the P2P lending market from 2014 to 2019; and the contractionary monetary policy has a significant effect on the future rise of the scale of shadow banking and in the P2P lending market; meanwhile, the local financing demand will have a significant positive effect on the scale of the shadow banking and P2P lending market.

Keywords: Shadow Banking, P2P Lending; Monetary Policy; Local Government Financing Demand; Local Government Bond Issued

JEL classification: G21, G28

4. The Effect of the Central Government Monetary Policy and the Local Government Financing Demand on the Scale of the Shadow Banking: Evidence from P2P Lending Market

4.1.Introduction

Shadow banking refers to the unregulated credit market that operates outside of the traditional banking sector (Financial Stability Board, 2011). Shadow banking in China has grown rapidly since 2010, particularly after the 4 trillion RMB stimulus plan in 2008, implemented to address the global financial crisis (GFC) (Chen et al., 2020). However, the large scale of shadow banking may contribute to more economic bubbles which could harm the healthy development of the national economy (Moody, 2012). The Chinese government started to regulate this market with a series of governance policies beginning in 2017 (China Banking and Insurance Regulatory Commission, 2020). As a result, the total scale of shadow banking decreased from 2018 to 2019.

The scale of shadow banking is hard to monitor and measure because such capital is not supervised by the government (also called off-balance-sheet financing) and the demand for and the benefit of the financial innovation continues to generate interest in this new type of shadow banking. Based on the data that I collected from Moody's reports (2012-2020) and the CSMAR (China Stock Market Accounting Research), Chinese shadow banking drew rapidly during 2010-2017 (the size of Chinese shadow banking increased by a factor of 12, with an average growth rate of 50.89%); between 2014 to 2017, most of the growth in total shadow banking resulted from some new types of shadow banking, i.e., peer-to-peer lending, rather than the existing shadow banking venues.[73] Meanwhile, the unregulated use[74] of existing shadow banking funds, especially entrusted loans, increased the difficulty in governing shadow banking. There are several reasons for the difficulty: first, the emerging financial innovation will continue to hasten new shadow banking, and the regulatory lag will make government supervision difficult; second, it is hard for the government to trace the source of funds in the innovative market and new shadow banking market[75], and also difficult to regulate the use of funds in the existing shadow banking market. Therefore, in this paper, I examine the factors affecting the scale of shadow banking and try to find more efficient mechanisms for regulating the shadow banking market.

Prior literatures found that the contractionary monetary policy and the local government financing demands were the major factors for the growth of banks' off-balance sheet financing, such as entrusted loans (Chen et al., 2018; Chen et al., 2020). This inspires me that the recent increasing scale of peer-to-peer lending market could also be driven by the monetary policy (controlled by central government) and local government financing demands. In addition, the arbitrage behavior also exists in the peer-to-peer lending market (Tian et al., 2021), the high return in peer-to-peer lending (because the innovative market always provides high interest rate) attracts a lot of capital inflows.

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[73] Existing shadow banking: the traditional shadow banking before the Fintech and recent financial innovation.

[74] The CBIRC (China Banking and Insurance Regulatory Commission) has found that the purpose of entrusted loan funds is not in conformity with the regulations, some of them entered into the P2P lending market.
http://field.10jqka.com.cn/20200715/c621880995.shtml
https://baijiahao.baidu.com/s?id=1672267991345891861&wfr=spider&for=pc

[75] New shadow banking: the new type shadow banking after the Fintech and recent financial innovation, such as the P2P lending market.

There are two sources of this large capital inflow: capital in banking or other financial market; capital in other shadow banking. What is certain is that, the concealment of shadow banking will increase the internal capital flows, especially the capital inflow to peer-to-peer lending.

Based on that, I used a new dataset of shadow banking and local government bonds issued to examine the monetary policy and local financing demand effects on shadow banking. Meanwhile, because of the complicated sources of funds in the new shadow banking market, I also test the amplifying effect of existing shadow banking on the P2P lending market. By using monthly data of money supply (*M2*), the monthly data of the scale of core shadow banking (*SBC*), and the quarterly data of local government bonds issued (*LGBI*), I find that both the central government's contractionary monetary policy and the local government bond issuance could increase the scale of core shadow banking and P2P lending markets; moreover, the scale of existing shadow banking (i.e., the core shadow banking) significantly boosts the level of the P2P lending market.

My paper contributes to the literature in several aspects: first, my paper contributes to the existing literature on shadow banking (Adrian and Ashcraft, 2012; Claessens, et al., 2012; Deng, et al., 2015; Chen, et al., 2018; Chen, et al., 2020; Allen, et al., 2019; etc.) by extending the effect of the existing shadow banking scale, contractionary monetary policy, and local government bonds issued on the increasing scale of P2P lending market; second, my paper contributes to the Fintech literature (Freedman and Jin, 2008;

Berkovich, 2011; Herzenstein, et al., 2011; Duarte, et al., 2012; Liao, et al., 2017; Xiang, et al., 2019; etc.) by extending the effect of existing shadow banking on the current Fintech market (P2P lending market); last, my paper contributes to the local government debt literature (Hildreth and Miller, 2002; Liu, et al., 2017; Chen, et al., 2020; etc.) by examining one of the consequences of local government bonds being issued.

My study offers some policy suggestions for Chinese regulators: first, the regulating and monitoring efforts on shadow banking should be enhanced during the contractionary monetary policy period because the shadow banking activities are more active during this period; second, except for the management of the scale of local government bonds being issued, the sources and destination of local government bonds should also be monitored because they will amplify shadow banking activities without being regulated; third, besides the regulation on the scale and development of the P2P lending market, regulators should monitor and regulate the use of funds in existing shadow banking (i.e., the entrusted loans, trust loans, etc.).

This paper is structured as follows. Section 4.2 provides the development of shadow banking, Section 4.3 shows the literature review, Section 4.4 provides the hypothesis development, Section 4.5 presents the methods and research models, Section 4.6 shows results and analysis, and the conclusions are provided in Section 4.7.

4.2.The Development of Shadow Banking

The definition of shadow banking is relative vague and the scope of shadow banking differs across countries. Pozsar et al. (2010) define shadow banking in the United States (US) as a financial network that provides a funding channel from the depositors to the investors through securitization and financing techniques but without using the discount window[76] of the Federal Reserve and the Federal Deposit Insurance Corporation. The China Banking and Insurance Regulatory Commission (CBIRC) defines shadow banking in China as all kinds of financial intermediary business outside of the traditional banking system.[77] Shadow banking usually transfers the credit, liquidity, maturity and other risk factors of financial assets through non-bank financial institutions, and plays a role similar to a bank (CBIRC, 2020). There are various classifications of shadow banking. Moody (2012-2020) classifies shadow banking into two types: the broad shadow banking and the core shadow banking. CBIRC (2020) divides shadow banking into two categories: the broad shadow banking and the narrow shadow banking. I will discuss the different types of shadow banking in the following sections in detail.

4.2.1. Shadow Banking in the World

McCulley (2007) first put forward the idea of 'operate in shadow' in 2007, which means

[76] The discount window is a mechanism used by the Federal Reserve to make short-term loans to qualified banks to maintain their cash liquidity.
[77] Traditional banking system means the traditional financial business (take deposits, make loans) within balance sheet of bank.

financial credit intermediary activities outside the traditional banking system. The International Monetary Fund (2008) issued its global financial stability report which first proposed the concept of "near bank", which refers to those special financial entities that affect conventional banking systems by issuing asset-backed securities (ABS)[78], mortgage-backed securities (MBS)[79], collateralized debt obligations (CDOs)[80] and asset-backed commercial paper (ABCP).[81] The Financial Stability Board defines shadow banking in a broad sense (called broad shadow banking) as all credit intermediary activities outside the conventional banking system, and in a narrow sense (called narrow shadow banking) as financial activities with credit, liquidity and term conversion functions and leverage transactions that may cause systemic risks (Financial Stability Board, 2011). Figure 4.1 shows the classification and definition of shadow banking by the Financial Stability Board.

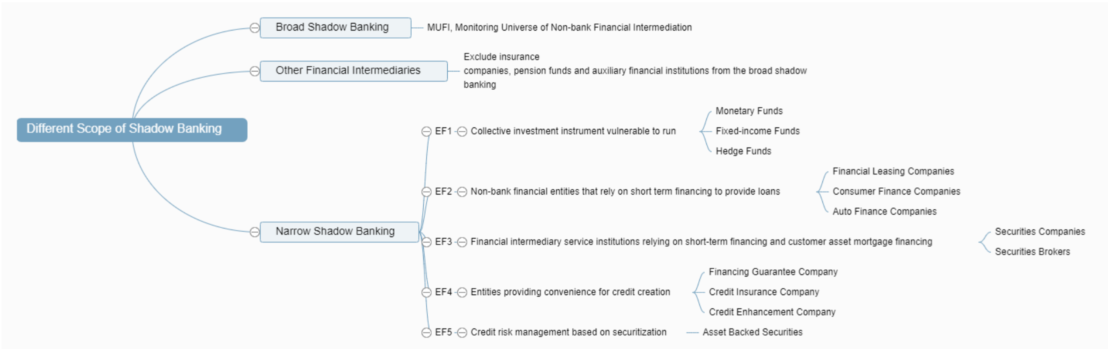

Figure 4.1. Classification and Definition of Shadow Banking by the Financial Stability Board
Data source: Financial Stability Board https://www.fsb.org/

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[78] An asset-backed security (ABS) is a type of financial investment that is collateralized by an underlying pool of assets.

[79] A mortgage-backed security (MBS) is an investment similar to a bond that is made up of a bundle of home loans bought from the banks that issued them.

[80] A collateralized debt obligation (CDO) is a complex structured finance product that is backed by a pool of loans and other assets and sold to institutional investors.

[81] An asset-backed commercial paper (ABCP) is a short-term investment vehicle with a maturity date that is typically between 90 and 270 days.

The growth of shadow banking in the world has been phenomenal. According to the data published by Financial Stability Board (FSB, 2020)[82], from 2006 to the end of 2019 the broad shadow banking increased from 90.9 trillion dollars to 201.5 trillion dollars, OFIs increased from 49.9 trillion dollars in 2006 to 123.8 trillion dollars, and the narrow shadow banking increased from 27.2 trillion dollars to 57.1 trillion dollars in the world.

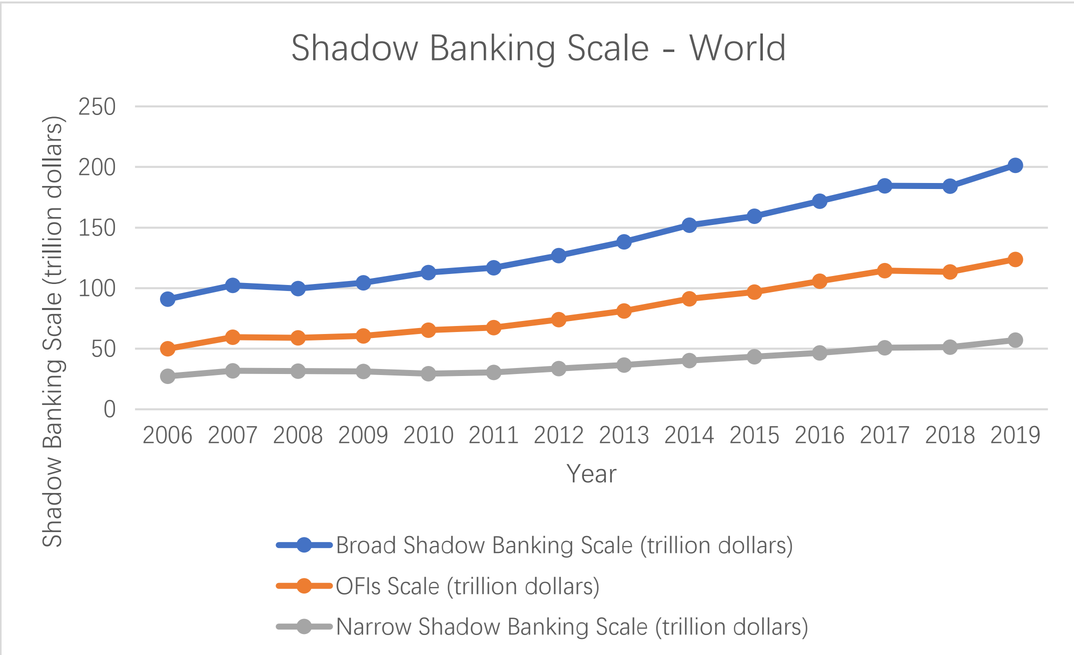

Figure 4.2. Shadow Banking Scale – World
Data source: Financial Stability Board https://www.fsb.org/

4.2.2. *Shadow Banking in China*

Shadow banking in China has grown rapidly since 2010 following the 4 trillion RMB stimulus plan in 2008 which followed the global financial crisis (GFC) (Chen et al.,

[82] The world shadow banking includes 28 economies as following: Argentina, Ireland, Australia, Brazil, Belgium, Germany, Russia, France, South Korea, Netherlands, Canada, Cayman Islands, United States, Mexico, South Africa, Japan, Saudi Arabia, Turkey, Spain, Singapore, Italy, India, United Kingdom, Chile, China-Mainland, Hong Kong-China, Indonesia, Luxembourg.

2020). Shadow banking in China could be classified as broad shadow banking and core shadow banking (Moody, 2016-2019). Broad shadow banking refers to all financial intermediary businesses outside the conventional banking system, which include entrusted loans[83], trust loans[84], undiscounted bankers' acceptances[85], banks' off-balance sheet assets[86], securities firms' funds, loans by finance companies, informal lending[87], P2P lending, and others[88]; the core shadow banking only includes the entrusted loans, trust loans, and the undiscounted bankers' acceptances. The core shadow banking has high risks and supervision is difficult. Core shadow banking accounts for a high proportion of broad shadow banking. Figure 4.3 shows the classification of shadow banking in China according to Moody's reports (2016-2019).

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[83] An entrusted loan is a lending arrangement organized by an agent bank between borrowers and lenders. The agent bank which is the trustee is only responsible for the collection of principals, the interest, and the service fee, rather than the loan risks; the company providing the funds is trustor.

[84] Trust loan refers to a financial business in which the trustee accepts the trustor's entrustment to grant the trustor's funds according to the specified object, purpose, term, interest rate and amount, etc., and is responsible for recovering the principal and interest of the loan at maturity.

[85] The undiscounted bank acceptance bill refers to the bank acceptance bill issued by the company that has not been discounted and financed by the local financial institution, that is, all the bank acceptance bills issued by the company deduct the part that has been discounted in the local bank statement.

[86] The asset of bank that off-balance sheet, such as guarantee (letter of guarantee), standby letter of credit, documentary credit, acceptance bill.

[87] Informal lending market: a market for credit transactions outside the formal banking system.

[88] The others include financing leasing, microcredit, pawn shop loans, asset-backed securities, and consumer credit companies.

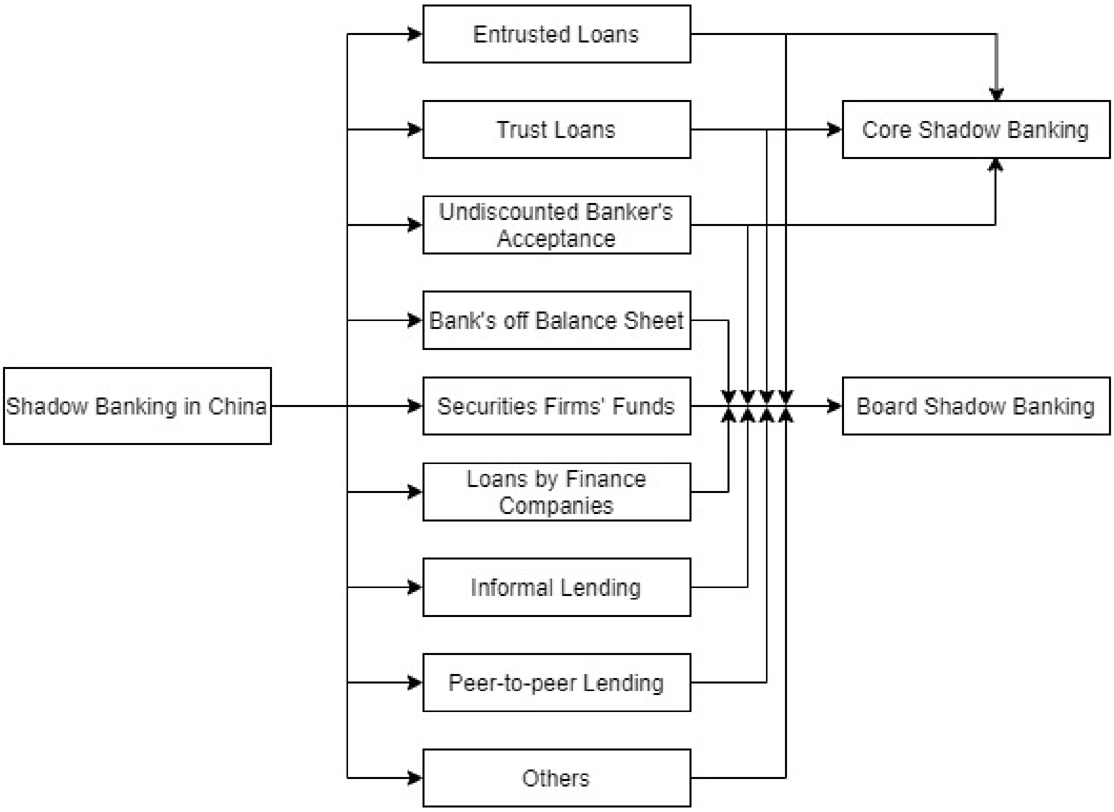

Figure 4.3. Classification of Shadow Banking in China by Moody's Report
Data Source: The China Shadow Banking Quarterly Monitoring Report. www.moodys.com

Chinese broad shadow banking mushroom between 2010-2016. As shown in Figure 4.4, the growth trend of shadow banking in China and the world was relatively consistent. The growth rate of Chinese shadow banking reached the highest level in the end of 2016 and started to decrease by the end of 2018 (Figure 4.4).

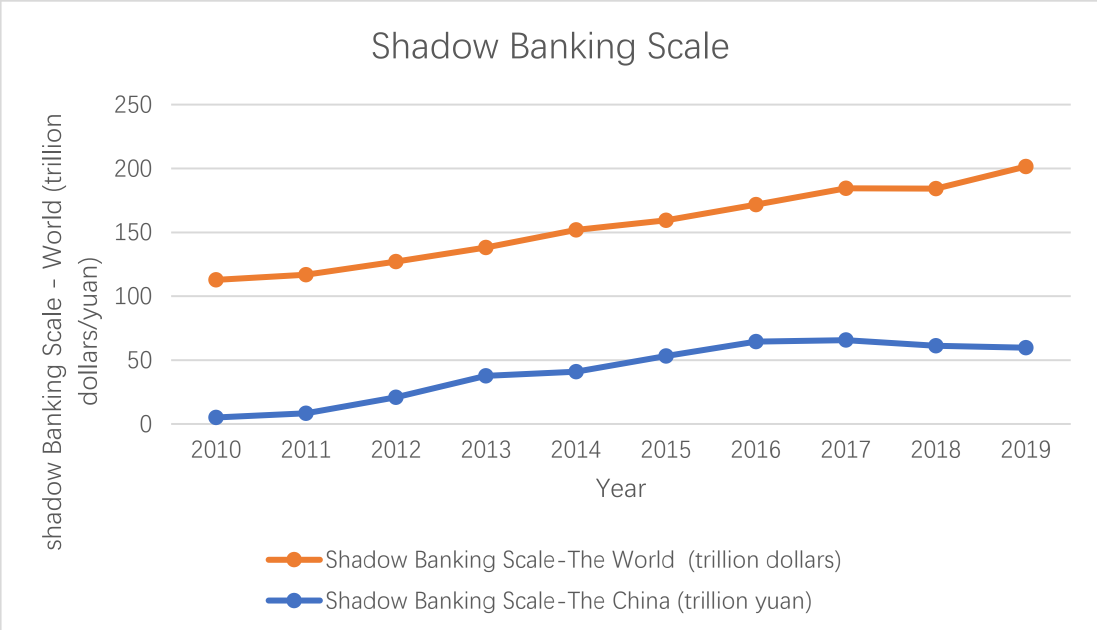

Figure 4.4. Shadow Banking Scale both the World and the China
Data Sources: The China Shadow Banking Quarterly Monitoring Report. www.moodys.com & CSMAR

According to Figure 4.5, the broad shadow banking scale grew steadily before the start of 2018, and the traditional core shadow banking scale had the similar trend as the broad shadow banking scale during 2014-2019. Since the start of 2018, both the broad and core shadow banking scales decreased but the rate of decrease is much lower than the rate of increase had been.

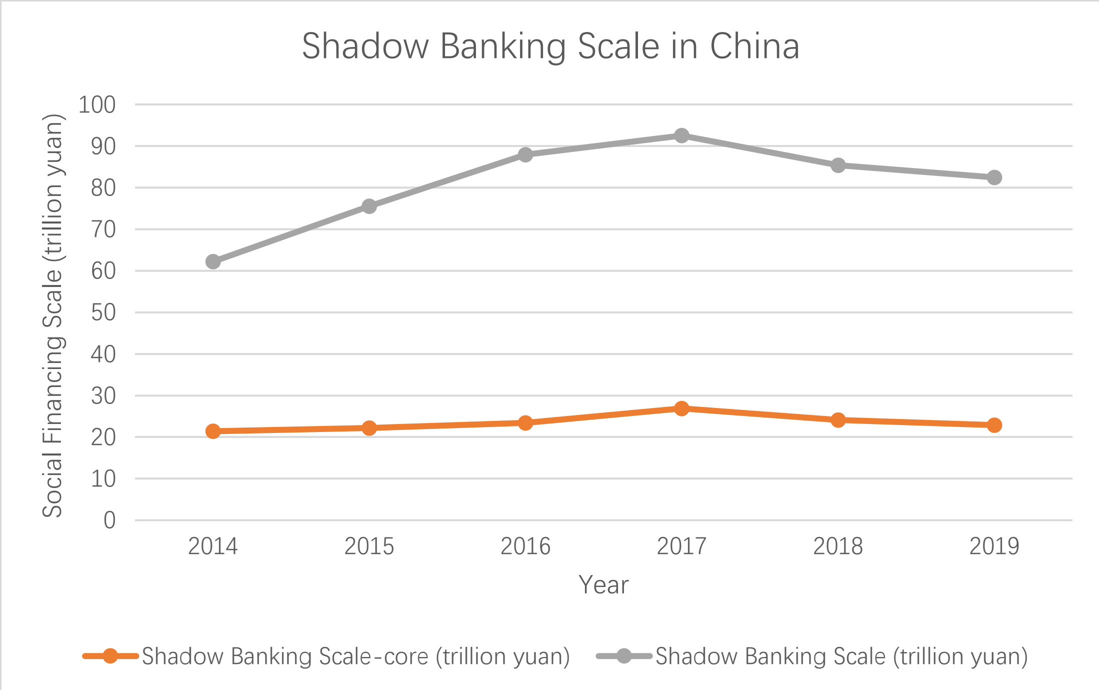

Figure 4.5. Shadow Banking Scale in China

Data Sources: The China Shadow Banking Quarterly Monitoring Report. www.moodys.com & CSMAR

4.2.3. New Shadow Banking Market in China-P2P Lending Market

As a new type shadow banking, the P2P lending market developed quickly beginning in 2010 based on new technology for electronic commerce and online payments. There are a large number of platforms, individual borrowers, individual lenders, and huge information asymmetry in the Chinese P2P lending market, which led to the high systemic risk within this market.

There have been different stages in the development of the Chinese internet lending market: from 2010-2016, there was a sharp increase of P2P platforms; from 2016-2017, the P2P lending market entered into a stable development period; and since the end of

2017, the Chinese P2P lending market has been in a degenerating stage. Currently, there are different types of platforms existed in this market: the operating platform, the transforming platform, the closed platform, and the default platform.

After the explosive growth period of the peer-to-peer lending market from 2010-2016, the number of default platforms had a sharp increase in the second half of 2017 until 2019. The high default rate attracted more government regulatory interventions between August 2016 and March 2018. In August 2016 [89], the China Banking Regulatory Commission published 'P2P Platforms Management Document'; and in March 2018, the China Banking Regulatory Commission - Office of the Leading Group for the Special Campaign against Internet Financial Risks published the 'Notice on Intensifying the Corrective Action on Asset Management Business through the Internet and Conducting Acceptance Work'. [90] In 2019 and 2020, the operating number of P2P platforms plummeted, but the number of default platforms, closed platforms, and transforming platforms all continued to increase. By the end of 2020, there were only three normal operating platforms in the Chinese P2P lending market: Yilong Dai; Manyi Dai; and Zhishang Finance.

Figure 4.6 shows the trend among the shadow banking, core shadow banking, and the

[89] In August 2016, the China Banking Regulatory Commission published 'P2P Platforms Management Document', which is available at: www.cbrc.gov.cn

[90] In March 2018, the China Banking Regulatory Commission - Office of the Leading Group for the Special Campaign against Internet Financial Risks published the 'Notice on Intensifying the Corrective Action on Asset Management Business through the Internet and Conducting Acceptance Work' (available at: http://www.wfgx.gov.cn/GXQXXGK/TRZZX/201804/t20180408_2759009.html).

trading volume in the P2P lending market. The growth of the P2P lending market shows a similar trend as in the shadow banking scale, with both starting to fall since the end of the 2017. The trend of the P2P lending market and the shadow banking market indicates that the trading volume of the P2P lending contributes significantly to the rapid growth of the shadow banking market in China during 2010-2016, since the growth of the core shadow banking size remained flat during this period.

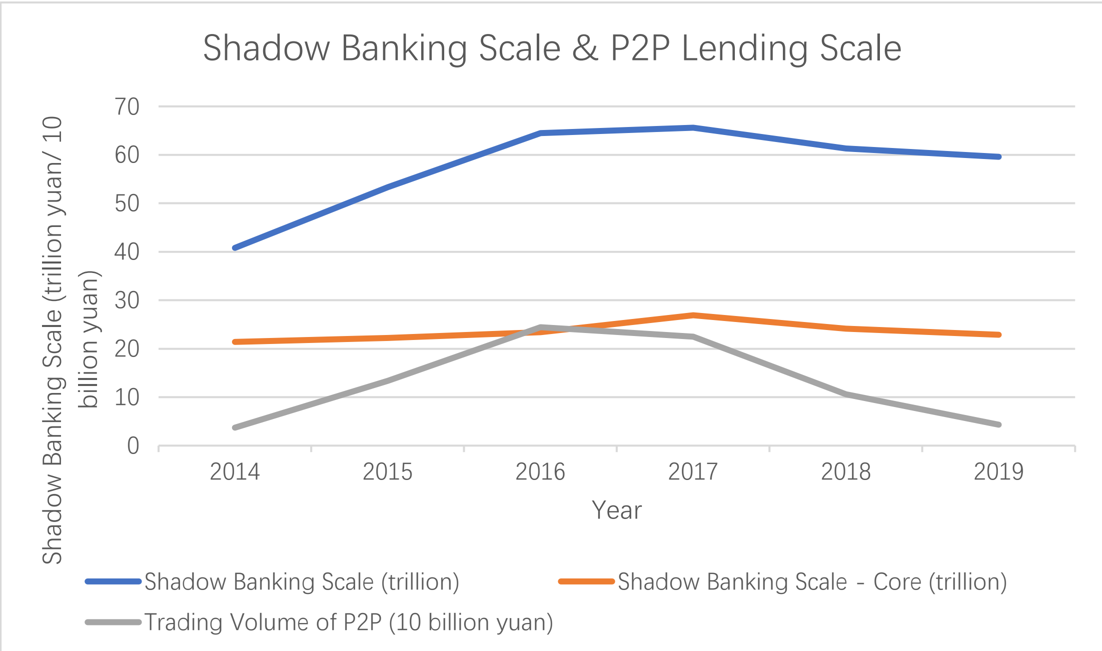

Figure 4.6. The Scale of Shadow Banking Scale and P2P Lending Scale
Data Source: WDZJ & CSMAR

Although the operating platforms dropped precipitously, this does not mean that the online lending market has completely disappeared. Currently, P2P platforms can be classified into: operating platforms, transforming platforms, closed platforms, and default platforms. Almost all the operating and transforming peer-to-peer lending platform still operate the similar business in the internet lending market, including peer-to-peer lending, business-to-person lending, and business-to business lending.

4.2.3.1. The Transforming Platform

After the strict regulation of 2018 (see the previous section above), many internet peer-to-peer lending platforms transformed to the other types of lending or financial companies. There are three main transforming directions: the small loan company; the loan aid company, and consumer finance company.

A small loan company is a limited liability company that is invested in and established by natural persons, corporate legal persons, and other social organizations. It does not take public deposits, but operates to provide small business loans. According to 'The 2019 Annual Report of Internet Lending Market' (WDZJ, 2020), there are 16 peer-to-peer lending platforms[91] which transformed into small loan companies. Based on current news and announcements, several additional P2P lending platforms[92] were transformed to small loan companies successfully by the end of 2021. However, these transformed platforms still operate the similar small lending business as the online P2P lending platforms.

The loan aid company is the company or institution that provides loan assistance to a

[91] Bojin Dai, Dian Rong, Haironggyi, Yiren Lending, Mindai Tianxia, Renren Lending, Xiang Xin, Niwo Dai, Kaixin Jinfu, Jizi Licai, Souyi Dai, Xuesongpuhui, Weidai, 51 renpin, Caimi, Yangqianguan.

[92] Yi e Dai, Jintouxing, Linhai Internet Finance, Zhenong Finance.
http://p2p.hexun.com/2020-10-27/202309883.html
https://baijiahao.baidu.com/s?id=1689041528908716253&wfr=spider&for=pc
https://www.sohu.com/a/445599430_660924

business. The loan assistance business means that a loan aid company selects targeted customer groups through its own systems or channels, and after completing its own risk control procedures. It then recommends high-quality customers to licensed financial institutions and quasi-financial institutions. After the final review of the risk control by these financial institutions, a loan is provided (Beijing Internet Finance Association, 2019). According to 'The 2019 Annual Report of Internet Lending Market' (WDZJ, 2020), there are 4 peer-to-peer lending platforms[93] that transformed into the loan aid companies.[94]

The Consumer finance companies are non-bank financial institutions established based on the approval by the China Banking and Insurance Regulatory Commission (CBIRC). According to the regulation published by CBIRC of China (2009)[95], the consumer finance company cannot take deposits from the public, but could provide loans to individuals for consumption purposes. According to 'The 2019 Annual Report of Internet Lending Market' (WDZJ, 2020), there are 2 P2P lending platforms[96] that transformed into the consumer finance companies.

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[93] Lexin, 360 Finance, Jiufu Shuke, Ppdai, Xiaoying Tech.
[94] CITIC Trust, Everbright Trust, Minsheng Trust etc.
[95] In July 2009, the CBIRC promulgated and implemented the measures for the administration of consumer finance companies. http://www.gov.cn/gzdt/2009-08/14/content_1391485.htm
[96] Jiufu Shuke, Lufax.

4.2.3.2. The Default Platform and Closed Platform

There is a significant difference between the default platform and the closed platform. The closed platform is a platform that has suspended the bid issuance and the sale of financial products, while a default platform is a platform which cannot pay the interest and capital to investors. Figure 4.7 shows the trend of the number of closed and default platforms from the end of 2010 until the end of 2020. Both the numbers of default and closed platforms increased sharply during 2014-2016, and decreased gradually since 2018.

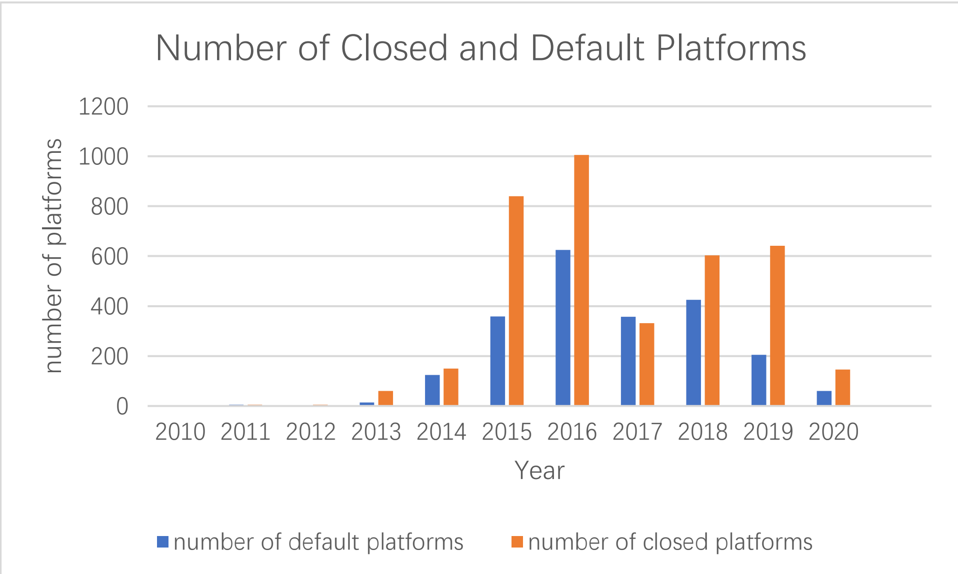

Figure 4.7. Number of Closed and Default Platforms

4.2.3.3. The Operating Platform

Figure 4.8 displays the numbers of operating platforms during 2010-2020. The number of operating platforms increased sharply since 2012, but this rapid growth stopped by the end of 2015. Since 2016, the number of operating platforms started to decrease.

After the issuance of government regulations (see Chapter 2), the number of operation platforms continued to decline with the increase in government's supervision and guidance of platform exit and transformation.

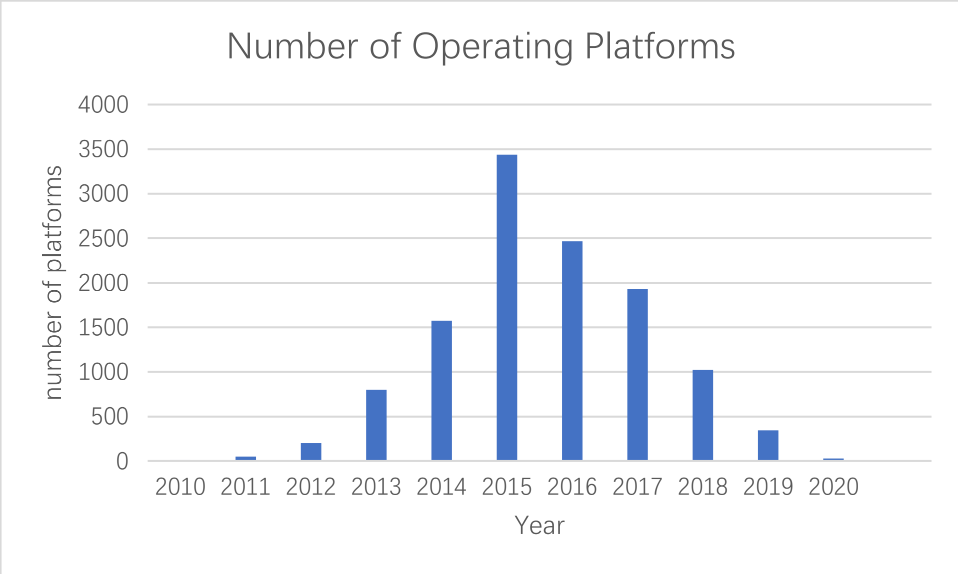

Figure 4.8. Number of Operating Platforms

Even though most of the peer-to-peer lending platforms have transformed or will be transformed (to a small loan company, a loan aid company or a consumer finance company), they are still operating similar lending businesses in the Chinese financial market which will continue to increase the scale of shadow banking and raise financial risks. In addition, for the transformed platforms (i.e., small loan company; loan aid company; consumer finance company), how to regulate these semi-internet/small lending platforms is still a controversial issue in the Chinese financial market. Furthermore, the regulations implemented for P2P lending market have only come later and tend to be 'one-size-fits-all' policies. All these factors make the study of the scale of P2P lending market even more essential.

4.2.4. Sources of Shadow Banking in China

There are three main sources of shadow banking in China: firms, the government, and individual persons. Figure 4.9 shows the relations and the capital flows between the bank, other financial institutions, core shadow banking and the peer-to-peer lending market. All firms, government, and individuals would deposit in and offer capital to a bank, so the bank loans are the traditional on-balance sheet business. There are four main banking off-balance sheet businesses: commitment business, guarantee business, financial asset service business, and derivatives trading business. Under these services, the undiscounted banker's acceptance and entrusted loans are derived. On the other side, the trust company issued trust loans. As the flow chart in Figure 4.9 indicates, money flows from firm/ government/ individual to the shadow banking market though many financial institutions (bank, trust company, other financial institution) and financial products (trust loans, bank loans, entrusted loans, undiscounted banker's acceptance).

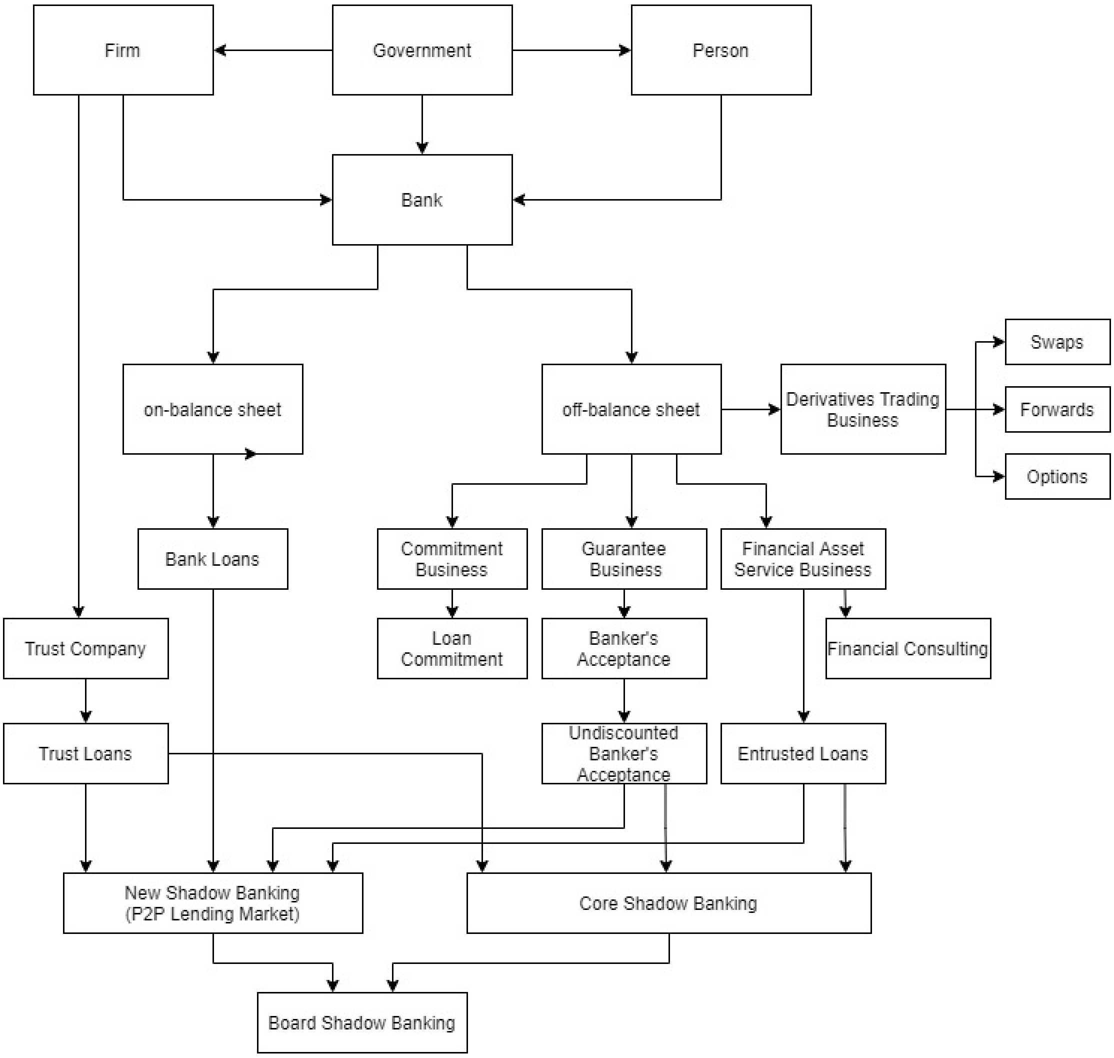

Figure 4.9. The relations between the scale of core shadow banking and P2P lending market
Data Source: WDZJ & CSMAR

After 2008, the number of local government bonds issued gradually became another important source of financing for Chinese shadow banking (Chen et al., 2020). Figure 4.10 displays the capital flows from government to shadow banking. The local government receives the money by issuing the local government bond and spends the capital on the construction of local public facilities. The money then flows into the bank account of contractor businesses, and is invested in fixed assets, the stock market or other avenues. Later, similar to Figure 4.9, the core shadow banking (entrusted loans, trust loans, undiscounted banker's acceptance) and new shadow banking (P2P lending market) will be generated.

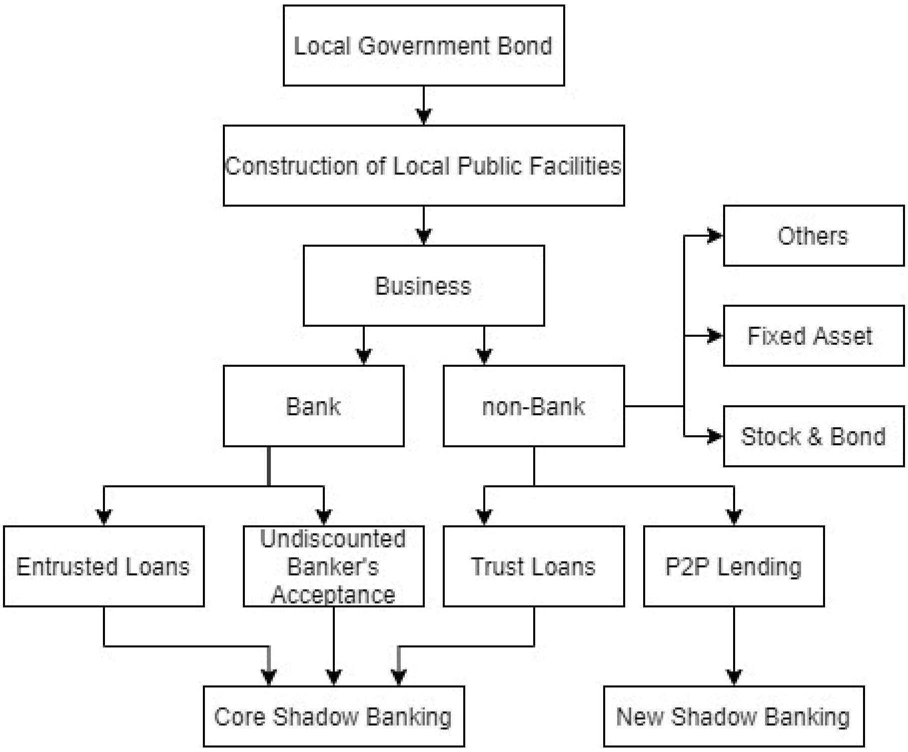

Figure 4.10. The relations between the local government bond and the scale of shadow banking

4.3.Literature Review

Shadow banking has received extensive attention following the 2008 financial crisis. Massive credit expansion and financial innovation brought on the huge shadow banking scale (Verona, 2011), and the growing scale of shadow banking contributed to the financial crisis (Financial Stability Board, 2011). This makes it particularly important to study shadow banking, monitor and control the scale of shadow banking and reduce the risk of shadow banking. There are many issues about shadow banking identified in the previous literature (what impact, how to monitor and supervise) (Pozsar et al., 2010;

Adrian and Ashcraft, 2012; Moreira and Savov, 2017, etc.), however the research on shadow banking is still in its early stage.

4.3.1. Shadow Banking in the World

The increasing trends of the scale of shadow banking have attracted many studies about shadow banking from several aspects: the definition and characteristics of shadow banking; the scale and trends of shadow banking; the risk of shadow banking; and the effects of shadow banking.

Prior literature has studied the scope and characteristics of shadow banking (Pozsar et al., 2010; Financial Stability Board, 2011; Yuan, 2011; Ba, 2009). Pozsar et al. (2010) states shadow banking was in tune with the 'Parallel Bank' and 'Quasi Bank", as they are all the unregulated financial institutions with banking functions. The Financial Stability Board (2011) states there are two concepts of shadow banking: the broad shadow banking[97] and narrow shadow banking.[98] Yuan (2011) points out that shadow banking relies on the businesses of commercial banks and non-bank financial institutions. Ba (2009) states the characteristics of shadow banking: first, most transactions are over-the-counter trading; second, there is a serious information asymmetry; and third, the market has high leverage.

[97] Broad shadow banking: all credit intermediary activities outside the conventional banking system.

[98] Narrow shadow banking: financial activities with credit, liquidity and term conversion functions and leverage transactions that may cause systemic risks.

The risk is the most concerning issue in shadow banking studies (Brunnermeier, 2009; Hsu and Moroz, 2010; Epstein, 2005; Adrian and Shin, 2009; Delottei, 2009; Pozsar et al., 2010). This risk comes from three perspectives. The first one is the high leverage risk. Brunnermeier (2009) argues that the shadow banking with high leverage will lead to more serious loss during the asset depreciation and de-leveraging in a financial crisis. Hsu and Moroz (2010) state that the high leverage in shadow banking was a critical reason for the crisis spreading to the whole financial system in the world in 2008. Yi (2009) suggests that there are many financial innovations without regulation in shadow banking market which will increase the leverage and risk for the whole shadow banking system. The second risk is the liquidity risk.[99] Epstein (2005) states that the asset securitization in the shadow banking over-expands the value of financial assets, which increases the liquidity risk in the market. Adrian and Shin (2009) state that the maturity mismatch causes the high liquidity risk in the shadow banking market. The assets maturity of shadow banking is longer than the liabilities which leads to the liquidity problem once the market stability decreases. The last risk is the risk caused by the severe information asymmetry problem existing in shadow banking. Delottei (2009) states that the information disclosure has substantially reduced the selling scales and the yield of the shadow banking market. Pozsar et al. (2010) argues that the existence of information asymmetry will increase the risk of shadow banking.

[99] Liquidity risk: liquidity risk is the risk that a given security or asset cannot be traded quickly enough in the market to prevent a loss (or make the required profit).

In terms of the influence of shadow banking on the economy, scholars have different views, with some of the literature believing that shadow banking will benefit the economy (Ackermann and Sands; 2012; Claessens et al., 2012), while other studies hold the opposite opinion (Adrian and Shin, 2009; Adrian and Ashcraft, 2012; Moreira and Savov, 2017). Ackermann and Sands (2012) state that shadow banking could increase financial innovation, increase the diversification of financial products, and decrease the company's over-reliance on traditional financing sources. Claessens et al. (2012) argues that shadow banking will benefit the economy through supporting the credit supply but will impair the macro-economy by aggravating the burden on government and will decrease both consumption and government spending. Adrian and Shin (2009) state that shadow banking will increase the vulnerability of financial markets which will harm the development of the real economy. Adrian and Ashcraft (2012) find that shadow banking will increase the money supply which will amplify the consequences of any financial crisis. Moreira and Savov (2017) find that shadow banking aggravates the instability of the financial system and the vulnerability of the macro-economy.

4.3.2. Shadow Banking in China

China's economy has been developing rapidly at the beginning of the 21st century, but the financial market and financial supervision have been relatively lax. The financing difficulties of small and medium-sized enterprises and individuals have not been solved, which has led to the rapid growth of shadow banking in China. The large scale of Chinese shadow banking compared to other parts of the world and the trends have brought scholarly concern on shadow banking in China. Prior literature studied shadow banking in China from several different aspects: the specific characteristics of the Chinese shadow banking market; the impact of Chinese government policies on shadow banking; and the effect of shadow banking on the Chinese economy.

In the studies which examined the characteristics of shadow banking in China, Dang et al. (2014) find that shadow banking in China is a bank-centric system rather than a market-based system as in the US market, therefore, shadow banking in China has more interactions with commercial banks, trust companies, and insurance companies. Chen et al., (2018) state that Chinese commercial banks tend to choose the risky entrusted loans rather than loans within the balance sheet, which will increase the total risk of shadow banking. Allen et al. (2019) finds that the nonaffiliated loans[100] have much higher interest rates than both affiliated loans[101] and official bank loans in China, and largely flow into real estate sector.

Government policies have significantly affected the scale of shadow banking (Chen et al., 2018; Li, 2020; Chen et al., 2020). Chen et al. (2018) state that the contractionary

[100] Non-affiliated Loans means a loan made by Lender to an entity non-affiliated with borrower or borrower principal.
[101] Affiliated Loans means a loan made by Lender to a parent, subsidiary or such other entity affiliated with borrower or borrower Principal.

monetary policy during 2009-2015 lead to the sharp increase in shadow banking activities in China, especially in the non-state banks. Li (2020) finds that the expansionary monetary policy decreases the interest rate of P2P lending market because such (expansionary monetary) policy reduces the demand for P2P lending products. In addition, the monetary policy has less of an effect on the high-risk platforms. Chen et al. (2020) state that the local government bank loans increased sharply after the 4 trillion RMB stimulus plan by the central government during the financial crisis in 2008. Since then, the issuance of municipal corporate bonds and the shadow banking activities were flourishing until 2015.

The impact of shadow banking has always been a research hotspot. Acharya et al. (2020) states the Wealth Management Products (WMPs) issued by banks increased sharply after the 4 trillion RMB stimulus plan. Therefore, they believe the swift rise of shadow banking in China was caused by the stimulus and had contributed to greater instability of the financial system. Gabrieli et al. (2018) show that an increase in the size of shadow banking increases the independence of commercial banks from the regulatory supervision of the central bank of China; furthermore, they state that shadow banking in China amplifies the money supply but weakens the effects of interest rate-based restrictive monetary policies.

4.3.3. New Shadow Banking – P2P Lending Market

The P2P lending market is the most important new type of shadow banking in recent years. The sharply increasing trends on scale and the number of platforms boosts the research into peer-to-peer lending market. Prior literature studied the P2P lending market from the perspective of borrowers' behavior (Freedman and Jin, 2008; Berkovich, 2011; Herzenstein et al., 2011; Michels, 2012; Pope and Syndor, 2011; Duarte et al., 2012; Liao et al., 2017; Chen et al., 2018; Lin et al., 2018) and market performance (Xiang et al., 2019; Zhang et al., 2018; Lu et al., 2020).

P2P lending market is suitable for studying the behavior of individuals and investigating the effect of voluntary disclosure (because this is a new and less regulated market with lots of individual participation). Much literature focuses on the significantly effect of borrowers' voluntary information disclosure (picture, gender, friendship, loan description and etc.) on the default probability and the lending rate in the P2P lending market (Herzenstein et al., 2011; Michels, 2012; Pope and Syndor, 2011; Duarte et al., 2012; Lin et al., 2018). Some literature found the existence of adverse selection (Freedman and Jin, 2008) and herding effect (Berkovich, 2011) in P2P lending market. Liao et al. (2017) find that unexperienced investors in Chinese P2P lending market tend to invest in loans with high-interest rates and have high default rates while experienced investors tend to invest in loans with low risk. Chen et al. (2018) find that loans invested in by female investors have higher default probability and lower loan return in the

Chinese P2P lending market.

The market performance is another important research topic in the P2P lending market. Zhang et al. (2018) find that the excess return exists in the P2P lending market, with 75% of loans having positive excess return. Xiang et al. (2018) state that interest rates of platforms are significantly and positively related to the risk of platforms. Lu et al. (2020) find that the borrowers from U.S. states with higher levels of social capital have less probability to be rejected during loan application, have lower default probability, and enjoy lower loan cost. Meanwhile, the loans to states with higher levels of social capital earned higher returns.

4.4.Hypothesis Development

Monetary policy has always been strongly linked to China's economic development and financial risks. Fernald et al. (2014) claim that the monetary policy transmission channels in China have moved closer to those of Western market economies and become more effective. Conversely, Hou and Wang (2013) test the effect of reserve requirements on the lending channel and find that with the increase of banking marketization, China’s monetary policy transmission through the bank lending channel weakens. Deng et al. (2015) state that the monetary stimulation after the global financial crisis in 2008 rapidly boosted the GDP in China, and, after the central government ordered state-owned enterprises (SOEs) to invest, most of investment flowed into the real-estate market. This episode mimics the credit channel of Chinese monetary policy, actually, the capital transfers between the central government and local government, with pressure pushing real estate prices upwards.

Although there are different results about the effect of Chinese monetary policy, the evidence shows that the existence of shadow banking has weakened the effectiveness of government monetary policies (Chen et al., 2018; Gabrieli et al., 2018; Li, 2020). Gabrieli et al. (2018) reveal that shadow banking in China reduces the effects of restrictive interest rate-based monetary policy. Chen et al. (2018) state that the contractionary monetary policy increased the scale of shadow banking activities in China, especially in the non-state banks. However, this paper only uses the scale of the entrusted loans and the scale of the ARIX[102] to measure the scale of activities of shadow banking in China. The CSMAR has published the monthly core shadow scale data since 2014, which not only includes the entrusted loans, but also includes the trust loans and the undiscounted bank acceptances. Moreover, there are more new types of shadow banking since 2014, such as the P2P lending market which has not yet been considered in the Chen et al. (2018) paper. Li (2020) studies the relationship between monetary policy and P2P lending market performance. His results show that the expansionary monetary policy decreases the market interest rate of P2P lending market by decreasing the market demand[103] for P2P lending products. Based on prior studies,

[102] ARIX: Quarterly series of ARI excluding central bank bills and government bonds. ARI: Quarterly series of account receivable investment (ARI) on the asset side of an individual bank’s balance sheet. The series is based on WIND, which collects the ARI series from quarterly reports of 16 publicly listed commercial banks.
[103] The monetary policy has more effect on market demand and less effect on market supply in peer-to-peer

4. *The Effect of the Central Government Monetary Policy and the Local Government Financing Demand on the Scale of the Shadow Banking: Evidence from P2P Lending Market*

I believe that government monetary policy has significant influence on the scale of shadow banking and P2P lending market. So, my first hypothesis is stated as follows:

H1. The contractionary monetary policy has a significant positive effect on the scale of shadow banking and the P2P lending market.

According to a Moody (2006) report, there are two main types of shadow banking, one of them being core shadow banking which only includes the entrusted loans, trust loans, undiscounted bankers' acceptance; the other is the broad shadow banking which includes all the types of off-balance assets. The core shadow banking is frequently used, because it is out of government surveillance, to redeem private equity bonds, to withdraw the risk swaps from some wealth management products, and to invest in some high-risk markets (e.g., the P2P lending market).

Allen et al. (2019) find that the nonaffiliated loans have much higher interest rates than both affiliated loans and official bank loans, and the nonaffiliated loans have largely flowed into the real estate market. This study indicates the capital flows between different markets to seek high returns. As an innovative and less regulated market, peer-to-peer lending market is always considered to have high returns, and the capital flow in this market is hidden and is less regulated. According to Tian et al. (2021), the arbitrage opportunity and behavior exist within peer-to-peer lending. This arbitrage

lending market. Because most of borrowers in peer-to-peer lending market are individuals and small firms, it is hard for them to make loans from banking or other large financial institution.

opportunity will attract large capital inflow to peer-to-peer lending. And since most of investors in peer-to-peer lending market are risk lovers (because the high default rate and high return in this market), one of the most important capital inflow channels could be the existing shadow banking which also is less regulated and suffer high relative risk. Therefore, even though the China Banking Regulatory Commission issued "Commercial Bank Entrusted Loan Management Measures" to regulate the uses of the entrusted loans (CBIRC, 2018), there were still many improper usages of the entrusted and trusted loans until July 2020.[104] In addition, Figure 4.9 (in Section 4.2.4.) shows that capital in traditional core shadow banking (the trust loans, undiscounted banker's acceptance and entrusted loans, etc.) could be the source of the peer-to-peer lending through banks' off-balance-sheet operations (guarantee business and financial asset service business), and trust company, which is consistent with the market phenomenon. Therefore, the core shadow banking is envisaged to be a contributor to the rising of P2P lending market. Therefore, my second hypothesis is stated as follows:

H2. The scale of core shadow banking has a significantly positive effect on the scale of the P2P lending market in China.

Except the effect of the monetary policy and the emergence of the new types included in the shadow banking, such as the P2P lending market, the local government financing demand is another reason for the shadow banking activities. Chen et al. (2020) state

[104] In January 2018, the CBIRC issued "measures for the administration of entrusted loans of commercial banks". http://www.gov.cn/xinwen/2018-01/09/content_5254622.htm

that the local government bank loans increased sharply after the 4 trillion RMB stimulus plan by the central government during the financial crisis in 2008. The bank loans of the local government had increased significantly since 2009, and more municipal corporate bond issuances had fueled the shadow banking activities since then until 2015. Therefore, the local government financing demand was a reason for the rapid increases of the shadow banking and the P2P lending markets. Chen et al. (2020) find a significant effect of government financing demand on the increasing scale of entrusted loans, I want to test such effect on provincial-level and prove more convincing results by expending this effect on the core shadow banking and the peer-to-peer lending market. Therefore, my third hypothesis is stated as follows:

H3. The local government financing demand has a significantly effect on the scale of provincial core shadow banking and the P2P lending market.

4.5.Methods

The objectives of my study are examining whether the monetary policy has a significant effect on the scale of P2P lending market and core shadow banking; whether the scale of core shadow banking could affect the scale of P2P lending market; and whether local government bonds issued have power over the scale of P2P lending market and core shadow banking. The detailed definitions and data sources are explained in the appendix 4.1. *OL* represents outstanding loans, which is the outstanding loans in the whole P2P lending market, and it is the measurement of the scale of P2P lending. *SBC* represents core shadow banking scale, which is the core shadow banking scale (ending balance) in China. *M* represents money supply, which is the M2 in China. *LGBI* represents local government bond issued, which is the quarterly issued local government bond. *GDPC* represents GDP per capita, which is the per capita Gross National Product in China. *SSE* represents Shanghai Composite Index which is the closing value Shanghai Composite Index. *FD* represents financial deficit which equals the financial revenues minus financial expenditures. *CPI* represents consumer price index, and *FAI* represents fixed asset investment.

The following model (1-1) and (1-2) are used to examine the effect of monetary policy on the scale of core shadow banking and the scale of the P2P lending market from 2014 to 2019. The monthly ending balance of core shadow banking (*SBC*) and outstanding loans of P2P lending market (*OL*) are the dependent variables in model (1-1) and (1-2) respectively, while the money supply (*M*) is the testing variable. Following Chen's paper (Chen et al., 2020), my control variables include the monthly Gross Domestic Product Per Capita *GDPC* (*GDPC*), Fixed Assets Investment (*FAI*), and Fiscal Deficit (*FD*). In addition, the Shanghai Composite Index (*SSE*) and Consumer Price Index (*CPI*) are controlled in my paper because the main investing and financing channels in China are the stock market, the bond market and the fixed asset market. The Shanghai T-Bond Index (*SSE T-Bond*) are dropped because of the multicollinearity.[105] According to prior literature (Chen et al., 2018; Li, 2020) and my best knowledge, I expect the higher

[105] The *SSE T-Bond* has the multicollinearity problem with the *GDPC* & *FD*.

Gross Domestic Product Per Capita (*GDPC*), Fixed Assets Investment (*FAI*), Fiscal Deficit (*FD*), Shanghai Composite Index (*SSE*), and Consumer Price Index (*CPI*), the larger scales of shadow banking and P2P lending market because the higher *GDPC*, *FAI*, *SSE*, and *CPI* indicate the better economic development and the higher capital flow in the society, which may increase the scale of shadow banking; and the higher *FD* represents the larger government debt which also may boost the scale of shadow banking. I also expect the lower money supply (*M2*), the larger scale of shadow banking and P2P lending market because the contractionary monetary policy will reduce bank loans and will stimulate the capital demand for shadow banking (see Figure 4.9 in Section 4.2.4.) (Chen et al., 2018). Following prior studies, the VAR (Vector Autoregression Model) is used to test the model (1-1) and (1-2) because of the strong lag effect of monetary policy.

$$SBC_t = \alpha_t + \beta_1 M_t + \sum_{n=2}^{n} \beta_n Controls_t + \varepsilon_t \quad (1\text{-}1)$$

$$OL_t = \alpha_t + \beta_1 M_t + \sum_{n=2}^{n} \beta_n Controls_t + \varepsilon_t \quad (1\text{-}2)$$

Controls includes *GDPC*; *FAI*; *FD*; *SSE*; *CPI*.

I then test the relationship between existing shadow banking scale and the scale of peer-to-peer lending market in the model (2). In model (2), the dependent variable is outstanding loans of P2P lending market (*OL*) and testing variable is scale of core shadow banking (*SBC*). Also, controls include the national monthly *GDPC*, *SSE*, *FD*, *FAI*, *CPI* and the time variable from Jan. 2014 to Dec. 2019. As the discussion in H2 (see 4.4), the scale of core shadow banking (*SBC*) is expected to have significant positive impact on the scale of P2P lending market (*OL*).

$$OL_t = \alpha_t + \beta_1 SBC_t + \sum_{n=2}^{n} \beta_n Controls_t + \varepsilon_t \; (2)$$

Controls includes *GDPC*; *FAI*; *FD*; *SSE*; *CPI*.

The effect of local government bond issuance on the scales of shadow banking and P2P lending market is investigated in model (3-1) and (3-2). In Model (3-1) and (3-2), the dependent variables are the quarterly scale of core shadow banking (*SBC*) and outstanding loans of P2P lending market (*OL*), and the testing variable is the amount of local government bonds issued (*LGBI*). Followed the prior literature (Chen et al., 2020), the controls include quarterly Gross Domestic Product Per Capita (*GDPC*), Fixed Assets Investment (*FAI*), Fiscal Deficit (*FD*) from Jan. 2015 to Dec. 2019. I expect the higher *GDPC*, *FAI*, *FD*, the larger *SBC* (scale of core shadow banking) and *OL* (outstanding loans of P2P lending market) because higher *GDPC*, *FAI*, and *FD* means the higher capital inflows in provinces which could increase the scale of shadow banking. I also expect the higher local government bond issued (*LGBI*), the larger scale of core shadow banking (*SBC*) and outstanding loans of P2P lending market (*OL*) because the more local government bonds issued, the more capital likely flows into non-bank financial institutions and off-balance sheet asset (see Figure 4.10 in Section 4.2.4.) (Chen et al., 2020).

$$SBC_{it} = \alpha_{it} + \beta_1 LGBI_{it} + \sum_{n=2}^{n} \beta_n Controls_{it} + \varepsilon_{it} \; (3\text{-}1)$$

$$OL_{it} = \alpha_{it} + \beta_1 LGBI_{it} + \sum_{n=2}^{n} \beta_n Controls_{it} + \varepsilon_{it} \; (3\text{-}2)$$

Controls includes *GDPC*; *FAI*; *FD*.

4.6.Results and Analyses

4.6.1. Descriptive Analysis

Descriptive statistics of the data in national level is shown in Table 4.1. The mean of core shadow banking scale (*SBC*) is 23.42 trillion, the median is 22.73 trillion, and the standard deviation is 1.84 which implies relatively normally distributed. Compared to the mean (79.35 trillion) and median (78.92) of raw GDP, the scale of core shadow banking takes around 30% of the GDP. The mean of P2P lending scale (*OL*) is 599.57 billion, and the media is 644.54 billion, and the standard deviation is 396.56 (this is because the relative high gap between minimum value (30.87) and maximum value (1311.39) which represent the relatively large variance and fluctuations of *OL*. And for the *M2*, the mean (median) is 155.14 trillion (156.30 trillion) with 25.62 standard deviation, which also displays the relative normal distribution. And all the data shows the normal distribution after the log and winsorized by 1% (top and bottom).

Insert Table 4.1 about here

Table 4.2 displays the sample descriptive of the data in the provincial level. The core shadow banking scale (*SBC*) and P2P lending scale (*OL*) have relatively high standard deviation (132.21 and 345.26), and also for the main testing variable, local government bond issued (*LGBI*). The mean and median of *LGBI* are 50.86 billion and 49.56 billion, with 23.74 standard deviation, which display relative normal distribution and high variance and fluctuations. And after the log and winsorization (by 1% on top and bottom), all the data shows the normal distribution.

Insert Table 4.2 about here

4.6.2. Correlation Analysis

The correlation matrix of all variables in model (1) and (2) is shown in Table 4.3. All correlations are less than 0.5, most of them are less than 0.3, which means that the possibility of multi-collinearity is low. Table 3 also shows the univariate relationships between core shadow banking scale (*SBC*) and P2P lending scale (*OL*), the significant 0.4046 represent a positive relation between *SBC* and *OL*, which indicates the significant positive impact of core shadow banking scale on the P2P lending scale. Even though the univariate analysis shows an insignificant relationship between *M* and core shadow banking scale (*SBC*), the insignificant relationship between P2P lending scale (*OL*) and *M2*, it doesn't reflect the real relations between them because the other influencing factors are not controlled for in the univariate analysis.

Insert Table 4.3 about here

The correlation matrix of all the variables in model (3) is shown in Table 4.4. All the results of the coefficients among testing variable and control variables are less than 0.5 which indicate that the possibility of multicollinearity is low. The univariate analysis shows the relations between dependent variables and testing variable. The coefficient 0.4066 proves the significant positive relations between provincial local government bond issued (*LGBI*) and provincial core shadow banking scale (*SBC*), and the coefficient 0.0254 indicates the significant positive impact of provincial local government bond issued (*LGBI*) on the provincial P2P lending scale (*OL*). However, the results should be examined again in the multi-regressions with controlling other factors and with time-lag.

Insert Table 4.4 about here

4.6.3. The Effect of Monetary Policy on the Core Shadow Banking Scale and P2P Lending Scale

Table 4.5 shows the result of the effect of *M* on the scale of core shadow banking in the VAR regression.[106] According to the results in Panel A of Table 4.5, the model has passed the ADF test which shows that the model is stationary. Meanwhile, the results in Panel B of Table 4.5 indicate that the *M* negatively affects the scale of core shadow banking (*SBC*). The coefficient -0.0902 means that each 1% increase of *M* could significantly reduce the scale of shadow banking (*SBC*) by 9.02%. Similar as the results

[106] VAR is the vector autoregressive model, which is a commonly used econometric model, which was proposed by Christopher Sims in 1980. The VAR model uses all current variables in the model to regress several lagged variables of all variables.

in Table 4.5, the model has passed the ADF test which shows that the model is stationary. According to the results in Panel B of Table 4.6, there is the negative relationship between *M* and scale of outstanding loans in peer-to-peer lending market (*OL*). The coefficient -0.0128 represents each 1% increase of *M* will decrease the scale of outstanding loans (*OL*) by 1.28%. These results are consistent with my hypothesis 1 and previous studies (Chen et al., 2018; Li, 2020) showing that the contractionary monetary policy will aggravate the shadow banking scale. The decreased *M* will increase the size of core shadow banking and the size of outstanding loans in peer-to-peer lending market.

Insert Table 4.5 about here

Insert Table 4.6 about here

4.6.4. The Effect of Core Shadow Banking Scale on P2P Lending Scale

Results of the hypothesis 2 display in Table 4.7. According to the OLS results in Panel A, all the control variables show the weak power on the outstanding loans in the P2P lending market, while the testing variable, scale of the core shadow banking, show the significant positive effect on the outstanding loans in the P2P lending market in current time, one-month lag, one-quarter lag, and half-year lag. The coefficient 0.460 (0.437 with one month lag, 0.425 with one quarter lag, 0.380 with half-year lag) indicates that for each additional scale of core shadow banking (*SBC*), the current (one month later, one quarter later, half-year later) peer-to-peer lending market size (outstanding loans in peer-to-peer lending market, *OL*) increased by 46% (43.7%, 42.5%, 38%). In general, the scale of core shadow banking could generate the P2P lending market both currently and in the future. Even though there is little published literature demonstrating this result, there are many arguments and examples in the real world because of the wide-spread improper uses of core shadow banking in the world, especially in China (CBIRC, 2020).[107] The relative high interest rate in the new shadow banking (i.e., peer-to-peer lending market) (see Chapter 2 in the thesis) attracts the improper use of capital from the core shadow banking (entrusted loans, trust loans, and the undiscounted banker's acceptance), and this capital actually flows between the bank (in-balance sheet), core shadow bank (off-balance sheet), and new shadow bank (i.e., peer-to-peer lending market). Figure 4.9 (see in Section 4.2.4.) shows that the traditional core shadow banking (the trust loans, undiscounted banker's acceptance and entrusted loans, etc.) is a main source of the new shadow banking, which is a much less regulated sector by the government.

In order to resolve the potential endogenous problem that exists in the models (that the scale of the P2P lending market could have the reverse effect on the scale of the core shadow banking), I use two dummy IVs[108] that only have the impact on the scale of

[107] CBIRC (China Banking and Insurance Regulatory Commission) found that the use of entrusted loan funds was non-conforming, and some of them flowed into the new financial market without supervision. https://baijiahao.baidu.com/s?id=1672267991345891861&wfr=spider&for=pc

[108] The IV1 in this regression is the instrumental variable which is a dummy variable that only affect the core shadow banking size (*SBC*) rather than the P2P lending market (*OL*). This is an important event that the "Administrative Measures for Entrusted Loans of Commercial Banks (Consultation Draft)" announced by the China Banking Regulatory Commission in Jan 2015

the core shadow banking (e.g., the entrusted loans) rather than the P2P lending market. All the 2SLS results are listed in the Panel B, the results still show the significant positive effect of the scale of core shadow banking on the outstanding loans of P2P lending market in current time, one-month lag, and one-quarter lag. The coefficients are 1.128 in current, 1.323 with one month lag, 1.289 with one quarter lag, and 1.060 with half-year lag. All the results prove that the increase of scale of core shadow banking provide more funds invested in the peer-to-peer lending market in current and future periods.

Insert Table 4.7 about here

Furthermore, I controlled the *M* to look at the relations between the core shadow banking and the P2P lending market again. The OLS results in Panel A of Table 4.8 show the coefficients of *SBC* is 0.395 in current month, 0.409 with month lag, 0.368 with one quarter lag, and 0.271 with half-year lag. All these significant coefficients demonstrate the positive impact of the core shadow banking scale (*SBC*) on the peer-to-peer lending market scale (*OL*) after controlling the *M2*. And the 2SLS results in Panel B of Table 4.8 display the coefficient of *SBC* is 1.109 in current, 1.338 with one month lag, 1.309 with one quarter lag, and 1.111 with half-year lag which indicate the significant positive effect of the core shadow banking scale (*SBC*) on the peer-to-peer

(http://www.cbirc.gov.cn/cn/view/pages/ItemDetail.html?docId=66608&itemId=951&generaltype=2).
The IV2 is another instrumental dummy variable which is an event that the China Banking Regulatory Commission issued "Commercial Bank Entrusted Loan Management Measures" in Jan 2018 (http://www.cbirc.gov.cn/cn/view/pages/ItemDetail.html?docId=167238&itemId=915&generaltype=0).

lending market scale (*OL*) after controlling the *M2*.

Obviously, all the results in Table 4.8 demonstrate the significant positive effect of the core shadow banking (*SBC*) and the outstanding loans in peer-to-peer lending market (*OL*). The results prove that the scale of core shadow banking still shows a significantly positive effect on the scale of P2P lending market both in current and the future which indicates strong evidence of the existing shadow banking creating peer-to-peer lending market.

Insert Table 4.8 about here

4.6.5. The Effect of Local Government Bond Issued on the Core Shadow Banking Scale and P2P Lending Scale

According to the results in Table 4.9 & 4.10, the local government financing demand has a significant effect on the increasing scale of the core shadow banking and the P2P lending market. The results show that the local government bond issued (*LGBI*) have the significantly positive effect on the scale of core shadow banking (*SBC*) and the outstanding loans of P2P lending market (*OL*) in current time, one-quarter lag, and one year lag. The coefficients of *SBC* in Table 4.9 are 0.0362 in current quarter, 0.0258 with one quarter lag, and 0.0321 with one year lag. These results show each additional local government bond issued (*LGBI*) could increase the scale of core shadow banking at 3.62% in the current quarter, 2.58% in one quarter later, and 3.21% in one year later.

Similar as the results in Table 4.9, results in Table 4.10 (coefficients of *OL* are 0.414 in current quarter, 0.536 with quarter lag, 0.519 with one year lag) still represents each increased local government bond issued (*LGBI*) could increase the scale of outstanding loans in P2P lending market. All these results indicate that the local government financing demand contributes to the rising of the shadow banking (both core shadow banking and peer-to-peer lending) in China.

Insert Table 4.9 about here

Insert Table 4.10 about here

4.7.Conclusion

Although previous studies state that monetary policy and government financing demand have significant impacts on shadow banking, there are few studies which focus on the factors affecting the new shadow banking (P2P) which grows rapidly with financial innovation and Fintech development. My paper displays a new perspective to study shadow banking monitoring and supervising by examining the relations between money supply and P2P lending scale, local government bond issued and P2P lending scale, and most importantly, the relations between the existing shadow banking scale (core shadow banking) and the P2P lending market.

There are three main findings in my paper: first, that the existing shadow banking creates new shadow banking, which means that the scale of the core shadow banking has a significant positive effect on the scale of the P2P lending market; second, the contractionary monetary policy has a significant effect on the increase of the scale of shadow banking and the P2P lending market; third, the local government financing demand has a significant positive effect on the scale of the core shadow banking and P2P lending market.

My paper contributed to the literature in several aspects: first, it adds to the literature on the shadow banking research area by proving the significant relationship of existing shadow banking (core shadow banking) on the P2P lending market; second, it contributes to the existing literature in the money and banking research area by stating the impact of monetary policy on the P2P lending market; third, it enriches the previous literature in the government debt research area by analyzing the significant effect of local government bonds issued on the scale of P2P lending market.

Notwithstanding the main contributions of this study, one of the important limitations of the paper is the data limitation, because of the limited data disclosed by CSMAR, WDZJ, the People’s Bank of China, the Bureau of Statistics, and the Bureau of Finance, I could only collect the monthly national data from 2014 to 2019 and the quarterly provincial data from 2015 to 2019 in eight provinces, however I hope this limitation could be addressed in future research.

References

Acharya, V. V., Qian, J., Yang, Z. S., 2020. In the shadow of banks: Wealth management products and issuing banks' risk in China. NYU Stern School of Business. Available at: http://dx.doi.org/10.2139/ssrn.3401597

Ackermann, J., Sands, P., 2012. Shadow banking: A forward-looking framework for effective policy. Washington: Institution of International Finance Report.

Adrian, T. and Ashcraft, A.B., 2012. Shadow banking: A review of the literature. Staff Report, Federal Reserve Bank of New York, 580.

Adrian, T. and Shin, H.S., 2009. The shadow banking system: Implications for Financial Regulation. Financial Stability Review 19, 1-10.

Allen, F., Qian, Y., Tu, G., Yu, F., 2019. Entrusted loans: A close look at China’s shadow banking system. Journal of Financial Economics 133, 18-41.

Ba, S.S., 2009. Strengthen supervision of the shadow banking system. China Finance, 2009 (14).

Beck, T., Chen, T., Lin, C., Song, F.M., 2016. Financial innovation: The bright and the dark sides. Journal of Banking and Finance 72, 28-51.

Beijing Internet Finance Association, April 2019, Reminders on strengthening business standards and risk prevention and control of lending institutions. Available at: https://www.bjp2p.com.cn/news/20190402001.

Berkovich, E., 2011. Search and herding effects in peer-to-peer lending: evidence from prosper.com. Ann Finance 7, 389-405.

Brunnermeier, M.K., 2009. Deciphering the liquidity and credit crunch 2007-2008. Journal of Economic perspectives 23(1), 77-100.

Chen, J., Jiang, J., Liu, Y., 2018. Financial literacy and gender difference in loan performance. Journal of Empirical Finance 48, 307-320.

Chen, K.J., Ren, J., Zha, T., 2018. The nexus of monetary policy and shadow banking in China. American Economic Review 108(12), 3891-3936.

Chen, Z., He, Z., Liu, C., 2020. The financing of local government in China: Stimulus loan wanes and shadow banking waxes. Journal of Financial Economics 4, 39.

China Banking and Insurance Regulatory Commission, 2020. China Shadow Banking Report. Financial Supervision Research, 11.

Claessens, S., Pozsar, Z., Ratnovski, L., Singh, M., 2012. Shadow banking: Economics and policy. International Monetary Fund. IMF Staff Discussion Notes, December 4, 2012.

Dang, T. V., Wang, H. L., Yao, A., 2014. Chinese shadow banking: Bank-centric misperceptions. HKIMR Working Paper, 22.

Delottei, I.M., 2009. The future of banking and securities industry. University of Harvard Press.

Deng, Y., Morck, R., Wu, J., Yeung, B., 2015. China’s pseudo-monetary policy. Journal of Finance 19, p.55-93.

Duarte, J., Siegel, S., Young, L., 2012. Trust and credit: the role of appearance in peer-to-peer lending. Review of Financial Studies 25, 2455-2484.

Epstein, G.A., 2005. Financialization and the world economy. Edward Elgar Publishing, 3-16.

Fernald, J, Spiegel, M.M, Swanson, E.T, 2014, Monetary policy effectiveness in China: Evidence from a FAVAR model. Journal of International Money and Finance 49, 83-103.

Financial Stability Board, 2012-2020. Global Monitoring Report on Non-Bank Financial Intermediation 2020. https://www.fsb.org/

Freedman, S., Jin, Z.G., 2008. Do social networks solve information problems for peer-to-peer lending? Evidence from prosper.com. Available at SSRN: https://papers.ssrn.com/s013/papers.cfm?abstract_id=1936057.

Gabrieli, T., Pilbeam, K., Shi, B., 2018. The impact of shadow banking on the implementation of Chinese monetary policy. Int Econ Policy 15, 429–447.

Global Monitoring Report on Non-Bank Financial Intermediation. 2020. Financial Stability Board. Avaliable at: https://www.fsb.org/wp-content/uploads/P161220.pdf.

Grinblatt, M., Longstaff, F., 2000. Financial innovation and the role of derivative securities: an empirical analysis of the Treasury STRIPS program. Journal of Finance 55, 1415–1436.

Henderson, B.J., Pearson, N.D., 2011. The dark side of financial innovation: A case study of the pricing of a retail financial product. Journal of Financial Economics 100, 227-247.

Herzenstein, M., Sonenshein, S., Dholakia, M.U., 2011. Tell me a good story and I may lend you money: the role of narratives in peer-to-peer lending decisions. Journal of marketing research XLVIII, 138-149.

Hildreth, W.B., Miller, G.J., 2002. Debt and the local economy: Problems in benchmarking local government debt affordability. Public Budgeting & Finance 22(4), 99-113.

Hou, X., Wang, Q., 2013. Implications of banking marketization for the lending channel of monetary policy transmission: evidence from China. Journal of Macroeconomics 38, 442–451.

Hsu, J.C., Moroz, M., 2010. Shadow Banks and the Financial Crisis of 2007-2008. In 'THE BANKING CRISIS HANDBOOK', Chapter 3, 39-56. Available at SSRN: https://ssrn.com/abstract=1574970

Laeven, L., Levine, R., Michalopoulos, S., 2015. Financial innovation and endogenous growth. Journal of Financial Intermediation 24, 1-24.

Li, C., 2020. Monetary Policies versus Regulatory Policies: Management of Peer-to-Peer Market Interest Rates. China & World Economy 28, 41-63.

Liao, L., Wang, Z., Xiang, J., Yang, J., 2017. Thinking fast, not slow: evidence from peer-to-peer lending. Available at SSRN: http://papers.ssrn.com/so13/papers.cfm?abstract_id=2830326

Lin, M., Prabhala, P.N., Viswanathan, S., 2018. Judging borrowers by the company they keep: friendship networks and information asymmetry in online peer-to-peer lending. Management Science 59, 17-35.

Liu, C., Moldogaziev, T.T., Mikesell, J.L., 2017. Corruption and state and local government debt expansion. Public Administration Review 77(5), 681-690.

Lu, H., Wang, B., Wang, H., Zhao, T., 2020. Does social capital matter for peer-to-peer-lending? Empirical evidence. Pacific-Basin Finance Journal 61, 101338.

McConnell, J., Schwartz, E., 1992. The origin of LYONS: a case study in financial innovation. Journal of Applied Corporate Finance 4, 40–47.

McCulley, P. 2007. Teton reflections. PIMCO Global Central Bank Focus, 2.

Michels, J., 2012. Do unverifiable disclosure matter? evidence from peer-to-peer lending. The Accounting Review 87, 1385-1413.

Miller, M., 1986. Financial innovation: the last twenty years and the next. Journal of Financial and Quantitative Analysis 21, 459–471.

Risk, M.S., Soundness, R.F., 2008. Global financial stability report. International Monetary Fund, Washington. Available at: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.359.9600&rep=rep1&type=pdf

Moody, 2006-2020. The China Shadow Banking Quarterly Monitoring Report. www.moodys.com

Moreira, A., Savov, A., 2017. The macroeconomics of shadow banking. Journal of Finance 72, 2381-2434.

Niu, W.X., 2018. Why is the M2 invalid?, China Economic Weekly, 2018.3.12. http://www.ceweekly.cn/2018/0312/220020.shtml

Pope, D.G., Sydnor, J.R., 2011. What's in a picture? evidence of discrimination from prosper.com. Journal of Human Resources 46, 53-92.

Pozsar, Z., Adrian, T., Ashcraft, A., Boesky, H., 2010. Shadow banking. *Federal* Reserve Bank of New York Staff Report, 458.

Ross, S.A., 1989. Institutional markets, financial marketing, and financial innovation. Journal of Finance 3, 541-556.

Shiller, R.J., 2013. Capitalism and financial innovation. Financial Analysts Journal 69, 21-25.

The China Banking Regulatory Commission, April 2016. P2P Platforms Management Document. www.cbrc.gov.cn.

The People's Bank of China, September 2019. 'Notice on Strengthening the Construction of Credit Investigation System in the P2P Online Loan Field', http://www.pbccrc.org.cn/zxzx/zhengcfg/202004/b3e370d88d974643a35977c8e3792bd3.shtml.

Tian, G., Wang, X., Wu, W., 2021. Borrow low, lend high: Credit arbitrage by sophisticated investors. Pacific-Basin Finance Journal 67, 101544.

Xiang, H., Wang, Z., Jiang, J., Liao, L., 2019. Pie or trap: what is represented by interest rate in peer-to-peer lending platform? China Financial Research Conference, July 7, 2019.

Yi, X.R., 2011. Financial analysis of credit crisis in shadow banking system. Jianghai Journal, 3.

Yuan, Z.T., 2011. The nature and supervision of Chinese and foreign shadow banking systems. China Finance, 1.

Zhang, Z., Hu. W., Chang, T., 2019. Nonlinear effects of P2P lending on bank loans in a Panel Smooth Transition Regression model. International Review of Economics and Finance 59, 468–473

Zhao, Y., Ye, Z., 2016. The Influence of P2P Online Lending on the Effectiveness of China’s Monetary Policy, Lan Zhou Xue Kan, 2016.04

WDZJ, 2020. The 2019 Annual Report of Internet Lending Market, https://www.wdzj.com/news/yc/5568513.html.

Tables

Table 4.1. Sample Descriptive-National (Raw Data)

Variables	Mean	Median	Std.	Min	Max	Obs.	Unit
SBC	23.42	22.73	1.84	20.40	27.06	72	trillion yuan
OL	599.57	644.536	396.56	30.87	1311.39	72	billion yuan
M2	155.14	156.30	25.62	112.35	198.65	72	trillion yuan
GDPC	11.17	11.04	5.65	2.44	22.82	72	1000 yuan
SSE	3003.63	3051.45	507.58	2026.36	4611.74	72	
FD	-274.98	-311.66	636.95	-2099.60	1069.35	72	billion yuan
FAI	5.14	5.22	1.20	1.78	8.15	72	trillion yuan
CPI	101.89	102	0.43	100.8	102.9	72	

Note: all continuous variables are the raw data in this table, and I have taken log and winsorized all the data in the later regressions.

Table 4.2. Sample Descriptive-Provincial (Raw Data)

Variables	Mean	Median	Std.	Min	Max	Obs.	Unit
SBC	203.63	167.20	132.21	42.23	737.450	152	billion yuan
OL	259.83	96.29	345.26	1.15	1433.82	160	billion yuan
LGBI	50.86	49.56	23.74	5.60	115.6	160	billion yuan
GDPC	26.38	20.74	21.17	7.60	164.24	160	1000 yuan
FD	-66.67	-56.04	86.15	-747.85	91.92	160	billion yuan
FAI	824.86	751.98	884.78	35.62	8052.61	160	billion yuan

Note: all continuous variables are the raw data in this table, and I have taken log and winsorized all the data in the later regressions.

Table 4.3. Correlation Metrix-National

	OL	SBC	M2	GDPC	SSE	FD	FAI	CPI
OL	1							
SBC	0.4046*	1						
M2	0.0853	-0.1142	1					
GDPC	-0.1111	-0.1996	-0.3386*	1				
SSE	0.0307	0.0421	0.0284	-0.1614	1			
FD	0.1077	-0.0388	0.0017	0.0733	0.1374	1		
FAI	-0.0389	0.1012	0.3091*	-0.1676	0.1383	0.0086	1	
CPI	-0.0744	-0.0081	0.0359	-0.0072	-0.1507	0.09	-0.1484	1

Notes: *p>0.05

OL is the dependent variables, SBC is the testing variables, and *GDPC*, *SSE*, *FD*, *FAI*, *CPI* are control variables in Model 1.

SBC & *OL* are the dependent variables, M is the testing variable, and *GDPC*, *SSE*, *FD*, *FAI*, *CPI* are control variables in Model 2.

Table 4.4. Correlation Metrix-Provincial

Variables	SBC	OL	LGBI	GDPC	FD	FAI
SBC	1					
OL	0.127*	1				
LGBI	0.4066*	0.0254*	1			
GDPC	0.4380*	0.3322*	0.0608	1		
FD	-0.2863*	0.2565*	-0.2764*	0.1693*	1	
FAI	0.2089*	-0.4267	0.1948*	-0.4672*	-0.2987*	1

Notes: *p<0.05

SBC & *OL* are the dependent variables, *LGBT* is the testing variable, and *GDPC*, *FD*, *FAI* are control variables.

Table 4.5. The Effect of Monetary Policy on the Scale of shadow banking – M2

Panel A	ADF Test
Equation	P>chi2
SBC	0.0000
M2	0.0000
Panel B	VAR Results
SBC	(1-1)
M2 (L1)	-0.0902**
	(0.0416)
GDPC	0.0388
	(0.09)
SSE	0.0006
	(0.0008)
FD	-0.0006
	(0.0013)
FAI	2.0105*
	(1.1704)
CPI	0.0333
	(0.0587)
Cons	0.0784
	(0.152)
AIC	32.9063
Log likelihood	-1079.27
No. Obs.	69

Notes: All the variables in Table 4.5 have been passed the unit-root test and are stationary.

The VAR model (VARSOC) shows that the 1 lag should be used in the model.

Table 4.6. The Effect of Monetary Policy on the Scale of P2P Lending Market – M2

Panel A	ADF Test
Equation	P>chi2
OL	0.0355
M2	0.0000
Panel B	VAR Results
OL	(1-2)
M2 (L1)	-0.0128*
	(0.0069)
GDPC	0.0189
	(0.0162)
SSE	0.0002
	(0.0001)
FD	0.0001
	(0.0002)
FAI	0.2255
	(0.1978)
CPI	0.0113
	(0.01)
Cons	0.0237
	(0.026)
AIC	28.2978
Log likelihood	-920.274
No. Obs.	69

Notes: All the variables in Table 4.6 have been passed the unit-root test and are stationary.
The VAR model (VARSOC) shows that the 1 lag should be used in the model.

Table 4.7. The Effect of Scale of Shadow Banking on the scale of P2P Lending Market – National

Panel A	OLS			
OL	(2-1-1)	(2-1-2)	(2-1-3)	(2-1-4)
SBC	0.460***			
	(0.119)			
SBC-L1		0.437***		
		(0.118)		
SBC-L4			0.425***	
			(0.114)	
SBC-L6				0.380***
				(0.110)
GDPC	-0.0474	-0.142	-0.0635	-0.149
	(0.110)	(0.113)	(0.120)	(0.124)
SSE	0.0001	0.0001	0.0016	0.0014
	(0.0011)	(0.0008)	(0.0010)	(0.0011)
FD	0.0022	0.0012	0.0009	0.0015
	(0.0016)	(0.0016)	(0.0018)	(0.0018)
FAI	0.492	0.516	-0.906	-0.302
	(0.776)	(0.682)	(0.882)	(0.788)
CPI	-0.0379	0.0032	0.0219	0.0754
	(0.0692)	(0.0585)	(0.0629)	(0.0701)
T	YES	YES	YES	YES
Cons.	-0.242	-0.281	-0.0191	-0.257
	(0.216)	(0.201)	(0.230)	(0.231)
Observations	70	70	67	65
Prob > F	0.0054	0.0084	0.0023	0.0056
R-sq	0.2428	0.2456	0.2154	0.2046

Notes: ***p<0.01, **p<0.05, *p<0.1

Dependent variable is *OL*.

Robust standard errors in parentheses.

All the variables in Table 4.7 – Panel A have been passed the unit-root test and are stationary.

Panel B	2SLS			
OL	(2-1-1)	(2-1-2)	(2-1-3)	(2-1-4)
SBC	1.128***			
	(0.263)			
SBC-L1		1.323***		
		(0.350)		
SBC-L4			1.289***	
			(0.354)	
SBC-L6				1.060***
				(0.384)
GDPC	0.104	-0.140	0.136	-0.109
	(0.162)	(0.169)	(0.176)	(0.144)
SSE	-0.0019	-0.0024	0.0025	0.0013
	(0.0016)	(0.0016)	(0.0018)	(0.0014)
FD	0.0032	0.0003	-0.0005	0.0012
	(0.0020)	(0.0024)	(0.0026)	(0.0022)
FAI	1.475	1.892**	-2.846*	-0.651
	(1.061)	(0.957)	(1.588)	(1.033)
CPI	-0.103	0.0025	0.0333	0.177*
	(0.0947)	(0.128)	(0.0758)	(0.107)
T	YES	YES	YES	YES
Constant	6.142	1.964	6.522	10.66
	(4.651)	(6.625)	(6.854)	(7.562)
Observations	70	70	67	65
Prob > chi2	0.0001	0.0001	0.0001	0.0001
Instrumented	SBC			
Instruments	GDPC SSE FD FAI CPI T IV1 IV2			

Notes: ***p<0.01, **p<0.05, *p<0.1

Dependent variable is *OL*.

Robust standard errors in parentheses.

All the variables in Table 4.7 – Panel B have been passed the unit-root test and are stationary.

The IV1 in this regression is the instrumental variable which is a dummy variable that only affect the core shadow banking size (SBC) rather than the P2P lending market (OL). This is an important event that the "Administrative Measures for Entrusted Loans of Commercial Banks (Consultation Draft)" announced by the China Banking Regulatory Commission in Jan 2015 (http://www.cbirc.gov.cn/cn/view/pages/ItemDetail.html?docId=66608&itemId=951&generaltype=2). The IV2 is another instrumental dummy variable which is an event that the China Banking Regulatory Commission issued "Commercial Bank Entrusted Loan Management Measures" in Jan 2018 (http://www.cbirc.gov.cn/cn/view/pages/ItemDetail.html?docId=167238&itemId=915&generaltype=0).

The r-squared reflects the square of the angle cosine between the explanatory variable and its projection in the explanatory variable generating subspace. Since it is the projected cosine value, it is of course in the interval [0,1]. When using the instrument variable, the instrument variable is not among the explanatory variables, and the geometric interpretation does not exist anymore. The value of r may be negative, which exceeds the interval of [0, 1]. In fact, R2 is not statistically significant in 2SLS or instrumental variable regression, so it may not be reported (https://www.stata.com/support/faqs/statistics/two-stage-least-squares/).

Table 4.8. The Effect of Scale of Shadow Banking on the scale of P2P Lending Market – *M* Controlled

Panel A	OLS			
OL	(2-2-1)	(2-2-2)	(2-2-3)	(2-2-4)
SBC	0.395***			
	(0.122)			
SBC-L1		0.409***		
		(0.115)		
SBC-L4			0.368***	
			(0.122)	
SBC-L6				0.271**
				(0.116)
M2	-0.142***	-0.161***	-0.153***	-0.152**
	(0.0518)	(0.0493)	(0.0543)	(0.0578)
GDPC	-0.111	-0.199*	-0.134	-0.210*
	(0.105)	(0.105)	(0.115)	(0.116)
SSE	0.0008	0.0008	0.0021*	0.0017
	(0.0014)	(0.0010)	(0.0012)	(0.0013)
FD	0.0040**	0.0033**	0.0030*	0.0036**
	(0.0016)	(0.0016)	(0.0018)	(0.0018)
FAI	3.867**	4.406***	2.997*	3.722**
	(1.475)	(1.442)	(1.787)	(1.775)
CPI	-0.0153	0.0223	0.0423	0.0758
	(0.0752)	(0.0545)	(0.0712)	(0.0769)
T	YES	YES	YES	YES
Constant	-0.104	-0.118	0.0864	-0.124
	(0.197)	(0.183)	(0.204)	(0.208)
Observations	70	70	67	65
Prob > F	0.0023	0.0002	0.0003	0.0005
R-sq	0.3256	0.3559	0.3113	0.2852

Notes: ***p<0.01, **p<0.05, *p<0.1

Dependent variable is *OL*.

Robust standard errors in parentheses.

All the variables in Table 4.8 – Panel A have been passed the unit-root test and are stationary.

All the VIF value are less than 2.

Panel B	2SLS			
OL	(2-2-1)	(2-2-2)	(2-2-3)	(2-2-4)
SBC	1.109***			
	(0.265)			
SBC-L1		1.338***		
		(0.346)		
SBC-L4			1.309***	
			(0.353)	
SBC-L6				1.111***
				(0.390)
M2	-0.0451	-0.160*	-0.0715	-0.0798
	(0.0687)	(0.0916)	(0.0793)	(0.0708)
GDPC	0.0790	-0.216	0.110	-0.0740
	(0.172)	(0.159)	(0.180)	(0.149)
SSE	-0.0016	-0.0015	0.0031*	0.0009
	(0.0018)	(0.0014)	(0.0016)	(0.0014)
FD	0.0038	0.0024	0.0003	0.0002
	(0.0024)	(0.0026)	(0.0029)	(0.0024)
FAI	2.541	5.785**	-1.257	-2.602
	(1.884)	(2.394)	(2.695)	(2.285)
CPI	-0.0944	0.0291	0.0427	0.175
	(0.0967)	(0.112)	(0.0767)	(0.110)
T	YES	YES	YES	YES
Constant	4.515	-4.564	2.962	13.68
	(5.094)	(7.691)	(7.644)	(8.918)
Observations	70	70	67	65
Prob > chi2	0.0001	0.0001	0.0001	0.0001
Instrumented	SBC			
Instruments	GDPC SSE FD FAI CPI T IV1 IV2			

Notes: ***p<0.01, **p<0.05, *p<0.1

Dependent variable is *OL*.

Robust standard errors in parentheses.

All the variables in Table 4.8 – Panel B have been passed the unit-root test and are stationary.

The IV1 in this regression is the instrumental variable which is a dummy variable that only affect the core shadow banking size (SBC) rather than the P2P lending market (OL). This is an important event that the "Administrative Measures for Entrusted Loans of Commercial Banks (Consultation Draft)" announced by the China Banking Regulatory Commission in Jan 2015 (http://www.cbirc.gov.cn/cn/view/pages/ItemDetail.html?docId=66608&itemId=951&generaltype=2). The IV2 is another instrumental dummy variable which is an event that the China Banking Regulatory Commission issued "Commercial Bank Entrusted Loan Management Measures" in Jan 2018 (http://www.cbirc.gov.cn/cn/view/pages/ItemDetail.html?docId=167238&itemId=915&gene

raltype=0).

The r-squared reflects the square of the angle cosine between the explanatory variable and its projection in the explanatory variable generating subspace. Since it is the projected cosine value, it is of course in the interval [0,1]. When using the instrument variable, the instrument variable is not among the explanatory variables, and the geometric interpretation does not exist anymore. The value of r may be negative, which exceeds the interval of [0, 1]. In fact, R2 is not statistically significant in 2SLS or instrumental variable regression, so it may not be reported (https://www.stata.com/support/faqs/statistics/two-stage-least-squares/).

Table 4.9. The Effect of local Government Financing Demand on the Scale of Shadow Banking-Panel Regression

SBC	(3-1-1)	(3-1-2)	(3-1-3)
LGBI	0.0362***		
	(0.0075)		
LGBI-L1		0.0258***	
		(0.0086)	
LGBI-L4			0.0321***
			(0.0073)
GDPC	0.0690***	0.0627***	0.0552***
	(0.0152)	(0.0155)	(0.0173)
FD	-0.0116*	-0.0118*	-0.0101
	(0.0070)	(0.0068)	(0.0063)
FAI	0.0223***	0.0193***	0.0137**
	(0.0068)	(0.0072)	(0.0068)
T	YES	YES	YES
Constant	0.389***	0.512***	0.538***
	(0.0753)	(0.0812)	(0.0968)
Observations	152	144	120
No. Provinces	8	8	8
Prob > chi2	0.0001	0.0001	0.0001
R-sq	0.5864	0.5099	0.5116

Notes: ***p<0.01, **p<0.05, *p<0.1

Dependent variable is *SBC*.

Robust standard errors in parentheses.

Due to the data limitation, this dataset only covers the Beijing, Shanghai, Sichuan, Jiangsu, Zhejiang, Shandong, Hubei, Guangdong's data during 2015-2019.

Table 4.10. The Effect of local Government Financing Demand on the Scale of P2P Lending Market-Panel Regression

OL	(3-2-1)	(3-2-2)	(3-2-3)
LGBI	0.414*		
	(0.236)		
LGBI-L1		0.536***	
		(0.173)	
LGBI-L4			0.519***
			(0.151)
GDPC	0.553*	0.449	0.598**
	(0.314)	(0.310)	(0.252)
FD	0.0975	0.109	0.0386
	(0.149)	(0.151)	(0.134)
FAI	0.0727	0.0051	0.0042
	(0.191)	(0.171)	(0.101)
T	YES	YES	YES
Constant	2.466	2.884	3.587***
	(2.260)	(2.005)	(1.030)
Observations	160	152	128
No. Provinces	8	8	8
Prob > chi2	0.0192	0.0001	0.0001
R-sq	0.1265	0.1409	0.2560

Notes: ***p<0.01, **p<0.05, *p<0.1

Dependent variable is *OL*.

Robust standard errors in parentheses.

Due to the data limitation, this dataset only covers the Beijing, Shanghai, Sichuan, Jiangsu, Zhejiang, Shandong, Hubei, Guangdong's data during 2015-2019.

Appendixes

Appendix 4.1. Variable Explanation

Variables	Full Name	Period	Meaning	Data Source
Dependent Variables				
OL	Outstanding loans	Monthly	The outstanding loans in the whole P2P lending market	WDZJ
SBC	Shadow Banking Scale-Core	Monthly/Quarterly	The core shadow banking scale (ending balance) in China	CSMAR & Moody's report
Testing Variables				
SBC	Shadow Banking Scale-Core	Monthly/Quarterly	The core shadow banking scale in China	CSMAR & Moody's report
M	Money Supply	Monthly	Money Supply	CSMAR
LGBI	Local Government Bond Issued	Quarterly	The issued local government bond	Bureau of Finance of each local government & News publish on WIND
Control Variables				
GDPC	GDP/capita	Quarterly/Monthly	National/ Provincial GDP/capita	CSMAR & Official website of provincial statistical Bureau
SSE	Shanghai Composite Index		The closing value Shanghai Composite Index	CSMAR
FD	Financial Deficit	Quarterly/Monthly	The financial revenues minus financial expenditures	Bureau of Finance of central government and each local government
CPI	Consumer Price Index	Quarterly/Monthly		CSMAR & Bureau of Finance of each local government
FAI	Fixed Assets Investment	Quarterly/Monthly		CSMAR & Bureau of Finance of each local government

5. Conclusion

Financial innovation has always been an important topic in the financial field, according to Tufano (2003), financial innovation means the act of creating and then popularizing new financial instruments as well as new financial technologies, institutions and markets. Before the financial crisis in 2008, financial innovation has always been considered positive and meaningful to economic development (Miller, 1986; Ross, 1989; McConnell and Schwartz, 1992; Merton; 1992; Tufano, 1996; Grinblatt and Longstaff, 2000), after the financial crisis, there are different views on financial innovation. Some literatures still state the positive or neutral opinion on financial innovation (Shiller, 2013; Laeven et al., 2015; Beck et al., 2016), others hold the pessimistic point of view and state the negative effect on the financial innovation (Henderson et al., 2011; Beck et al., 2016).

After the financial crisis in 2008, one of the important financial innovations is the peer-to-peer lending. Peer-to-peer lending has developed fast since 2007 in China with the rapid development of the online technology. There are large number of platforms, individual or small business borrowers, individual lenders in Chinese peer-to-peer lending market. The huge information asymmetry leads to high systemic risks in this market. After the explosive growth since 2011, the number of default platforms started increase since 2016 which led to the government intervention into Chinese peer-to-peer lending market in August 2016. Even with such government's intervention, a large-scale wave of defaults still occurred in 2017-2018. Therefore, Chinese government implemented more stringent regulatory measures in March 2018. In 2019 and 2020, the operating number of peer-to-peer platforms plummeted, and the number of default platforms, closed platforms, and transformation platforms all continued to increase.

The development of the Chinese peer-to-peer lending market shows the completed life cycle of a financial innovation from appearing – fast growing – declining - fading. Research on this market could help us study the financial innovation (the reason of the financial innovation, the potential risk in the innovative market, the participator's behavior in the market) and make the regulatory recommendations for future financial innovative market.

My study shows the significant effect of the information disclosure (third-party provided information; voluntary operational and financial information disclosure), and the public sentiments via media news and social media posts on the performance of platforms (default probability, cost of capital) in the Chinese P2P lending market. My study also provides evidence that central government monetary policy, the local government financing demand, and the existing shadow banking scale all have significant impacts on the scale of Chinese P2P lending market.

These results contribute to the existing literature from several aspects: first, my study contributes to the corporate finance literature on information disclosure (Diamond and

Verrecchia, 1991; Botosan, 1997; Sengupta, 1998; Healy et al., 1999a; Verrecchia, 2001; Lambert et al., 2007, Goldstein and Yang, 2017; Ahmad et al., 2019) by presenting the different effects of various sources of information disclosure on the default probability and cost of capital in a new innovative market (the P2P lending market). I find the impact of operational information disclosure and financial information disclosure are different on the cost of capital which brings the important inspiration for the future study on the quality and type of information disclosure.

Second, my study contributes to the government regulation literature (Schwert, 1981; Stiglitz, 1993; Weiss, 2008; Aikins, 2009; Kim et al., 2013; Pennathur et al., 2014; Li et al., 2017; Lo et al., 2019; Ashraf, 2020; Zhou and Chen, 2021) by demonstrating the influence of government regulatory interventions on default probability and cost of capital. My study shows government regulatory intervention has the significant impact on cost of capital, but has less effect on default. The results suggest government regulation may have different effects on platforms' performance (default probability; cost of capital).

Third, the evidence displayed in this study about the media sentiment and social media sentiment which have various effect on default probability and cost of capital contributes to behavior finance literature (Barber and Loeffler, 1993; Albert and Smaby, 1996; Das and Chen, 2007; Tetlock et al., 2008; Fang and Peress, 2009; Da et al., 2011; Bollen et al., 2011; Cahan et al., 2015; Ge et al., 2017) by providing the significant effect of news sentiment in an innovative market. Furthermore, the asymmetry effect between positive sentiment and negative sentiment on cost of capital indicates the important enlightenment for investors that only the positive change on sentiment could help reduce default probability and cost of capital.

Fourth, my study also contributes to the shadow banking literature (Adrian and Ashcraft, 2012; Claessens, et al., 2012; Deng, et al., 2015; Chen, et al., 2018; Allen, et al., 2019; Chen et al., 2020) by displaying the significant effect of central government monetary policy and local government bond issued on the scale of new type shadow banking (i.e., P2P lending market). Additionally, my study provides evidence that the existing core shadow banking could amplify the scale of P2P lending market. My study inspires the future research to focus on the relationships among different types shadow banking within the broad shadow banking system.

Last, my research contributes to the literature on the innovative market by presenting views from different parties (rating agencies, platforms, individuals, government), which is significantly different with previous studies of P2P lending markets (Berkovich, 2011; Herzenstein et al., 2011; Pope and Syndor, 2011; Duarte et al., 2012; Michels, 2012, Liu, et al., 2015; Ge et al.,2017; Breuer et al., 2020; Tian et al., 2021). This paper focuses more on the innovative market from the platform and regulation perspectives rather than individuals, which could bring deep thought to other participators (investors, borrowers, small firms, intermediaries, government) in the innovative market.

My study also has some unique implications to government: first, except the government regulation, the information disclosed by other parties (the third-party provided information; voluntarily disclosed information by P2P platforms (including both operational and financial information) and the public information (media news and social media posts) also helps on alleviating the information asymmetry in P2P market. Considering the interactive effect of the government regulation with other sources of information disclosure, my research suggests government should combine various sources of information to improve regulatory efficiency and reduce regulatory costs.

Second, the supervision of the issuance of local government bond should be stricter because the local government bond issued could increase the scale of shadow banking. This indicates the double risks: on the one side, the local government debt increased; and on the other hand, the money and capital drifted away from banking system was amplified. Therefore, the dual risk will make both the government and the financial system more vulnerable, thus further increasing the risk of the whole economic system.

Third, central bank should monitor the capital out from the existing shadow banking (the core shadow banking) since the core shadow banking has the impact on increasing the scale P2P lending market.

Additionally, there are some implications to investors in P2P market: first, investors in the P2P market should pay attention to the different types information in order to make a more accurate judgement. Second, public information has an asymmetry effect in the P2P lending market, therefore, investors should focus more on positive changes on news sentiment because the positive change contributes more on the market performance of platforms.

The main limitation of this research is that this study is limited to the Chinese P2P lending market and shadow banking system. It can be extended if the comprehensive data about the P2P lending market in other countries becomes available. In addition, relatively short time window is one of the shortcomings of this study, nevertheless, the Chinese P2P market has experienced a relatively complete development cycle, which has made up for this limitation to a certain extent.

Based on results and limitations in my study, there are many purposeful research topics could be investigated in the future, including but not limited to such as (1) the comparative study on the effects of public information on market performance in different markets. e.g., in the American and British P2P lending market; (2) the impact of various sources of information disclosure (third-party provided information; voluntary information disclosure) on other types of innovative markets (e.g., digital currency market; metaverse market[109]); (3) the study on the relationships among

[109] Metaverse market is a new market arising from the process of virtualization and digitization of the real world (Newzoo, 2021).

different types shadow banking and relationships between shadow banking system in China and US.

References

Tufano, P., 1996. Times mirror company peps proposal review and financial engineering and tax risk: The case of times mirror peps. Available at SSRN 234702.

Tufano, P., 2003. Financial innovation. Handbook of the Economics of Finance. Corporate Finance 1a, 307–336.