Peer-to-Peer Lending Platforms in China: Exploring Alternative Intermediation Models and Outcomes

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Abstract

China has the largest, and fastest growing, peer-to-peer (P2P) lending market in the world. P2P lending is a novel mode of alternative financing which operates outside of the more traditional institutional finance market by directly connecting consumers and businesses who are excluded from traditional lending channels and private individuals and households with surplus cash. The mechanism by which the two groups are connected to each other is the P2P platform. Individuals with a need (demanders) for funds post their request on the platform and individuals with surplus cash balances (suppliers) make an offer to provide the necessary funds. The unique feature of the Chinese P2P model is that there are two alternatives: the non-guarantee model, and; the guarantee model. The guarantee model is unique as it plays an active role in the market process in the form of a loan guarantee unlike the non-guarantee model in which the P2P platform simply acts as an intermediary and 'platform' for connecting demand and supply. It is this unique aspect of the guarantee model which disciplines the platform into acting as an honest information intermediary but, on the other hand, it also creates potential financial instability given the platform is also the credit risk taker.

Formally analysing the benefits and risks of the guarantee model and comparing it to the non-guarantee model can help policymakers design a more efficient P2P lending market and a bespoke regulatory framework. To do so, regulators need to understand and compare the different platforms' behaviours as information producers across the two lending models. And this is precisely the research gap this thesis intends to fill. To date, the extant literature on P2P lending mainly focuses on borrower-lender interactions, and the platforms are treated as honest brokers. To fill the gap, this research explores how different P2P lending models affect the P2P lending platform's screening and pricing strategies, and overall social welfare.

First, we develop game-theoretic models of the lending processes to derive the platform's optimal screening and pricing strategies under the two lending models. Under the non-guarantee model, the platform faces a dynamic trade-off between overstating borrower credit quality to increase short-term profits and honestly disclosing

borrower credit risk to improve the platform’s long-term reputation. Under the guarantee model, the platform only faces a trade-off between setting a higher guarantee fee (but with lower funding success probability) or a lower guarantee fee (but with a higher probability of funding success). We find that, under the non-guarantee model, the platform chooses the loosest screening standard, i.e., it approves a known “bad” borrower with the highest possible probability. This means reputation concerns are not enough to discipline the platform and consequently the non-guarantee model lowers the screening efficiency as known “bad” borrowers obtain credit. The main reason for this result is a bad loan cannot be unambiguously attributed to the platform’s dishonest information disclosure (deliberately lax screening standards) due to the imperfection of the platform’s screening technology. By contrast, the platform always screens borrowers truthfully under the guarantee model. The optimal pricing strategy of the guarantee model reflects a risk-sharing arrangement between the platform and the lender.

Next, we perform a welfare comparison of the two lending models. The welfare analysis shows that the guarantee model generates greater social welfare than the non-guarantee model. Then, we relax the assumption that the platform is rational/well-calibrated regarding its screening ability and analyse the welfare effect of overconfidence. We find that under the guarantee model, if the platform is overconfident about its own screening precision, it tends underprice borrower risk, which in turn creates welfare losses.

Finally, we develop an empirical procedure to examine whether the platform underprices the credit risk of P2P loans under the guarantee model. By using loan-level data from a Chinese P2P lending platform, we find that the guarantee fees preset by the platform are sufficient to neither cover the *ex-post* realized loan losses nor the *ex-ante* predictable loan losses, thus suggesting that the platform underprices the loan risk in both *ex-ante* and *ex-post* sense. This implies that the guarantee model could jeopardize the platforms’ soundness and further financial stability. In general, the theoretical and empirical findings together suggest that policymakers should balance financial stability against screening efficiency when developing regulations that define the role and function of P2P lending platforms.

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Abbreviations

AON— All-or-Nothing

BIS—Bank for International Settlements

CRA—Credit Rating Agency

CCAF—Cambridge Centre for Alternative Finance

EL—Expected Loss

FSB— Financial Stability Board

KIA— Keep-it-All

LGD—Loss Given Default

LCR—Loss Coverage Ratio

MLE—Maximum Likelihood Estimation

P2P—Peer-to-Peer

PBE— Perfect Bayesian Equilibrium

PD —Probability of Default

ROC— Receiver operating characteristic

S&P— Standard & Poor's

SME—Small and Medium-sized Enterprise

SFLGS—Small Firms Loan Guarantee Scheme

UL—Unexpected Loss

VIF—Variance Inflation Factors

WTL—Willingness to Lend

Dedication

I dedicate this thesis to my parents, Chengyan Liu and Yiding Yue. For their endless love, support and encouragement.

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Declaration

I declare that the research contained in this thesis, unless otherwise formally indicated within the text, is the original work of the author. The thesis has not been previously submitted to this or any other university for a degree and does not incorporate any material already submitted for a degree.

Signed:

Dated:

Chapter 1. Introduction

1.1 The rise of Peer–to-Peer lending in China: filling an "institutional" gap

Traditionally, we think of banks as the main provider of financial service and lending to consumers and businesses. However, in many countries, access to banking service is not available to all. This lack of access plus dissatisfaction with credit institutions has created a gap in the market for lending to consumers and smaller businesses. Peer–to-peer (P2P) lending, which is also known as debt-based crowdfunding or marketplace lending, allows consumers and small businesses to borrow money without the intermediation of traditional credit institutions. Consumers and small business borrowers post loan listings that contain borrowing needs and borrower profiles on a P2P lending website, and multiple lenders can then view and bid to fund a portion of the loans through the website. Specifically, P2P lending platforms usually play two roles in the lending process: information producers and credit matchmakers. As information producers, they use proprietary credit assessment technologies to pre-screen loan applicants (screen out "bad" borrowers) and to generate borrower risk profiles; as credit matchmakers, they bring borrowers who are seeking loans together with lenders who are looking to lend and thereby facilitate loan transactions. Since the 2005 inception of Zopa.com in the UK, P2P lending has quickly gained popularity around the world. According to the Cambridge Centre for Alternative Finance (CCAF) (2018a, 2018b, 2018c, 2018d), P2P consumer and business lending in the Americas (US, Canada and Latin America and the Caribbean) reached $16.48 billion in 2017 from $8.66 billion in 2014. In the Asia Pacific region (excluding China), P2P consumer and business lending accounted for $1,447.9 million in 2017, up an impressive 1547% from $87.93 million in 2013. In this region, P2P consumer lending served as the largest alternative finance model in 2016 and 2017, with market share of 24% and 22.9%, respectively. The UK is the volume diver for the online alternative finance market in Europe. There has been £9.67 billion P2P consumer and business lending loans generated since 2011, with 2017's volume making up 35.6% (£3.44 billion) of the total. In this market, the numbers of repeat lenders(investors) are markedly high at 89% (P2P business lending) 67% (P2P consumer lending) in 2017 . Among other European countries[1], P2P consumer and business lending grew from €197 million in 2013 to €1,047 million in 2016, with the average size for P2P consumer loans is €6,382, and for P2P business loan €111,633.

In China, P2P lending has enjoyed exponential growth in the past a few years, with P2P lending platforms having mushroomed across the country. According to WDZJ.com (网贷之家), an information provider tracking China's P2P lending sector, there were 1,931 active P2P lending platforms in China at the end of 2017, and the P2P lending industry originated ¥2,804.85 billion (≈£316.08 billion) in loans in 2017 (see Figures 1 and 2).

China's P2P lending industry has experienced three stages and is going through the third stage. The first stage (2007-2011) is the start-up stage. China's P2P lending model was introduced from the West. Launched in 2007, Shanghai-based PPDai is the first the P2P lending platform in China and considered to be a copy of the Prosper model. At this stage, as an Internet-based new business model, P2P lending mainly attracted entrepreneurs from Internet industry who have little financial background. This leads to poor risk management practice and insufficient borrower due diligence. Together with lack of regulation, some platforms setup in this stage suffered high bad loan rate even collapse. The second stage (2012-2014) is the growth stage. At this stage, professionals from banking or informal lending industry entered the P2P lending market. This improved the platform's borrower screening and loan monitoring process. With the development of China's Mobile Internet (i.e. the internet connection through 3G or 4G mobile phone networks), borrowers and lenders were able to connected through the smart phone-based APPs developed by the platforms. This greatly simplified the lending process and increased the access to this financial service. Meanwhile, Chinese investors started to interest in the online wealth management market given the introduction of the money market fund Yu'e Bao. All these factors contributed the market's expansion at

[1] It includes 44 European countries, for the full country list, see CCAF (2018d).

this stage, as the number of the platforms grew by 687.5% from 200 in 2012 to 1,575 in 2014. The third stage (2015-2016) is the risk outbreak stage. At this stage, the huge market size and loose regulation environment created motives for some platforms to use so-called "fund pools" to illegally finance their own projects. The "fund pools" aggregate money from the sale of P2P investment products or even from fake borrowers that created by the platforms into a single account, rather than strictly matching each investment/lender with a specific loan. This practice later led to platform collapse/shutdown and even runaway bosses. In August of 2016, the financial regulator issued the first draft of P2P regulation and later started to crackdown the platforms' illegal fundraising. From 2017, China's P2P lending is going through the shakeout stage. The industry has been seeing wave of bankruptcies. Hundreds of platforms have encountered serious difficulties. This is due to a combination of factors: economy slowdown, tightening liquidity conditions and investor panic caused by massive platform collapse. The regulators are now focusing on the platforms' regulatory compliance and continuing crackdown platform fraud.

In general, the main driver behind the rise of China's P2P lending is its potential to fill the "institutional" gap (Deer et al.,2015) created by China's structurally imbalanced financial system. As stated by Justin Yifu Lin, former World Bank Chief Economist, the so-called "institutional" gap can be viewed as a "mismatch between China's real economy and the financial system":

"There is a mismatch between China's real economy and the financial system. The country's real economy is largely comprised of farmers, small and medium-sized businesses, and yet the financial sector is dominated by big banks that prefer to deal with big companies."[2]

—Justin Yifu Lin, Peking University, 28 August 2014

[2] Cite by, Tsai, K.S., 2017. When shadow banking can be productive: Financing small and medium enterprises in China. The Journal of Development Studies, 53(12), pp.2005-2028.

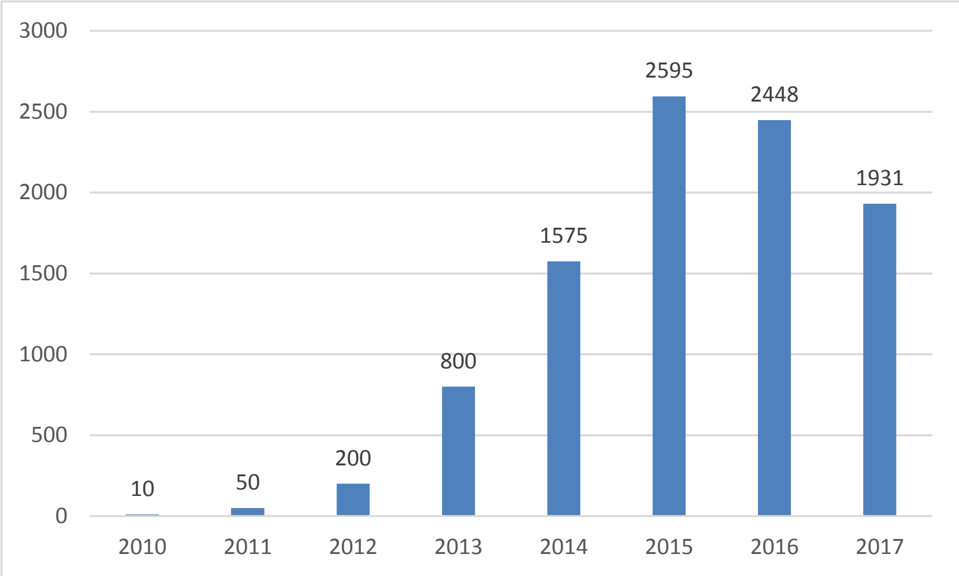

Figure 1 The number of P2P lending platforms in operation in China

Source: WDZJ.com

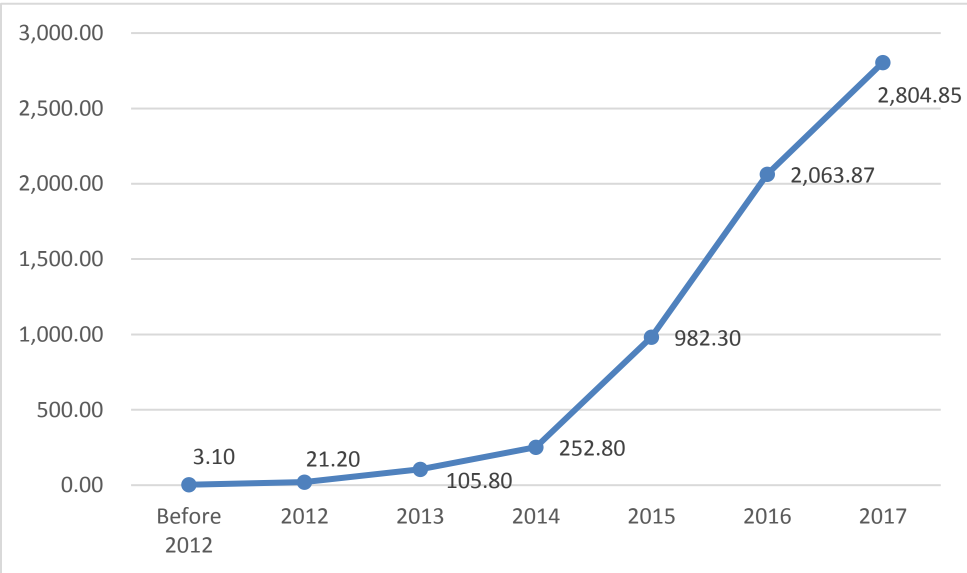

Figure 2 The loan origination volume in China's P2P lending sector in ¥ billion

Source: WDZJ.com

Specifically, China's P2P lending is filling the "institutional" gap by coordinating the potential demand and supply of funds. With respect to the demand side, China's consumers and small (and micro) businesses struggle to access credit, given that the state-dominated financial system directs much of its funds to state-owned enterprises and listed companies. A nationwide survey revealed that credit accessibility for China's micro and small businesses[3] is only 46.2% as shown in Figure 3; Among 100 micro or

[3] National Bureau of Statistics of China issues industry-specific classification standards for large, medium, small and micro firms. The classification standards are based on turnover or number of

small businesses with demand for loans, only 46 firms eventually obtain loans. Also, the survey shows a high percentage of discouraged borrowers (42.2%), which can be a result of the perceived high transaction costs. Despite the low credit accessibility, loans for micro and small businesses create greater efficiency. Figures 4 and 5 report the profit generation and job creation for micro and small businesses and (state-holding) listed firms. It shows that in terms of per unit of loans, micro and small businesses generate higher profits and create more employment than (state-holding) listed firms. Similar to small and micro firms, China's consumers also face credit constraints. A recent household survey estimated that the household credit gap is ¥80,000, and only 43.7% of the credit demand is met (see Table 1).

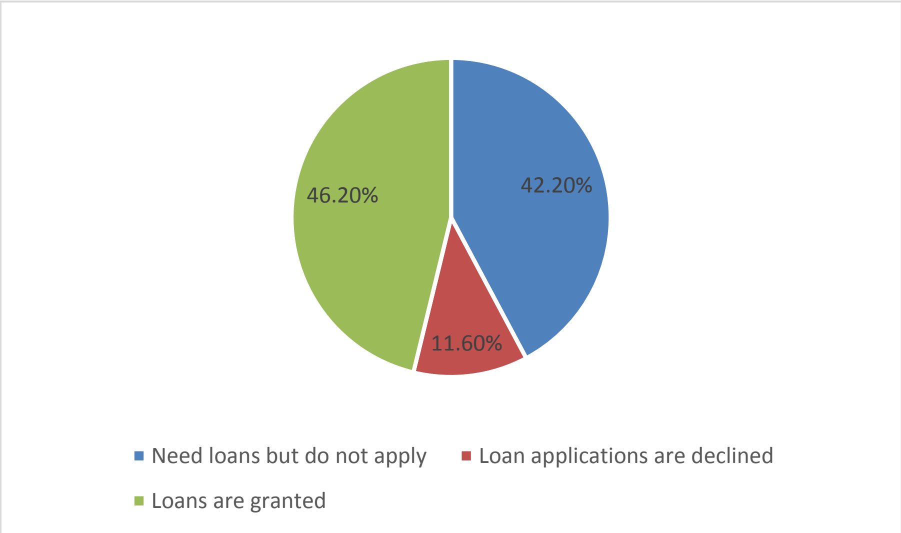

Figure 3 Credit accessibility for micro and small businesses

Source: China micro and small businesses development report (2014) by The Survey and Research Centre for China Household Finance, Southwestern University of Finance and Economics

employees and vary from industry to industry. For example, a firm of catering industry is classified as micro firm if its turnover is below one million RMB OR its number of employees is below ten. The full standards can be found at http://www.stats.gov.cn/tjgz/tzgb/201801/t20180103_1569254.html

Figure 4 Profit generation and job creation per unit of loans for micro and small firms and (state-holding) listed firms

Source: ibid. Figure 3

With respect to the supply side, on one hand, the average investable assets of Chinese households doubled from ¥170,000 in 2011 to ¥343,000 in 2016[4]. On the other hand, China's household financial asset allocation is highly dominated by cash assets, as shown in Figure 5. The current low deposit rate gives China's growing middle-class incentives to diversify their assets. In this context, P2P lending provides them an attractive investment option through its solid interest rate and the risk/return balance of diversified loan portfolios. At the end of 2017, the number of lenders in China's P2P lending market had reached 17.13 million, according to WDZJ.

[4] Source: ibid. table 1.

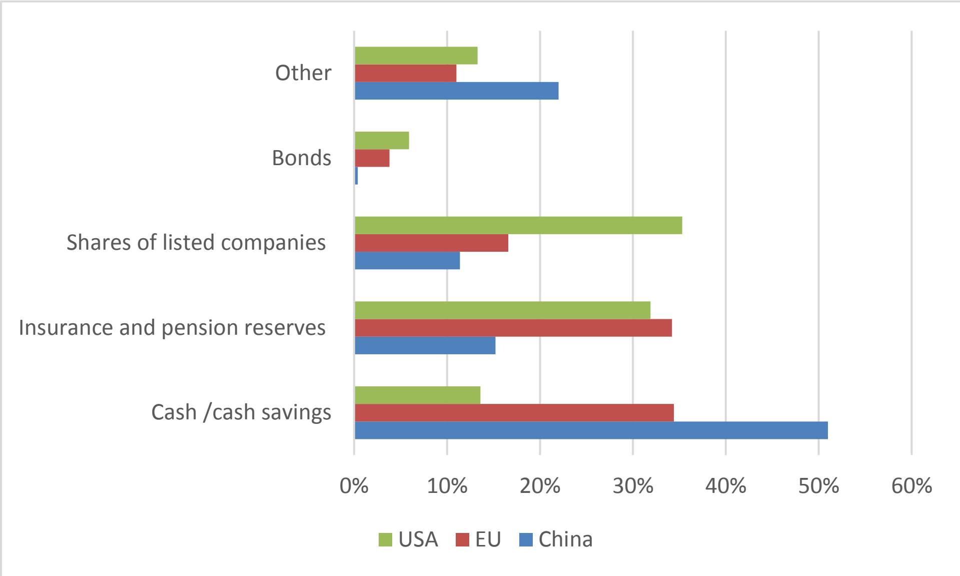

Figure 5 Household financial asset allocation across countries

Source: China household financial asset and risk allocation report (2016) by The Survey and Research Center for China Household Finance, Southwestern University of Finance and Economics

By matching the aforementioned demand and supply of funds, China's P2P lending market improves the credit accessibility of consumers and small businesses and thus the country's credit allocation efficiency. Figure 6 provides straightforward evidence. It depicts the money flows for ppdai.com (拍拍贷), one of the largest and earliest P2P lending platforms in China. We can see that through ppdai, the money flows from rich investors in the developed eastern coastal areas to borrowers in the less developed inland regions of mid-western China.

Table 1 Household credit gaps

	Credit demand (¥10,000)	Credit obtained (¥10,000)	Credit gap (¥10,000)	Credit accessibility (%)
Working households	26.5	12.5	14	47.2
Non-working households	13.3	5.7	7.6	42.9
All	14.2	6.2	8.0	43.7

Source: China working class credit development report (2017) by The Survey and Research Centre for China Household Finance, Southwestern University of Finance and Economics

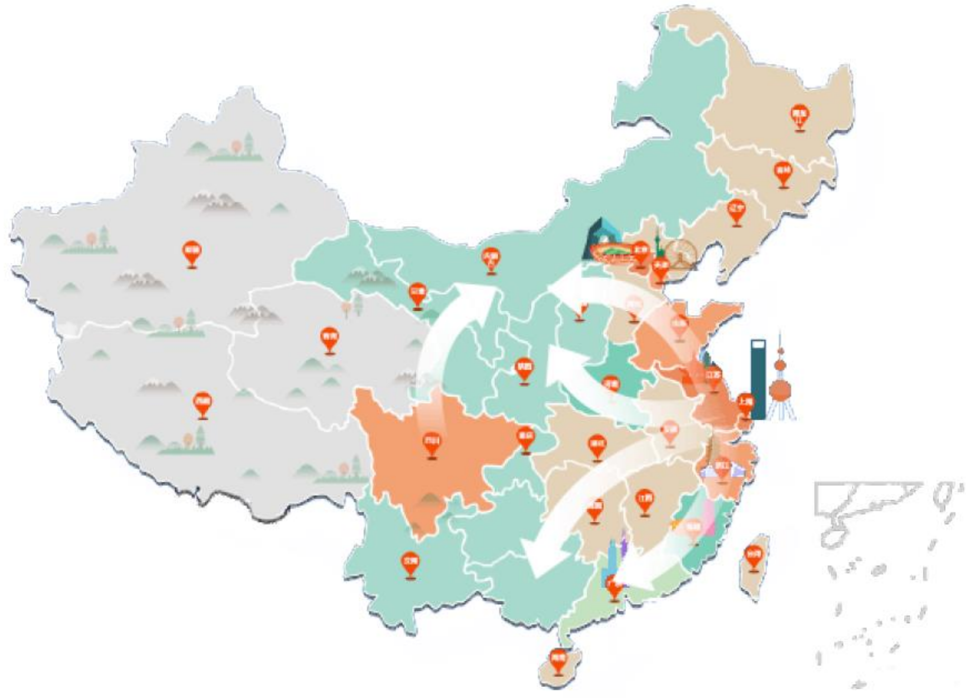

Figure 6 Money flow on ppdai.com

Source: China Digital Inclusive Finance Report (2016)

1.2 The non-guarantee model and the guarantee model of P2P lending: transaction structures and incentive problem

In China, P2P platforms usually operate under one of the two most common lending models, the non-guarantee model or the guarantee model. In this section, we introduce each model's transaction structures and discuss the potential incentive problem.

1.2.1 The non-guarantee model

The non-guarantee model of P2P lending, which is also referred as the traditional P2P lending model (FSB and BIS,2017), is actually a pure matching model. Specifically, under this model, as mentioned previously, P2P lending platforms play two roles in the lending process: information producers and credit matchmakers. As information producers, they use proprietary credit assessment technologies to pre-screen loan applicants (screen out "bad" borrowers), generate risk profiles of ("good") borrowers and price loans based on their riskiness. As credit matchmakers, they bring borrowers who are seeking loans together with lenders who are looking to lend and thereby facilitate loan transactions. This model is summarized in Figure 7, which is modified from (FSB and BIS, 2017). The most notable feature of this model is that platforms *do not* guarantee the loan repayments and thus potential loan losses are absorbed directly by lenders.

Under the non-guarantee model, the separation of the loan's originator and the bearer of the loan's default risk creates an incentive problem. That is, without a financial interest in the loans, the platforms have an incentive to loosen their screening standards to boost origination volume and the resulting transaction fees. In this sense, the non-guarantee model can generate welfare losses due to platform's inclination to approve low quality borrowers who are *ex-ante* inefficient to finance. However, in a dynamic setting, the incentive problem may be mitigated by platforms' reputation concerns. In particular, after observing realized loan outcomes (defaulted or fully repaid), a lender can form (update) her belief about the platform's credibility, which will affect the lender's lending decision. That is, a realized loan default will reduce the lender's willingness to continue to invest in loans originated by that platform. From the platform's point of view, the lender's belief about the platform's credibility is essentially the platform's reputation. The platform therefore faces a dynamic trade-off between overstating borrower credit quality (by setting lax screening standards) to increase short-term profits and honestly disclosing borrower credit risk to improve its long-term reputation (resulting in higher expected long-term profits).

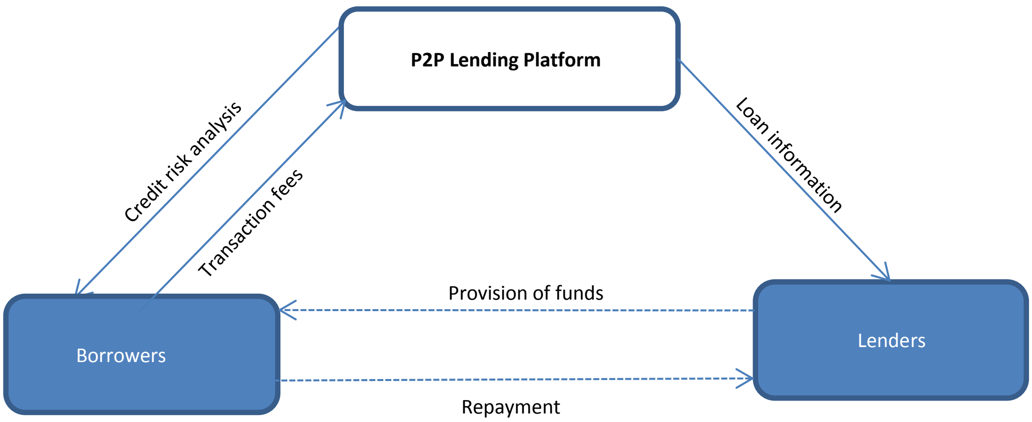

Figure 7 Stylized non-guarantee model of P2P lending

1.2.2 The guarantee model

Although some platforms, for example ppdai, use the non-guarantee model to facilitate loans, the other model, the guarantee model of P2P lending has been prevalent in China over the past a few years. Under the guarantee model, platforms act not only as the aforementioned information producers and credit matchmakers, but also credit risk taker. Specifically, in practice, the platforms act as guarantors for the repayment of the principal in the event of a default. In turn, the platforms charge guarantee fees to borrowers. This model is summarized in Figure 8, which is modified from (FSB and BIS ,2017). There are two main reasons for the popularity of the guarantee model in China's P2P lending market. One is that for the platforms, providing loan guarantee services is a means to attract more lenders in a highly competitive environment. The second reason is that in China, investing through a platform that has no guarantee for the initial principal is much less popular than investing through platforms that do guarantee their loans. This is due to trust deficiencies in China's poor institutional environment, as well as a deeper-rooted cultural aversion to risk.

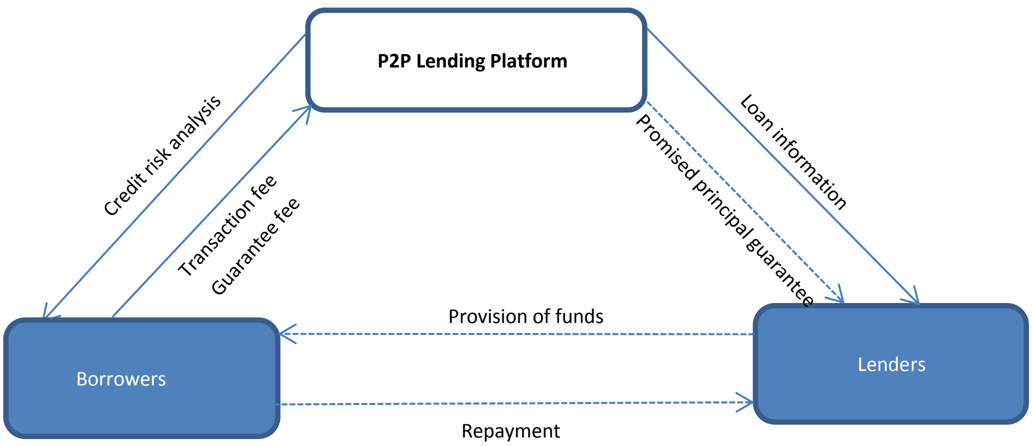

Figure 8 Stylized guarantee model of P2P lending

It is worth mentioning that China's finance law actually forbids any institution without a banking license from guaranteeing investor payouts in the same manner that a bank guarantees its deposits for customers. However, in practice, platforms offer indirect guarantees for loans they facilitate and signal this to lenders in a roundabout way. A typical way of providing such an implicit guarantee is that a platform sets up a provision fund, with money that comes from the guarantee fees paid by borrowers to compensate lenders in the event of a borrower makes a late payment or defaults. Under such an implicit guarantee, although the platforms are not legally obliged to compensate the lenders, platforms that fail to do so would suffer huge reputation costs due to the long-upheld tradition of "rigid repayment" in China's asset management market. The "rigid repayment" assumption means that investors generally assume that wealth management products from state-owned banks carry an implicit guarantee even when the financial products are not supposed to be guaranteed, and this assumption has also largely carried over to P2P platforms[5]. Specifically, this situation is similar to what an industry insider told the Financial Times "When it comes to rigid repayment, many platforms signal this to investors in a roundabout way. No one dares to say explicitly that they won't honour rigid repayment. In China, they couldn't survive this way"[6]. In this sense, the aforementioned reputation costs can be viewed as a sharp decline in a platform's fee-based revenues driven by a loss of investor confidence in the platform. Therefore, platforms are always expected to reimburse lenders, even using their own capital, in order to avoid greater reputation costs.

Therefore, the nature of the guarantee model can provide an incentive for platforms to truthfully screen out "bad" loan applicants, given that the platforms have enough skin in the game. However, under this model, the credit risk is concentrated in the platforms and cannot be diversified across lenders. This means that the platforms' soundness can be jeopardized by their inappropriate identify, assess and handle credit risk.

1.3 Research questions

Traditionally P2P lending is conducted through a lending platform that acts as a passive intermediary which matches individuals with surplus funds (lenders) with individuals who need funds (borrowers). But P2P lending in China has developed in a unique way and has a variety of alternative transaction models which can include the

[5] China curbs 'Wild West' P2P loan sector, Financial Times, April 5, 2017. https://www.ft.com/content/b0e40438-fda7-11e6-8d8e-a5e3738f9ae4
[6] China curbs 'Wild West' P2P loan sector, Financial Times, April 5, 2017. https://www.ft.com/content/b0e40438-fda7-11e6-8d8e-a5e3738f9ae4

P2P platform taking a more active role in the transaction process, often in the form of a loan guarantee.

It is the intention of this thesis to explore the implications of these different P2P lending models and, in particular, trace how different lending models shape the nature of transactions undertaken and the incentive structures that underpin them. It will also identify the relative costs and benefits derived from different incentive and transaction structures.

A particularly interesting P2P model under which no guarantee is offered by the platform, and hence no risk is underwritten by the platform has specific implications for the financial stability of the whole system of credit they should pose much lower prudential and systematic risk than traditional banks, provided that arrangements and measures have been made to minimize operational risks (Käfer, 2016).

However, improvements in the efficiency of credit allocation can be offset by the platforms' tendency to overstate borrower credit quality, given that they have little skin in the game. This platform moral hazard problem is similar to the reduced subprime lenders' screening incentives under the pre-crisis "originate-to-distribute" model, where securitization practices separate a loan's originator from the bearer of the loan's credit risk (Keys et al.,2010). It is also similar to the inflated ratings under the "issuer-pays" model in the credit rating industry (Strobl and Xia, 2012), where rating agencies' earn more revenue from issuers whose products they rate. In general, reputation concerns have the potential to act as a disciplinary device to induce information producers to provide honest information disclosure, but its effectiveness on P2P lending platforms remains unknown.

In contrast, the alternative guarantee model can act to curb the platforms' opportunistic behaviours in information production, since the platforms have enough skin in the game. However, a prerequisite for a well-functioning guarantee model is the soundness of the platforms, which can be jeopardized by their inappropriately identify, assess and handle of credit risk. Specifically, as Trichet (2009) points out, the underpricing of the "unit of risk" and the underestimation of the "quantity of risk" were at the core of the recent financial crisis. If the platforms under-price the risk of the loans' they have to undertake, it makes the platforms susceptible to failure. This potential fragility of the platforms could pose a threat to financial stability.

We have outlined how different models of P2P lending can shape platform behaviour and traced out how this might impact on the financial stability of the whole system of credit and lending. Specifically, we identified how different lending models have the potential to affect the behaviours of market participants, transaction outcomes, and the social welfare. This leads to an obvious and important question in relation to China's P2P lending industry:

W*hich P2P lending model produces the most socially desirable outcome?*

The answer to the question can help policymakers design a more efficient P2P lending market and a bespoke regulatory framework for P2P lending platforms. Despite the obvious importance of this question, research to date has not fully addressed the issue of social welfare and financial stability in this context and has largely focused on borrower and lender interactions. In order to understand the relative efficiency of the two lending models, one needs to open the black box of P2P platforms' decision-making process and modelling their behaviours under the different lending models. But the extant literature on P2P lending mainly focuses on borrower-lender interactions, in particular, how different mechanisms related to lender screening or borrower signalling mitigate classic information problems, and what factors affect individual funding decisions and final funding success. These works do not endogenize the behaviours of P2P platforms and the platforms are treated as exogenously given honest brokers. Little attention has been paid to the role of the platforms' information transmission in affecting lending efficiency (see section 2.7 for a comprehensive discussion of the research gap).

This thesis attempts to fill this gap. We investigate the question from a theoretical perspective first, and then we formally test the theoretical predictions against a large P2P lending dataset for China. Specifically, we address the following three questions:

(1) Can reputational concerns discipline P2P lending platforms in information production?

(2) Which lending model generates the greatest level of social welfare?

(3) Is P2P loans' credit risk underpriced under the guarantee model?

For questions (1) and (2), we develop game-theoretic models of the lending processes to derive P2P lending platforms' screening and pricing strategies under the two lending models in monopolistic and competitive markets. First, we develop our model under the non-guarantee model of P2P lending based on Chemmanur and Fulghieri (1994), Mathis et al. (2009) and Fulghieri et al. (2013). A penniless borrower who seeks to post a loan request on a P2P lending platform must first go through the platform's screening process. A borrower's type ("good" or "bad") is *a priori* unknown to lenders. A "good" borrower repays the loan with a fixed probability, while a "bad" borrower always defaults. The model incorporates three critical elements of the P2P lending platforms: (1) the imperfection of the platform's screening technology, (2) the platform's tendency to overstate the borrower's credit quality, and (3) the platform's reputational concerns.

Specifically, the imperfection of the platforms' screening technology means that the platform imperfectly observes the borrower's type and only detects "bad" borrowers with a certain probability. In other words, the platforms can make "honest" mistakes by erroneously approving "bad" borrowers. For a loan request approved by the platform, lenders can view the loan profile (loan rate, loan term, loan amount, borrower credit grade, etc.) and decide whether or not to invest in the loan. The borrower pays a transaction fee to the platform only when her loan listing is successfully funded. This fee-based revenue model creates an incentive for the platforms to strategically choose their screening policy to boost transaction fees. A platform's screening policy is simply characterized by the probability that the platform intentionally approves a known "bad" borrower. Because lenders cannot observe the platform's actual screening policy, they use observed loan performance to form their beliefs about the platform's screening policy (that is, the platform's reputation). Lenders' lending decisions then depend on the platform's reputation and the loan rate predetermined by the platform. Therefore, under the non-guarantee model, the platform's choice of screening and pricing policy balances a higher short-term transaction fee against a higher long-term reputation. By solving such a dynamic decision problem, we can obtain the platform's optimal strategies, which provides an answer to question (1).

Next, we solve the platform's strategies under the guarantee model. As a risk-sharing mechanism, the guarantee model straightforwardly prevents the platform from overstating borrower credit quality. Then, in this case, the platform only faces a trade-off between setting a higher guarantee fee (which implies a lower loan rate and therefore a lower probability of funding success) or a higher loan rate (which suggests a higher probability of funding success but a lower guarantee fee). The platform's optimal pricing strategy is therefore can be obtained by solving such a single-period maximization problem.

Having solved the platform's optimal strategies under the two lending models, we move to question (2). Specifically, we address the question by performing a welfare comparison of the P2P lending models in a competitive market. We first conduct the comparative welfare analysis under perfect rationality assumption by using the platform's optimal strategies obtained in question (1). In this analysis, the platform is assumed to be well-calibrated, which means that it has unbiased beliefs regarding risk parameters such as its screening ability. Further, we relax this assumption and allow the platform to be overconfident and to overestimates its screening precision. Then, we analyse how the overconfidence affects the platform's choices of strategies and social welfare.

To address question (3), we empirically test whether the credit risk of P2P loans is under-stated by the platform. In particular, we examine whether the guarantee fees charged by the platform are sufficient to cover the *ex-post* realized loan losses and the *ex-ante* predictable loan losses, by using loan-level data from a Chinese P2P lending platform that uses the guarantee model. The dataset consists of 5,594 loans, 1,026 of which end up in default. For each loan, the data contain information on the loan characteristics, borrower characteristics, loan outcomes, etc. For the *ex-post* test, we use Mincer-Zarnowitz regression(suggested by Lopez and Saidenberg, 2000) to test whether a guarantee fee is an unbiased predictor of the *ex-post* realized loan losses; If not, it means then, on average, the actual realised loan losses cannot be absorbed by the guarantee fees and thus the platform has underpriced the credit risk in *ex-post* sense. For the *ex-ante* test, we first develop a procedure to generate *ex-ante*, predictable loan losses for each credit grade from historical data. Then, we design a loss coverage ratio regression to test whether the predictable losses can be compensated by the guarantee fees. If not, it suggests that the platform under-prices credit risk in *ex-ante* sense.

1.4 Thesis structure

The rest of the thesis is structured as follows:

Chapter 2 reviews the related literature and identifies the research gap. In the first part, we review the some empirical works that intend to directly identify the presence of information asymmetries (in terms of adverse selection and moral hazard) and equilibrium credit rationing in the credit market. Then we discuss the theoretical and empirical research that focus on the role of mechanisms (e.g. collateral, relationship lending, etc.) for mitigating information problems in the credit market. In the second part, we review the expanding literature on P2P lending and reward or equity crowdfunding. We organise the literature around several big questions. For P2P lending, how do mechanisms mitigate information problems by improving borrower signalling and lender screening? What determines lending decision and funding success? What is the role of P2P lending in the extant financial system, and what is the impact on financial stability? For reward or equity crowdfunding, how can one generate optimal market design? That is, how can campaign features to be designed to maximize the campaign's success or overcome entrepreneurial moral hazard? What determines the individual investment behaviour and funding success? What happens to firms after funding success in crowdfunding? The third part of the chapter reviews some post-crisis studies of the credit rating industry and the securitization process. These works mainly examine :1) whether the potential conflicts of interest inherent in the "issuer-pay-model" of credit rating agencies and the "originate-to-distribute" model in securitization processes lead to lower rating quality and lax screening and monitoring standards; and 2) the effectiveness of reputation concerns' in mitigating these conflicts of interest. We conclude the chapter by discussing the research gap that motivates our key research questions.

Chapter 3 introduces the basic setup for the theoretical models. First, we discuss our assumptions about market participants and the environment, two of which are worth mentioning here. Borrowers are assumed to have no acceptable collateral, as most P2P lending is unsecured lending in actual practice. This feature implies that the P2P platform cannot design different types of credit contracts in the sense of Bester (1985,1987) (high loan rate and low collateral or low loan rate and high collateral) as a self-selection device to sort borrowers. Instead, the platform can obtain the borrowers' type via its screening technology. However, the screening technology is not flawless. It identifies "good" borrowers with certainty but "bad" borrowers only with a specific probability. After discussing the assumptions, we outline the structure of the lending game under both the non-guarantee model and the guarantee model. The game structure describes how the platform interacts with borrowers who approach the platform seeking loans and lenders who fund these loans.

Based on the theoretical modelling framework developed in chapter 3, chapter 4 first characterizes the lender's lending decision process. In particular, the lender computes the perceived expected return for a specific loan in her mind and decides to invest in the loan if her willingness to lend (WTL) is no greater than the perceived expected return. Next, taking the lender's behaviour as given, we discuss the platform's maximization problem under different lending models and competition structures. That is, the platform chooses screening and pricing policies to maximize its payoff. Then, we derive the optimal strategies for screening and pricing by solving the platform's maximization problem and discuss their implications. We are primarily interested in the platform's screening strategies, that is, whether the platform approves known "bad" borrowers under certain conditions. Finally, we calculate and compare social welfare generated under the two lending models in a competitive market.

In chapter 5, we extend the comparative welfare analysis by relaxing the standard specification that the platform is well-calibrated. Specifically, in this chapter, the platform is assumed to be overconfident and to overestimate her screening ability. We analyse the potential welfare cost caused by such overconfidence under the guarantee model. In particular, welfare losses may result from the platform's *ex-ante* losses due to underpricing the loan's risk and the potential public cost of platform failure.

Chapters 6 and 7 attempt to provide empirical evidence of a platform's overconfidence under the guarantee model using loan-level data from a Chinese P2P lending platform. Specifically, we examine whether the platform underprices the loan risk it has to bear in both *ex-post* and *ex-ante* senses. In chapter 6, we first describe renrendai's funding procedure and the dataset. Then, we develop the empirical methods for the *ex-post* and *ex-ante* tests. The *ex-post* test examines whether the real loan losses can be covered by the guarantee fees, whereas the *ex-ante* test looks at whether the guarantee fees are enough to compensate the *ex-ante* predictable loan losses. In chapter 7, we first discuss the empirical results of the *ex-post* and *ex-ante* tests. Then, by combing the theoretical and empirical findings, we discuss the risks and benefits of the two lending models and the policy implications.

Chapter 8 concludes the thesis. We first summarize the main findings, and then we discuss the contribution. Finally, we discuss the possible limitations of the theoretical modelling and empirical analysis and possibilities for future research.

Chapter 2. Related literature

In this chapter, we review the related literature and identify the research gap. We begin with the literature on credit market. The exogenously assumption that borrowers have private information about their creditworthiness and lenders have no controls over borrowers' actions after loans are issued leads to equilibrium credit rationing in the sense of Stiglitz and Weiss (1981). We first review some of the empirical works that directly examine the existence of information asymmetries in the credit market in terms of adverse selection and moral hazard (e.g. Karlan and Zinman,2009). Such empirical efforts are challenging because it is difficult to isolate the effect of adverse selection from moral hazard on loan outcome. Then we discuss some empirical studies on equilibrium credit rationing (e.g. Berger and Udell, 1992; Cowling ,2010). For several reasons, directly identifying equilibrium credit rationing can be also challenging. Finally, we review the theoretical and empirical works that focus on the roles of mechanisms such as collateral, relationship lending, trade credit, information sharing and loan guarantee programmes, in mitigating information problems in the credit market (e.g. Bester, 1985; Berger and Udell, 1995; Petersen and Rajan, 1997; Pagano, and Jappelli, 1993; Cowling, 2010).

Then, we consider the expanding literature on P2P lending. In general, the main research interests in this area contribute to two main questions: "What affects the access to credit on this market?" (e.g., Kgoroeadira, Burke and van Stel, 2018) and "How can the finance outcomes be improved via different mechanisms?" (e.g., Lin, Prabhala and Viswanathan, 2013). In particular, one body of the literature on P2P lending analyses the effects of the mechanisms that improve borrower signalling or lender screening on lending efficiency (e.g., Iyer at al.,2015; Freedman and Jin, 2017). Another body of the literature focuses on the determinants of individual lending decisions and funding outcomes, and some of these studies examine the existence and extent of credit discrimination against certain groups on this market (e.g., Ravina, 2012). Moreover, as a new finance model, a series of papers look at the potential of P2P lending to foster financial inclusion and how it fits into the credit market (De Roure et al.,2016). For example, does P2P lending serve the borrowers that banks are unable or unwilling to serve? Additionally, while the volume of P2P lending is still far from approaching of traditional bank lending, a small number of recent studies investigate the potential impact of P2P lending on financial stability (e.g., Käfer, 2016). Finally, rather than focusing on the borrower-lender interaction, a few works model the decision-making process of the P2P platforms (e.g., Wei and Lin, 2016).

Next, we consider equity or reward-based crowdfunding. Theoretical explorations on this new model of entrepreneurial finance concentrate on the optimal market design. For example, they consider how to choose campaign features, such as reward price or funding target, to maximize campaign success or entrepreneur payoff under different settings of investor/backer preference (e.g., Ellman and Hurkens, 2015). They investigate how to address entrepreneurial moral hazard, that is, the entrepreneur's tendency to embezzle investment funds (e.g., Strausz, 2017). Other theoretical works provide comparison across different funding mechanism, for example, all-or-nothing and keep-it-all, pre-ordering and profit sharing (e.g., Marwell, 2015). Furthermore, similar to P2P lending, a body of empirical works of equity or reward-based crowdfunding investigates what shapes the individual investment decision and what affects campaign success (funding outcome). Finally, another body of empirical studies looks at the post-campaign performance for successful campaigns in terms of post-campaign survival rate and receipt of subsequent finance (e.g., Hornuf et al.,2018).

Under the standard model of P2P lending, the separation of the loan's originator and the bearer of the loan's default risk creates a conflict of interest. This conflict of interest is very similar to that in the "issuer-pay model" in credit rating agencies and the "originate-to-distribute model" in the secondary loan market, which are accused of contributing to the recent financial crisis. This spurs a body of post-crisis works that evaluate the effect of such distorted incentives on service quality in credit rating agencies and investment banks (e.g., Chemmanur and Fulghieri, 1994; Fulghieri et al., 2013). In practice, credit rating agencies and investment banks argue that this incentive problem can be mitigated by their reputation concerns. In this sense, a series of theoretical and empirical research examines the discipline effects of reputation concerns under different settings.

2.1 Information asymmetry and equilibrium credit rationing in the credit market

Since the seminal work of Stiglitz and Weiss (1981), much attention has been given to the theoretical importance of information asymmetry in lender-borrower interaction in the credit market (e.g., Bester, 1985,1987; Besanko and Thakor, 1987a, 1987b; Thakor and Udell, 1991). In the analysis of Stiglitz and Weiss, on one hand, given that borrower quality is not ex ante detectable, the lender uses interest rate as a screening device. However, raising the interest rate attracts riskier borrowers and discourages "good" borrowers, which leads to an adverse selection problem. On the other hand, raising the interest rate incentivizes the borrower to switch her funds to a riskier project since the lender does not have full control of the borrower's actions. This is termed as moral hazard. Taken together, because of the presence of the *ex-ante* hidden information problem (adverse selection) and *ex-post* incentive problem (moral hazard), the lender's expected profit is a nonmonotonic function of the interest rate, and the rational lender chooses not to raise the interest rates to clear the credit market as it suffers through lower profits.

Despite the theoretical significance, directly identifying adverse selection or moral hazard in the credit market is empirically difficult. This is because it is not easy to isolate the effect of adverse selection from moral hazard on loan outcome. For example, both adverse selection *ex-ante* and *ex-post* moral hazard predict a positive association between interest rate and loan default rate. Some recent works (Karlan and Zinman, 2009; Dobbie and Skiba, 2013; Adams et al., 2009; Agarwal et al., 2010; Rai and Klonner 2007; Crawford et al.,2017; Ausubel et al., 1999) address this issue by experimental design and exploitation of a unique data structure. For instance, Karlan and Zinman (2009) design a field experiment with some borrowers who select in at identical rates and then face different repayment incentives going forward and other borrowers who select in at different rates and then face identical repayment incentives. This setup distinguishes hidden information from hidden actions. The authors find that adverse selection and moral hazard coexist, while moral hazard has higher impact on loan default. By using auto loan data, Adams et al. (2009) isolate the two forces by jointly estimating down payment with default. The down payment residual contains the buyer's private information. After controlling this private information, the coefficient on loan size in the default model only captures the effect of moral hazard. They find that 16% of defaults are due to moral hazard, whereas adverse selection contributes to 8%.

Although it is a widely held perception, the presence of information-based, supply-side equilibrium credit rationing is empirically contentious (Cowling, 2010). Early studies (e.g., Jaffee,1971) use macro-level data to test the speed of adjustment on commercial loan rates compared to open-market rates; they find that adjustment is slow and take this as evidence of credit rationing. However, Berger and Udell (1992) argue that such a sticky loan rate is not sufficient evidence of credit rationing because the stickiness may be a result of the bank offering below-market rates during a period of high market rates for risk-averse repeat borrowers as implicit interest rate insurances or because the stickiness could be an outcome of loan recontracting between banks and financially distressed firms. To overcome these issues, Berger and Udell (1992) and Cowling (2010) use loan-level data to examine the variation of rate stickiness across loan contract features (loans with or without commitment). Additionally, a more direct assessment, called the proportion test, is conducted to examine whether commitment borrowing will increase as the open-market rate rises. Both Berger and Udell (1992) and Cowling(2010) find that non-commitment and commitment loans of comparable rates are of nearly identical stickiness. In addition, proportion test results indicate that the probability of a being issued under commitment does not increase substantially when real rates rise but that it actually decreases. Overall, the results of stickiness and proportion tests are inconsistent with the prediction of information-based equilibrium credit rationing. Other the hand, some recent works (e.g., Shen,2002; Banerjee and Duflo,2014; Kirschenmann, 2016) present evidence in favour of equilibrium credit rationing. For example, Shen (2002) identifies loan supply and demand by estimating the simultaneous equations model with truncation and finds a backward-bent loan supply curve, implying equilibrium credit rationing. Kirschenmann (2016) provides direct evidence on loan size rationing in the sense of Jaffee and Russell (1976) by using a data set containing information on requested and granted loan amounts. After controlling unobserved borrower heterogeneity via a fixed effects model, Kirschenmann(2016) finds that informationally opaque firms are more rationed than more transparent firms and that the degree of credit rationing decreases over loan sequences.

2.2 Mechanisms for mitigating information problems in the credit market

In the world of Stiglitz and Weiss (1981), the bank uses credit rationing as a response to adverse selection and moral hazard. Since their study, theoretical explorations have sought alternative means to cope with information problems. Bester (1985,1987) relaxes the setting in which banks only have one instrument available (loan rate or collateral requirement) and allows banks to simultaneously set the loan rate and collateral requirement. Then, banks can offer a menu of loan contracts with different combinations of loan rate/collateral requirement, which enables borrowers to self-select into preferable contracts. The collateral requirement acts as both a signalling mechanism and an incentive mechanism in which low-risk borrowers choose low interest rate and high collateral, whereas high-risk borrowers accept a high interest rate and low collateral contract. Besanko and Thakor (1987a, 1987b) and Thakor and Udell (1991) discuss the role of collateral as a sorting device in a similar sense. Recent empirical evidence (Edelberg, 2004; Berger et al.,2011a; Berger et al., 2011b; Uchida, 2017) broadly supports the theoretical intuition that the incidence of collateral relates to reducing *ex-ante* private information and/or *ex-post* incentive problems. For example, Berger et al. (2011a) and Uchida (2017) isolate the effects of *ex-ante* private information from *ex-post* frictions on the use of collateral by distinguishing unobserved risk from observed risk. Berger presents evidence that collateral is generally used to mitigate *ex-post* frictions and also *ex-ante* adverse selection when the borrower has short-term interactions with the lender. Similarly, Uchida finds strong evidence in favour of using collateral for *ex-post* incentive problems but weaker evidence for adverse selection in the Japanese credit market. Notably, Bester (1985,1987) assumes that the borrower always has enough initial wealth to pledge as collateral; in this case, credit rationing is eliminated. However, in a recent theoretical work, Burke and Hanley (2003) document that credit rationing is not necessarily monotonically related to the borrower's initial wealth. Specifically, focusing on the discipline effect of collateral on the borrower's risk-taking behaviour, they find that credit rationing is more likely to take place at the tails of the wealth distribution, that is, among borrowers with either very low or high levels of wealth.

The aforementioned classic collateral literature mostly assumes that the lender-borrower interaction is one-shot game. Some subsequent literature looks at the lending relationship in a dynamic sense (e.g., Boot and Thakor, 1994, Petersen and Rajan, 1995). In a repeated lending game, the lender may learn more about borrower quality through continued interaction or intertemporally subsidized borrowers. Boot and Thakor (1994) and Petersen and Rajan (1995) predict that loan price and/or collateral requirement may decrease with the length of the lending relationship. To test these predictions, empirical works (e.g., Berger and Udell, 1995; Petersen and Rajan, 1994; Cole, 1998; Elsas, and Krahnen, 1998; Harhoff and Körting, 1998; Uchida et al., 2012) examine the effects of the lending relationship on credit availability and credit terms such as interest rate and collateral requirement. The results broadly confirm the value of the lender-borrower relationship in mitigating information problems. For example, Berger and Udell (1995) use the duration of the bank-borrower relationship as a measure of its strength and find that a longer relationship reduces loan rate and collateral requirement. In the German SME lending market, Harhoff and Körting (1998) find that long-lasting bank relationships increase credit availability and link to more favourable loan contracts in terms of collateral requirements and interest rates but that the relationships have more impact on collateral requirement and credit availability than on loan price. Petersen and Rajan (1994), Cole (1998) and Elsas and Krahnen (1998) note that credit availability improves as lending relationships mature but that its effect on price is insignificant.

Despite the empirical efforts on the importance of relationship lending, Berger and Udell (2002) point out that the role of the loan officer in information production may be understudied. The loan officer-borrower relationship may be more relevant than the bank-borrower relationship in relationship lending, as the “soft information” is more likely produced by the loan officer. Uchida et al. (2012) provide supporting evidence on the significance of the loan officer-borrower relationship. They find that the loan officer’s activity contributes to soft information production. In particular, soft information accumulation is negatively associated with loan officer turnover and positively associated with loan officer contact frequency.

The wide use of trade credit[7] has been given much research attention. A body of trade credit literature provides evidence on its importance in alleviating credit constraints (e.g., Petersen and Rajan, 1997; Ogawa at al. 2013; Casey and O'Toole, 2014; Carbó - Valverde at al.2016). For example, Petersen and Rajan (1997) note that suppliers are more likely to extend trade credit to the most profitable and the most unprofitable firms, implying that they have an advantage in lending to firms that might otherwise be credit constrained. By using European SME survey data, Casey and O'Toole (2014) are able to directly test the link between trade credit usage and credit rationing. The results suggest that firms that were denied bank financing are more likely to use trade credit. Carbó-Valverde et al. (2016) identify financially constrained firms by simultaneously estimating loan supply and demand and find that unconstrained Spanish

[7] For example, as in Petersen and Rajan (1997), “Trade credit is the single most important source of short-term external finance for firms in the United States”.

SMEs use more bank financing, whereas constrained ones depend more on trade credit, and the magnitude of these effects increases during the financial crisis. Ogawa et al. (2013) find similar evidence among Japanese SMEs.

In theory, suppliers' cost of funds is higher than banks. Thus, when banks are not willing to lend, suppliers also should not be willing to lend. In this sense, these empirical findings raise a puzzle; that is, why is trade credit available when bank credit is rationed? Biais and Gollier (1997) develop a theory to answer this puzzle. By assuming that the suppliers have an advantage over banks in assessment of buyers' credit quality as well as in *ex-post* monitoring and enforcement, Biais and Gollier(1997) find that credit trade enables the seller to credibly convey the buyer's private information to the bank, which in turn helps the buyer purchase the input from the seller. Demirguc-Kunt and Maksimovic (2001) explore how trade credit fits into developing countries' financial system in a cross-country study. More precisely, are trade credit and bank credit substitutes or complements? They find evidence that firms in countries with large private banking systems use more trade credit, while there is less dependence on trade credit in countries with efficient legal systems, which supports complementarity hypotheses. This is also consistent with the prediction of Burkart and Ellingsen (2004). A possible explanation for these findings is that in countries with less efficient legal systems, it may be optimal for financial intermediaries to lend to suppliers, who then relend to their clients given that suppliers have better *ex-post* monitoring and enforcement ability. In contrast, Ge and Qiu (2007) offer evidence in favour of trade credit serving as substitute for bank loans in China. Specifically, they find that non-state-owned firms, which are more likely to be credit constrained than state-owned firms that are preferred by the state-dominated banking systems, use more overdue trade credit outstanding and long-term trade credit for financing motives instead of for transactional motives. Similarly, Cull et al. (2009) find that institutionally preferred state-owned firms have the potential to redistribute credit to firms that are struggling to access finance via trade credit. However, unlike Fisman and Love (2003), Cull et al. (2009) find that the effect of trade credit on economic growth is limited.

In the classic credit market literature mentioned before (e.g., Jaffee and Russell,1976; Stiglitz and Weiss,1981), information asymmetries are taken to be exogenous; thus, the *ex-ante* adverse selection problem and *ex-post* incentive problem (e.g., moral hazard) naturally exist. However, in practice, information asymmetries may be attenuated by exchanging information (about borrower creditworthiness) with other lenders. Such information sharing can be voluntary through private information brokers known as “credit bureaus” or required by regulators through “public credit registers”. Pagano and Jappelli (1993) formalize that information sharing increases lending activity if, without the credit bureau, safe borrowers would be priced out of the market due to adverse selection. In another theoretical work, Padilla and Pagano (2000) find that the sharing of a borrower’s “black information” (default and delinquent histories) disciplines the borrower to perform, as it raises the borrower’s default cost by affecting her credit ratings with other lenders. Subsequent empirical studies (e.g., Jappelli and Pagano,2002; Brown et al., 2009; Doblas-Madrid and Minetti, 2013; Dierkes et al., 2013) seek to examine the central predictions in the theories: does information sharing reduce default rates, and does information sharing increase lending volume/access to credit? For example, Jappelli and Pagano (2002) provide country-level evidence. They find that the presence of private or public information sharing increases a country’s bank lending level, proxied by total bank lending to the private sector /GDP, after controlling country and institutional characteristics such as economic growth, rule of law, and creditor rights. They also report that information sharing improves country-level credit risk, which is used as a proxy for default rate. Brown and Pagano (2009) assess the effects of information sharing on the cost and availability of credit in transition economies by using firm-level survey data. They construct an “information sharing index” to measure the presence and structure of a country’s private credit bureaus and public registries. They find that the information sharing index is positively correlated with a firm’s perception of the ease of access to finance and negatively correlated with the cost of finance. Doblas-Madrid and Minetti (2013) give loan-level evidence by analysing 28,623 loan contracts in the US. They find that the lender’s credit bureau affiliation reduces defaults and delinquencies. In addition, a further subsample analysis suggests that this effect is particularly stronger for the younger and smaller firms that are allegedly informationally opaque. Dierkes et al. (2013) compares default prediction accuracies with and without business credit information and finds that information sharing improves credit risk assessment.

In addition to the market-based mechanisms (collateral, relationship lending, trade credit, credit bureau) we discussed, policy instruments are used for correcting market imperfections and financing entrepreneurial businesses across the world. Specifically, almost without exception, loan guarantee programmes have been initiated by policy-makers throughout developed and developing economies to provide loan security to smaller firms that would not otherwise be able to obtain debt finance through conventional means (Cowling, 2003, 2010). A body of research (e.g., Cowling, 2003,2007, 2010; Cowling and Siepel, 2013; Cowling et al. 2018; Uesugi, et al.2010) focuses on the role of public intervention in improving SMEs' credit access and the wider economic impact of this intervention. For example, Cowling (2007) reports that, all else equal, having no assets to pledge as collateral reduces firms' maximum borrowing amount by half in UK SME lending. This provides direct support that a loan guarantee scheme increases some SMEs' access to finance. In the aforementioned study by Cowling (2010), both loan rate stickiness tests and proportions tests confirm that there is little evidence of credit rationing for firms in the UK Small Firms Loan Guarantee Scheme (SFLGS) and that these firms would be perfectly credit rationed without the SFLGS. These findings support the effectiveness of the SFLGS in alleviating credit rationing. In a recent work, Cowling and Siepel (2013) offer a justification for the SFLGS in terms of the provided welfare benefits. Specifically, the comparative analysis of post-investment performance between SFLGS-backed firms and otherwise similar firms shows that SFLGS-backed firms outperform the control group in terms of employment, sales and exporting. In addition, the further cost-benefit analysis of the SFLGS suggests that the economic benefits in job creation and sales outweigh the cost of the scheme (administration and cost of defaults).

2.3 P2P lending

2.3.1 Mechanisms for mitigating information problems

During P2P lending, the borrower-lender interactions are conducted anonymously via Internet-based platforms; this online anonymity could exacerbate the classical information problems of consumer lending even though part of a borrower's credit history (from the credit bureau) is disclosed to P2P lenders (Freedman and Jin,2017). In particular, Hertzberg et al. (2018) offer evidence on the existence of adverse selection in P2P lending markets. By using a natural experiment on LendingClub, a major American P2P lending platform, they compare two groups of observationally equivalent borrowers' repayment behaviours. They find when the long-term option is available, borrowers who choose the short-term loan have lower default rate. This implies that unobservable less creditworthy borrowers self-select into long-maturity loans.

In the sense of Spence (1973), borrowers can take costly actions to signal their credit qualities to potential lenders. Hence, borrower signalling has the potential to alleviate the market inefficacies arising from information asymmetry. One stream of the literature on P2P lending explores the roles of borrower signalling mechanisms, such as reserve rate, social/friendship networks, and soft information, in mitigating information asymmetry between borrowers and lenders.

Based on data from Prosper, another major US P2P lending platform, Kawai et al. (2014) estimate the welfare effects of a signalling mechanism where borrowers can signal their private information regarding credit quality through the reserve rate. In a counterfactual experiment comparing markets with and without such borrower signalling, they report that adverse selection destroys 16% of total surplus, up to 95% of which can be restored by the signalling mechanism. Lin, Prabhala and Viswanathan (2013) document that borrower friendship networks serve as signals of credit quality and repayment incentives. Using data from Prosper, they find that friendships increase the probability a full funding for a loan listing, lower interest rates on funded loans and improved *ex-post* loan performance. Freedman and Jin (2017) also suggest that social ties are associated with higher funding probability and lower loan rates on Prosper. Liu et al. (2015) provide similar evidence in China. They find that a lender is more likely to bid on her friend's loan listing than on a stranger's on renrendai.com, a major Chinese P2P lending platform. Michels (2012) demonstrates the role of borrower voluntary disclosure in attenuating inefficiencies. He finds that higher disclosure levels of voluntary and unverified information relate to more favourable funding outcomes and better loan performance.

Another stream of the literature looks at some mechanisms that improve lender screening. In addition to "hard" information such as credit grade, P2P platforms also provide nonstandard, "soft" information about borrowers, such as photos or loan purpose descriptions. Some studies examine the roles of soft or nonstandard information in assessing borrower credit quality. Lyer et al. (2015) provide evidence that soft information can improve default prediction. They find that, on Prosper, the interest rate set by lenders (by combining all available soft and hard information) has a higher predictive power of default than does the borrower's credit score. Moreover, even comparing with a benchmark prediction based on in-sample data on default realization, which is unobservable at the time of loan origination, the interest rate still achieves 87% of its predictive accuracy. Duarte et al. (2012) focus on how P2P lenders use a specific kind of soft information—appearance—to screen loan applicants. They note that impressions of trustworthiness can be an informative predictor. More trustworthy appearance relates to higher funding probability and lower default rate. Gao and Lin (2016) look at another kind of soft information, the linguistic features of texts. They analyse and extract the linguistic styles of "loan purpose" descriptions on Prosper by using machine learning and text mining techniques. They report that textual descriptions that are less readable, less optimistic, less objective, or richer in deception cues are linked to lower repayment rate and higher loss rate. However, Dorfleitner et al. (2016) do not find similar evidence on two European platforms. They observe that text-related factors are related to funding probability but are not informative in predicting loan default. Furthermore, in an early study on Prosper, Herzenstein et al. (2011b) even note that the power of narratives can be counterproductive. They demonstrate that identity claims constructed in narratives actually relate to better *ex-ante* loan outcome, higher funding probability and lower interest rate but worse *ex-post* loan performance.

Freedman and Jin (2011) find that P2P lenders improve their risk assessment over time, providing evidence that "learning by doing" can be a tool in alleviating the information asymmetry. Hildebrand, Puri and Rocholl (2016) examine whether sophisticated lenders, as group leaders, enhance screening efficiency on Prosper, based on the idea that the bids of group leaders may serve as signals about good loan quality that can be observed by unsophisticated lenders. However, they find that, in the presence of origination fees, group leader bids result in lower loan rates but higher default rates, which suggests a decrease in lending efficiency. By analysing a policy change concerning information availability on Prosper, Miller (2015) provides evidence that adding new borrower credit information improves lender screening performance. Zhang and Liu (2012) and Herzenstein, et al. (2011a) examine the existence of herding behaviour in P2P lending. The results show that herding is positively related to loan performance. In this case, as in Zhang and Liu (2012), lenders can make rational inference of borrower credit quality by observing others' lending decisions. This provides evidence that herding or "the wisdom of crowds" improves lender screening.

2.3.2 Determinants of individual lender behaviour and funding outcome

A body of P2P lending literature has sought to characterize lenders' lending decision and identify (other) factors that affect the funding success. The focus of the literature on lender behaviour is slightly different from the of the literature on funding outcome. That is, the "dependent variables" in lender behaviour literature are usually related to individual bid amount/indicators, whereas in funding success literature, the “dependent variables” are usually related to funding success indicator.

With respect to funding outcome, some studies examine the existence and extent of discrimination against certain groups in P2P lending markets. Such discrimination implies that lenders’ lending decisions are influenced not only by the standard risk-return trade-off but also by borrower characteristics such as gender, race, beauty, and age. After controlling *ex-ante* riskiness, Pope and Sydnor (2011) and Ravina (2012) find that black borrowers were less likely to get loans in the early years of Prosper (2006-2007), but Duarte, Siegel, and Young (2015) find no discrimination against black people by using a larger sample on Prosper (2006-2008). Pope and Sydnor (2011), Ravina (2012), and Duarte, Siegel, and Young (2015) find no discrimination against female borrowers on Prosper, similarly to Barasinska and Schäfer (2014) by using data from a German platform. Ravina (2012) also examines the “beauty effect” on Prosper. She reports that beautiful loan applicants enjoy higher funding probability. In a recent study on a German platform, after controlling *ex-ante* borrower quality through expected internal rate of return, Weizsacker and Zankiewicz (2017) estimate that the likelihood of the funding success of a below median-quality male borrower is approximately half of that of a female borrower, consistent with the hypothesis that predominantly male lenders have a less precise understanding of women’s applications than of men’s applications. Cumming and Hornuf (2017) note that in lending to SMEs, the platform ratings of the firms have more predictive power of funding success than do the firms’ financial variables, suggesting that the platforms plays a more important role in influencing lenders’ decisions. In a very recent study, Kgoroeadira, Burke, and van Stel (2018) analyse 14,537 loan applications with the purpose of small business funding on Prosper. They find that the entrepreneur’s personal characteristics, such as credit grade, have significant effects on funding success and loan price. On the other hand, business characteristics have little impact on those outcomes.

With respect to the individual lending decision, some literature studies the effect of geographical distance on the lending decision. Senney (2016) and Burtch et al. (2014) provide evidence that lenders on Prosper and Kiva prefer geographically proximate loan applicants. Lin and Viswanathan (2015) offer evidence of the existence of a “home bias” in P2P lending on Prosper, i.e., lenders favour home state borrowers. Lin et al. (2017) look at the interaction between the retail investors and institutional investors on LendingClub. They confirm the crowding out effects of institutional investors, which suggest that retail investors avoid competition with institutional investors by submitting fewer bids on institutional investors' participation. They report that such crowding out effects lead to lower funding probability and interest rate. Paravisini et al. (2016) test how the investors’ wealth affects their risk aversion. They document that wealthier investors show lower absolute risk aversion and higher relative risk aversion when building their loan portfolios on LendingClub. For a given investor, the relative risk aversion increases after a negative wealth shock. Li et al. (2018) examine how macro-level uncertainty influences credit access on Prosper. They reveal that policy uncertainty reduces credit access, and this can be explained by investors’ increased caution on deal selection and enhanced value of the “wait-and-see” option.

2.3.3 The roles of P2P lending in the credit market and fostering financial inclusion

While the volume of P2P lending is still far from approaching of traditional bank lending, some recent studies investigate how P2P lending interacts with the current financial system. The key question that these studies seek to answer is whether P2P lending is a substitute or a complement for traditional bank lending. By comparing P2P loans on Auxmoney and bank loans in Germany, De Roure et al. (2016) find that P2P lending serves the high-risk borrowers and small credit lines segment of the market that banks are unwilling or unable to serve. This result suggests that high-risk borrowers substitute bank loans for P2P loans. Based on US data, Wolfe and Yoo (2017) note that the crowding out effect of P2P lending on commercial banks is heterogeneous. Small (rural) commercial banks lose loan volume as P2P loan origination increases, but large (urban) bank loan volumes remain unaffected. Jagtiani and Lemieux (2017) present evidence that LendingClub expands credit availability and lowers borrowing cost. Their analysis suggests that LendingClub fills credit gaps in underserved areas that lose bank branches and in highly concentrated banking markets. Specifically, approximately 50% of LendingClub loans are made to borrowers in banking markets with high concentration. Additionally, for the same default risk, borrowers pay smaller spreads on loans from the LendingClub than on loans from traditional bank lending. Balyuk (2016) finds that, after controlling credit quality, borrowers who receive P2P loans have higher revolving limits, a measure of external credit supply, than borrowers who do not receive P2P loans. In this sense, P2P lending acts as certification device to relieve credit constraints for marginal borrowers who were credit-rationed by traditional credit institutions. In a UK study, Atz and Bholat (2016) focus on the geography of UK P2P lending by analysing loan origination data from Zopa, Funding Circle and RateSetter.

They reveal that lenders are more likely from London and the south of the UK, while borrowers are more evenly distributed across the country. This implies that P2P lending may fill the regional funding gap created by the perceived 'North-South' divide. Havrylchyk et al. (2017) give similar evidence in the sense of the geographic expansion of P2P lending in the US, as they find that P2P loan volume negatively correlates with branch density, which could be a measure of the financial exclusion. Alyakoob et al. (2017) provide insight into the interaction between P2P lending and traditional bank lending. They find that borrowers from areas with a high ratio of multi-state banks are more likely to prepay and less likely to default, suggesting that P2P borrowers may benefit more from multi-state banks than from regional banks.

2.3.4 P2P lending and financial stability

While the above empirical evidence generally supports the bright side of P2P lending, that is, improvement in credit access, several policy discussion papers raise concern over the dark side, the potential financial instability risk posed by P2P lending. Specifically, Kirby and Worner (2014), Lenz (2016), Käfer (2016) and FSB and BIS (2017) note that one source of such financial instability may be the deterioration of lending standards. They point out that the reduction in the lending standard may be caused by misaligned incentives inherent in the business model of P2P lending, which is similar to the "originate-to-distribute" model of pre-crisis subprime lenders. This may also be caused by the P2P platforms' (or lenders') systematic underestimation of risk given that their credit risk assessment algorithms have not been tested through a full economic cycle. Milne and Parboteeah (2016) argue that investor protection schemes such as loan loss reserve funds may not cover the unexpected loan losses in a business downturn. By exploiting China's regulatory change of increasing down-payment requirements for mortgages to separate credit demand from credit supply effects, Braggion et al. (2018) find that P2P lenders underestimate and underprice the credit risk of new borrowers. This suggests that lending can serve as a channel to circumvent regulatory loan-to-value caps, which undermines macroprudential regulation.

In addition to the deterioration of lending standards, there are concerns over the platforms' failure risk. Käfer (2016) and FSB and BIS (2017) state that the potential sudden drops in loan origination activity make P2P platforms susceptible to failure, as the platforms' revenue structures are dominated by up-front fees. It is worth noting that these works do not link the platforms' failure risk to systemic risk. We think there are two reasons for this. First, the platforms in Western countries usually use the non-guarantee model, under which the platforms do not bear credit risk, rather than the guarantee model, as used in China. In this case, the platforms are only subject to profitability risk, which is less likely to contribute to systemic risk than to credit risk. Second, given that the amount of P2P lending is still small compared with the amount of traditional bank lending, P2P lending is unlikely to pose an immediate systemic risk (Kirby and Worner, 2014). However, given the rapid growth of China’s P2P lending, the widely used guarantee model will pose a threat to financial stability if the platforms under-appreciate credit risk. Moreover, systemic risk can also be accumulated because the money acquired from the banks can easily flow to the grey (underground lending) market through the P2P platform (Wei, 2015).

2.3.5 P2P platforms’ decision-making

Only a few studies explicitly model the platforms’ behaviour, rather than only focusing on borrower-lender interaction. Wei and Lin (2016), Huang (2016) and Chen et al. (2014) analyse a platform’s pricing strategy under the posted price mechanism and compared the price and the efficiency with the auction mechanism. Considering that screening is costly and imperfect, Estrada and Zamora (2016) model both the bank’s and the platform’s choices of loan provision (amount of loan applications screened). Their model assumes that reputation cost is large enough that the platform makes honest screening mistakes only.

2.4 Reward or equity crowdfunding

2.4.1 Optimal market design in crowdfunding

A strand of theoretical works on (reward) crowdfunding investigates the optimal crowdfunding design problem. Most of these works focus on how to design an optimal reward scheme from the entrepreneur’s/creator’s perspective to fit backers’/investors’ preference and achieve a better crowdfunding outcome. Specifically, the entrepreneur’s problem is characterized as choosing reward items/products and prices (Xiao et al.,2017; Hu et al.,2015), choosing funding target and pre-sale price (Kumar et al.,2016; Chakraborty and Swinney, 2016; Sayedi and Baghaie, 2017), choosing the effort level necessary to deliver her campaign goal (Schwienbacher, 2017), choosing her funding target, minimal bids and reward prices (Ellman and Hurkens, 2016) or choosing the pledge level and fundraising duration (Zhang et al.,2017), to maximize her expected payoff. Alaei et al. (2016) model the entrepreneur's problem in a similar sense but also take into account the expected penalty of the funding target failing to cover the actual project costs. Du et al. (2017) propose the contingent stimulus strategy where campaign features are not fixed upfront but can be updated contingently. These works model the interactions between entrepreneur/creator and backers/donors by using different settings for backers/donors' decision-making, and the crowdfunding platforms' behaviours are not explicitly analysed. An exception is Wu et al. (2017), in which the platforms' information revelation strategy (i.e., objectively report or deliberately misreport project quality) is modelled. However, by assuming that the investor's expected return is the same under the truthful revelation of information, the signalling role of pricing is not considered.

The above works do not model entrepreneurial moral hazard, that is, the entrepreneur's inclination to embezzle investment funds. Strausz (2016) and Chemla and Tinn (2017) formally consider entrepreneurial moral hazard in their models. Strausz (2016) demonstrates how deferred payments address entrepreneurial moral hazard in reward crowdfunding by using a mechanism design approach. Chemla and Tinn (2017) illustrate how firm learning about future demand can endogenously mitigate moral hazard. Other works related to optimal crowdfunding design, such as Marwell (2015) and Cumming et al. (2015), offer comparisons of two existing funding mechanisms, all-or-nothing (AON) and keep-it-all (KIA). Marwell (2015) notes that fundraisers self-sort across the two funding mechanisms by project quality. On average, the quality of projects under AON is almost 30% higher than that of projects under KIA. Cumming et al. (2015) find that small projects enjoy higher funding probability under KIA, while large projects are more likely be funded through AON. Moreover, Chemla and Tinn (2017) note that AON generally has better effect in overcoming moral hazard than does KIA. As an early work of crowdfunding, Belleflamme et al. (2014) compare pre-ordering (reward crowdfunding) and profit-sharing (equity crowdfunding) in the presence of adverse selection in which *ex-post* project quality is out of the entrepreneur's control. The entrepreneur therefore faces a tradeoff between price discrimination and raising enough capital to cover the upfront cost. Their analysis shows that the entrepreneur prefers pre-ordering when the project is relatively small and profit-sharing otherwise. Li (2017) offers proof that the optimal profit-sharing contract is the equal split of net investment profit among investors rather than common stock. Although the result is counterintuitive, Li's analysis shows that such a profit-sharing structure perfectly harnesses the wisdom of the crowd that induces an optimal investment amount and gives a “smaller slice of a bigger pie”, which is bigger than a “bigger slice of a smaller pie”.

2.4.2 Determinants of investment/contribution behaviour and funding success in crowdfunding

While theoretical studies mostly seek optimal funding mechanism/contract design, empirical works focus on characterizing (individual) investment/contribution decision and identifying factors that affect campaign success. Similarly to P2P lending literature, the “dependent variables” in investment behaviour literature are usually related to individual investment amount/indicator or investment amount in a (short) given period, whereas in funding success literature, the “dependent variables” are related to the amount of the final raised funds as the funding success indicator.

With respect to the investment/contribution decision, Kuppuswamy and Bayus (2017) and Boudreau et al. (2017) identify the investors/backers’ motivation to contributing funding. By analysing funding dynamics, Kuppuswamy and Bayus (2017) find that campaigns on Kickstarter are likely have more backer support when they are close to but not over their funding targets. This suggests that perceived impact plays a role in motivating crowdfunding contribution. Boudreau et al. (2017) find that non-pecuniary benefits rather than consumer surplus and private gifts play a key role in incentivizing backers’ contribution by using observational and survey data from the crowdfunding of a popular online game. Hornuf and Schmitt (2016) and Günther et al. (2018) give evidence for the existence of home bias/local bias in equity crowdfunding, as do Lin and Viswanathan (2015) in P2P lending. That is, after controlling other factors, investors are more likely to invest in local firms/projects. However, Agrawal et al. (2015) present evidence that such a distance effect can be largely explained by the offline social ties with creators. That is, after controlling offline social relationships, there is little difference in investment behaviours between local and distant investors. Abrams (2017) notes that unsophisticated investors (family, friends, fools) are more likely to invest in the first week of the campaigns, regardless of the campaigns’ economic fundamentals, while sophisticated investors tend to invest thereafter. Hornuf and Schwienbacher (2018), Burtch (2017) and Burtch (2015) examine how market design features affect investment behaviour. In particular, Hornuf and Schwienbacher (2018) focus on the share allocation mechanism. They find that under the first-come, first-serve models, funding dynamics are L-shared, indicating a weak end-of-campaign effect. However, under second-price auction, funding dynamics are U-shared. Burtch et al. (2017) investigate the effect of the provision point mechanism (all-or-nothing) on reducing irrational herd behaviour. The results show that the provision point mechanism leads to more independent decisions. This can be explained because a) the entrepreneur's choice of provision point mechanism may signal the project quality and b) the provision point mechanism reduces the contributor's uncertainty about the campaign outcome by ruling out the possibility of partial financing. Burtch et al. (2015) estimate the impact of privacy control on contribution willingness by using a randomized experiment. They find that delaying the presentation of privacy control leads to a net increase in fundraising. Driven by the behavioural finance literature, Hervé et al. (2019) test some predictions on how gender and local living environment conditions affect individual investment decisions on a French equity and real estate crowdfunding platform. The results show that men invest in riskier (equity) projects and less safe (real estate) projects than do women, which is consistent with the idea that men exhibit lower risk aversion and/or more overconfidence. The influence of expert investors on other investors is discussed in Kim and Viswanathan (2014). They find evidence that the early investment by investors with expertise and experience relevant to the project can be interpreted as a credible signal of campaign quality for later investors.

With respect to funding success, several studies give attention to the importance of different types of information, equity retention, social capital and campaign management for funding outcome. Specifically, Knyazeva and Ivanov (2017) find that the issuer's hard information, such as asset and financial condition, contributes little to funding success on equity crowdfunding, while soft information, measured as social media and third-party certification about issuer quality, plays a significant role in campaign outcome. This may be partially explained by the idea that investors seek non-pecuniary payoffs and/or view the crowdfunding investment as a gamble rather than as a standard financial investment. However, the analysis of Lin and Pursiainen (2017) seems not to agree with this, as they find that social capital, a proxy for the level of institutional weakness that can mitigate entrepreneurial moral hazard, is positively associated with the probability of campaign success. However, Lin and Pursiainen (2017) do not control for soft and hard information as do Knyazeva and Ivanov (2017), which might lead to biased estimation. Vismara (2016) presents similar evidence as do Lin and Pursiainen (2017), in that their measurement of social capital also significantly contributes to the total amount of fundraising. Vismara (2016) also finds that both funding amount and number of investors decrease in proportion with the equity offered to investors. This implies that equity retention can signal potential project quality in crowdfunding as in other markets. Giga (2017) adds evidence to "the jockey vs. the horse" debate in the venture capital literature by comparing the effect of management and other business characteristics, such as patents, on funding success. The results show that investors place more emphasis on human capital than on other sources, as funding probability increases with management size and experience.

Although in general this body of research looks at the supply side of funds of crowdfunding, Kim and Hann (2017) look at the demand side. By modelling the adoption of crowdfunding as a function of the ease of collateral-based bank financing, proxied by housing prices, a decrease in housing prices increases the chance of using crowdfunding for the entrepreneurs under tighter credit conditions. Similarly, Butler et al. (2016) analyse how local access to finance affects borrowing costs. After isolating the effects of borrower characteristics and local economic conditions, they still find that borrowers who live in areas with good access to bank finance have less willingness to pay for loans on Prosper. Cumming et al. (2017) identify fraudulent crowdfunding through the four dimensions of creator characteristics, social media affinity, campaign funding and reward and campaign description. They find that fraudulent crowdfunding is linked to a lower probability of engagement in prior crowdfunding activities, social media presence, and poorly worded and confusing campaign pitches.

2.4.3 Post-campaign performance of crowdfunding projects

In a very recent study on SMEs failure, Gupta and Gregoriou (2018) find listed SMEs enjoy lower probability of financial distress and bankruptcy, compared with their unlisted counterparts, which suggests accessing external finance increases SMEs' survival rate. In a similar sense, several studies look at what happens to firms after crowdfunding success. Signori and Vismara (2017), Ryu and Kim (2017) and Hornuf et al. (2018) offer assessments of the post-campaign performance of firms that successfully raised funds through crowdfunding. The post-campaign performance is characterized by post-campaign survival rate and receipt of subsequent financing. Signori and Vismara (2017) find that, among 212 funded firms on Crowdcube, 17.9% failed, while 34.9% obtained follow-on financing. Ryu and Kim (2017) compare the likelihood of getting follow-on venture capital financing between crowdfunded firms and angel-backed start-ups. Using endogenous treatment regression to address self-selection bias, they find that crowdfunded firms are less likely to get subsequent venture capital financing than are comparable angel-backed start-ups. Hornuf et al. (2018) provide a comparison of UK and German firms. They estimate that, conditional on receiving crowdfunding, German firms enjoy a higher probability of obtaining subsequent financing from business angels or venture capitalists but also suffer a higher failure rate.

In contrast to the above studies, Viotto da Cruz (2016) and Xu (2017) look at the post-campaign effect of crowdfunding on firms that are unsuccessful in gaining funding. The rationale is that, although some firms remain unfinanced under the all-or-nothing scheme, backers' pledges can reveal consumers' valuation of and demand for the products. This information reduces market uncertainty and thus helps firms in subsequent decision-making. They provide consistent evidence that among unfunded firms, more backers' positive is are related to a higher probability of later commercialization/release of their products. One challenge of these empirical works is the endogeneity problem caused by the correlation between unobserved project and entrepreneur characteristics and consumer pledges. Xu (2017) addresses this issue by using local weather shocks as an instrument variable of campaign outcomes.

2.5 Rating inflation in credit rating industry and lax screening and monitoring standards in securitization practices

The potential conflict of interest inherent in the "issuer-pay model" of credit rating agencies and the "originate-to-distribute" model in securitization processes may lead to biased credit ratings and reduction in screening and monitoring incentives. Given this, market observers criticize the "failure" of these business models in directly contributing to the recent financial crisis of 2007-2009. A body of literature following the financial crisis provides empirical evidence of distorted incentives in credit rating and securitization.

To test the existence of rating inflation, several works (Xia, 2012; Dilly and Mählmann, 2015; Jiang et al.,2012; Cornaggia and Cornaggia, 2013) use ratings under the investor-pay model as a benchmark conflict-free ratings and compare these ratings with ratings under the issuer-pay model. The results are consistent; that is, rating agencies tend to issue more favourable ratings under the investor-pay model, after controlling other factors. Specifically, Xia (2012) finds that S&P is more likely to issue an inflated rating for an issuer with greater future rating needs, proxied by short-term debt. Dilly and Mählmann (2015) examine the variation in the difference of Egan-Jones Ratings (investor-pay, benchmark ratings) and issuer-pay ratings (S&P, Moody's, Fitch) across different periods. They find that issuer-pay ratings are overly optimistic during booms, supporting the hypothesis of "boom bias". He at al. (2012) provide similar evidence of such a "boom bias" by comparing initial yields on MBS between large and small issuers. Cornaggia and Cornaggia (2013) note that, compared with Moody's, ratings generated by Rapid Ratings (investor-pay, benchmark ratings) show less stability but more timeliness, which leads to less average loss. Jiang et al. (2012) offer historical evidence by considering S&P's switch in 1974 from the investor-pay model to the issuer-pay model. By using Moody's ratings for the same bond as a benchmark, they find that S&P increases ratings after the change of revenue model. Skreta and Veldkamp (2009) give a theoretical origin for rating inflation. That is, when assets are complex enough, the sufficient difference in ratings creates an incentive for issuers to shop for ratings and thus for raters to inflate ratings.

In a relatively early work, Berndt and Gupta (2009) give indirect evidence that the "originate-to-distribute model" reduces banks' screening and/or monitoring efforts in the US syndicated loan market. They estimate a 4-factor regression (Fama and French three factors and a momentum factor) to test the difference in stock return between borrowers (US publicly listed firms) with an active secondary loan market and borrowers without. The results show that the former underperforms the latter. Berndt and Gupta (2009) thus offer two possible explanations; either banks originate and sell lemons, or they employ loose loan monitoring. Subsequent research tries to provide deeper evidence on this topic by looking at the link between the securitization and loan performance. The most cited work is Keys et al. (2010), who (as do Keys et al., 2012) use the FICO score[8] (620) cutoff as exogenous variation in the ease of securitization, as not lending to borrowers with a FICO score below 620 is a rule of thumb. They find that borrowers with a FICO score of 621 (620+), who are more likely to be securitized, show a higher default rate than do borrowers with a FICO score of 619(620-) after controlling other observable characteristics, despite their nearly identical observable risk profiles. This suggests that, for loans that are more likely to be securitized, lenders have less incentive to carefully screen borrowers on unobservable dimensions (soft information). Rather than focusing on the *ex-post* loan performance, Griffin and Maturana (2016)

[8] FICO® Scores, developed by data analytics company Fair, Isaac and Company, are the widely used credit scores.

analyse the amount of mortgage misrepresentation around the FICO score thresholds. The analysis suggests that unreported second liens increase significantly from a FICO score of 619 to 620, but whether the originators facilitate such misreporting intentionally or unintentionally remains unclear.

As critics of the "originate-to-distribute model" argue that originators retain too little "skin in the game", which cannot incentivize sufficient screening efforts, Demiroglu and James (2012) examine this hypothesis. They report that, when the originator is also the sponsor, which means that the originator has more "skin in the game", these affiliated deals have a lower loss rate than do unaffiliated ones in low documentation loans. Nadauld and Sherlund (2013) note that observable hard information exhibits more explanatory power in loan pricing in areas with higher securitization activity, which implies that the active securitization market diminishes lenders' incentive to collect (costly) soft information. Purnanandam (2010) estimates the effect of participation in the originate-to-distribute market on banks' mortgage default rates by exploiting the sudden drop in liquidity in the secondary mortgage market in 2007Q2. The results show that banks with higher involvement in the originate-to-distribute transactions in the pre-disruption period have more bad loans and defaults in the immediate post-disruption period when they are unable to offload the originate-to-distribute loans to third parties. This suggests that banks' screening incentives are reduced by aggressive involvement in the originate-to-distribute transactions, which in turn leads to poor loan quality.

Apart from lax screening standards, the negative relationship between *ex-post* loan performance and securitization activity may also be due to reduced monitoring incentives. By using borrower-lender matching and the IV approach to isolate the effect of securitization on banks' *ex-post* monitoring from *ex-ante* screening, Wang and Xia (2014) report that securitization activity weakens banks' monitoring incentives. This is consistent with the results when using loan covenant strictness as a direct measure of monitoring intensity. Ongena et al. (2017) also provide related evidence by tracking and comparing the loan performance of collateralized versus non-collateralized loans over time. They observe that, among securitized loans, the expected default probability of collateralized loans, which require more monitoring, increases significantly more than the expected default probability of non-collateralized loans.

2.6 The discipline effects of reputation concerns

Facing accusation about the above conflict of interest, CRAs and investment banks argue that their reputation concerns can discipline their behaviours. As S&P states, “the ongoing value of Standard & Poor’s credit ratings business is wholly dependent on continued market confidence in the credibility and reliability of its credit ratings” (cite by Mathis et al.,2009). Furthermore, as Goldman Sachs partner Gus Levy says, “We’re greedy, but long-term greedy, not short-term greedy” (cite by Griffin et al.,2014). Therefore, researchers investigate whether CRAs and investment banks’ incentives to build long-term reputation can mitigate the conflict of interest from the empirical and theoretical perspectives.

To directly evaluate the discipline effect of reputation concerns empirically, some research (Griffin et al., 2014; Fang and Yasuda,2009; Fang,2005; Bedendo et al.,2018) examines the relationship between institutions’ reputation and service quality. Specifically, to measure reputation and service quality for investment bank analysts, Fang and Yasuda (2009) use analysts’ AA status and forecast errors; for investment banks, Fang (2005) uses a binary classification based on market share and offering yield; Griffin et al. (2014) use Carter-Manaster ranking and loan performance. For CRAs, Bedendo et al. (2018) use Enron/WorldCom scandals as an exogenous reputational shock and cumulative accuracy profiles curves. Under different measures for reputation and service quality, these works give mixed evidence of the discipline effect of reputation concerns. Fang (2005) reports that reputable underwriters offer higher quality services after controlling issuer-underwriter matching. Fang and Yasuda (2009) find that, rather than bank reputation, analysts’ personal reputations have a significant discipline effect against conflict of interest, proxied by underwriting volume. However, Bedendo et al. (2018) find no improvement in CRAs’ rating quality before and after an exogenous reputational loss. Griffin et al. (2014) even report that reputation is negatively associated with product quality in the underwriting process.

Several theoretical investigations (Chemmanur and Fulghieri,1994), Mathis et al., 2009) and Fulghieri et al.,2013) provide a possible explanation for the “failure” of reputation concerns. Specifically, in dynamic rational expectation settings, these works, which build on the seminal works of Kreps and Wilson (1982a) and Milgrom and Roberts (1982), formalize the following intuition. That is, although by observing past service quality, clients can infer CRAs’ or investment banks’ credibility through Bayesian learning, the clients may not unambiguously attribute a bad performance to the CRAs' or investment banks' opportunistic behaviour. This is because 1) CRAs' or investment banks' evaluation technology is not perfect, and they can make honest mistakes, and 2) an *ex-ante* worthwhile product may still end up with bad performance. Thus, CRAs' or investment banks' information production effort is not *ex-post* verifiable. In this case, clients cannot identify whether the source of a bad performance is due to honest error, opportunistic behaviour or bad luck. In this sense, under certain conditions, this *ex-post* non-verifiability limits the effectiveness of reputation concerns.

The above research implicitly assumes that past poor performance damages CRAs' or investment banks' reputation in the investor's mind, which in turn makes them less attractive to investors. Gopalan et al. (2011) empirically evaluate this assumption by exploring the effect of large bankruptcies on subsequent loans retained by lead arranger (lead allocation) in the loan syndication market. Accounting for borrower characteristics, loan characteristics, and borrower and year fixed effects, they find that, in general, lagged large bankruptcies do increase lead allocation. However, this effect is not present in dominant lead arrangers. Qian (2011) provides supporting evidence of such a reputation hypothesis from the mutual fund market. Using (after validated) flow sensitivity as a measure of investor vigilance, the results show that funds' flow sensitivity correlates negatively with their arbitrage potential, abnormal fund flows, and probability of scandal.

As CRAs' rating inflation decision balances short-term profit against long-term reputation (profits), the change in the expectation of short-term profits may in turn change the balance and thus the inflation decision. Bar-Isaac and Shapiro (2013) and Bolton et al. (2012) rationalize such conjecture by providing theoretical analysis showing that the effectiveness of reputation concerns in mitigating conflict of interest varies across economic cycles. That is, during boom periods when current fee income is high, risk of failure that could lead to reputation loss is low, and CRAs are more likely to issue inflated ratings because the short-term payoff in this case may outweigh the long-term payoff.

The works mentioned above on reputation concerns' role in CRAs focus on upward biased ratings or inflated ratings, while Dimitrov et al. (2015) document that the incentives to protect CRAs' reputation can lead to downward biased ratings. Specifically, the evaluation compares the rating accuracy of S&P, Moody's, or Fitch before and after the Dodd-Frank Act. They find that CRAs become more conservative following the Dodd-Frank Act; after controlling other factors, CRAs issue lower ratings and give more false warnings, and their downgraded credit rating becomes less informative. An explanation for this is that the punishment for biased ratings under the act is asymmetric; upward biased ratings are punished, while downward biased ones not. This motivates CRAs to issue pessimist ratings to protect their reputation. Mariano (2012) documents that competition may have a similar effect on making CRAs more conservative. Becker and Milbourn (2011) document that the reputation mechanism can be counterproductive in the credit rating industry. They find that increased competition (entry of Fitch) can actually reduce the incumbents' (S&P, Moody) rating quality. An explanation from reputation theory is that increased competition lowers the reputation cost, which distorts the raters' incentives for high-quality ratings. Bolton et al. (2007) find that the effect of competition varies across bank types. Reputation acquisition works better for specialized banks when there is competition, while one-stop banks are more likely to provide reliable information when they have market power. Chari et al. (2014) find that reputation considerations play a central role in the persistence of adverse selection, as low-quality banks have incentives to mimic the high-quality banks' strategies.

2.7 Research gap

The body of literature on P2P lending to date is mostly empirical and largely focuses on the interaction between borrowers and lenders, or more specifically, how different mechanisms shape borrowers or lender's behaviour during the interaction. These mechanisms, either enable borrowers signal their quality or act to improve the lenders' screening process. These behaviours, in turn, may alleviate information asymmetries and lead to more efficient transaction outcomes. Similarly, current research on the optimal market design of equity or reward crowdfunding concentrates on modelling the decision-making of entrepreneur/creator and investors/donors. These models discuss how to use different market design features and funding mechanisms to maximize likelihood of the campaign success or overcome entrepreneurs' moral hazard.

Although modelling borrower-lender and entrepreneur-investors interactions have been given much attention, and is important, the platforms' behaviours are assumed to be exogenous. Specifically, P2P (and crowdfunding) platforms are treated as honest information intermediaries that generate unbiased evaluations about borrower credit quality or conduct sufficient due diligence about projects. ***However, these works do not***

consider the effect of the platforms' opportunistic behaviours in information transmission on transaction outcomes and efficiency.

The platforms' opportunistic behaviours stem from the conflict of interest between the platform and lenders/investors. That is, platforms' volume-based revenue model and having little "skin in the game" reduces the platforms' incentive to carefully screen borrowers/projects. Similarly, incentive problems exist in the "issuer-pay-model" in credit rating process and in the "originate-to-distribute model" in secondary loan market, and these features have been blamed for contributing to the recent financial crisis. A series of post-crisis studies support this accusation by providing evidence of rating inflation and diminished screening and monitoring standards. While CRAs and investment banks claim that reputational concerns are enough to mitigate the conflict of interest, recent works indicate that such a disciplining effect is either limited or unclear. In a similar sense, ***whether reputation concerns are sufficient to discipline P2P lending or crowdfunding platforms remains to be studied.***

Among the small number of papers that have discussed the impact of P2P lending on financial stability, the platforms' tendency to underestimate or underprice loan risk has been widely referenced. Under China's unique guarantee model of P2P lending, this underestimation of risk can contribute greatly to financial instability, as the platforms accumulate credit risks by directly bearing the default losses and the soundness of the platforms therefore can be jeopardized by their inappropriate identification, assessment, and handling of credit risk. ***However, no empirical evidence has been provided regarding the presence of the underestimation of risk.***

China has the largest and fastest-growing P2P lending market in the world. China's P2P lending platforms either use the non-guarantee model or the guarantee model as mentioned in section 1.2. However, currently, ***there is no formal analysis of how platforms' behaviour varies across the two lending models.*** Specifically, to evaluate the pros and cons of the two lending models, two central questions remain to be investigated: 1) Can the platforms' reputation concerns minimize the tendency to overstate borrower quality under the non-guarantee model? 2) Do the platforms underestimate credit risk under the guarantee model?

Chapter 3. The theoretical modelling framework

This chapter presents the theoretical modelling framework. We first discuss the general assumptions regarding the players, screening technology and information environment. Then, we characterize the structure of the lending game under both the non-guarantee model and the guarantee model. The game structure describes how the platform interacts with borrowers who approach the platform to seek loans and lenders who fund these loans.

Under the non-guarantee model, the platform does not guarantee the repayment of loans that it approves and only serves as an information intermediary to assess borrowers' creditworthiness and facilitate loan transactions. Reputation acquisition therefore acts as a disciplinary device to curb the platform's tendency to overstate borrower credit quality. The platform faces an intertemporal trade-off between approving known "bad" borrowers to boost current profits and truthfully revealing borrowers' credit risk to improve its long-term reputation and the resulting future profits. Under the guarantee model, the platform acts as the guarantor for the repayment of the outstanding principal in the event of default. The platform therefore faces a trade-off between setting a higher guarantee fee (which implies a lower loan rate and a lower probability of funding success) or a higher loan rate (which suggests a higher probability of funding success but a lower guarantee fee).

3.1 Agents, technology and information environment

Consider an economy in which there are three types of agents: P2P lending platform(s), lenders and borrowers. A penniless borrower seeks to borrow ¥ 1 from (multiple) lenders via a platform. All loans last one period. The borrower can be of two types: $\theta = \{\theta_G, \theta_B\}$, i.e. $\theta = \theta_G$ when it is a "good" type; $\theta = \theta_B$ when it is a "bad" one. The *ex-ante* probability of "good" borrowers is the same at each period and is denoted by $\beta \in (0,1)$. A "good" borrower repays the loan with a probability of

$p \in (0,1)$, while a "bad" borrower always defaults. A borrower's outside option is $R \in (0,1)$. This means that the maximum acceptable borrowing cost(interest rate plus other fees) for a borrower is β, p and R are common knowledge to all agents. For simplicity, we assume default costs are sufficiently small; thus, applying for loans is always optimal for all borrowers regardless of their type.. Without loss of generality, the riskless rate is assumed to be 0 and the discount factor is normalized to 1.

There is information asymmetry between lenders and borrowers: the borrower type is private information and lenders cannot tell a "good" borrower from a "bad" one. To formally characterize the information asymmetry, we assume:

$$(1+R)\beta p - 1 - c < 0 \tag{A1}$$

where $c \in (0,1)$ is the fixed cost of the loan-monitoring process for a funded loan. This assumption means that uninformed lending is not feasible. In other words, a lender without any screening technique cannot make a profit by indiscriminately granting unsecured loans. Although lending indiscriminately to all borrowers is *ex-ante* (cost) inefficient, it is *ex-ante* (cost) efficient to finance a known good borrower; that is

$$(1+R)p - c - 1 > 0 \tag{A2}$$

The information asymmetry between lenders and borrowers creates a role for platform information production regarding borrower credit risk. The platform is endowed with a screening technology that produces information on the borrower type. By observing the borrower type and screening out "bad" borrowers, the platform reduces the information asymmetry. However, the platform's screening technology is *imperfect*. Specifically, it generates signal $s = \{s_B, s_\phi\}$ ($s = s_B$ when it is a "bad "signal; $s = s_\phi$ when it is a "no bad" signal) on the credit quality of borrowers, with the following conditional distributions:

$$P(s = s_B \mid \theta = \theta_B) = \alpha, P(s = s_\phi \mid \theta = \theta_G) = 1 \tag{1}$$

This implies that the platform erroneously assigns a "no-bad" signal to a bad borrower with a probability $1-\alpha$, $\alpha \in (0,1)$, while assigns a "no-bad" signal to a good borrower with certainty. As the focus of our model is the platform information manipulation under reputation concerns rather than strategic information acquisition as in Hauswald and Marquez (2006), the platform's screening precision, α, is assumed to remain constant and the screening cost per loan applicant is normalized to zero[9]. Although platform's screening technique is not perfect, it is *ex-ante* efficient:

$$(1+R)P(\theta=\theta_G \mid s=s_\phi)p-1-c=\frac{(1+R)\beta p}{\beta+(1-\beta)(1-\alpha)}-1-c>0 \qquad \text{(A3)}$$

That is, $\alpha > \dfrac{R\beta p+\beta p-c-1}{\beta c+\beta-c-1}$.

3.1.1 Discussion of the assumptions regarding borrower

As seen above, in our economy, the borrowers' behaviour is taken as exogenously given. That is, borrowers always seek loans as long as the total borrowing cost (loan rate plus transaction fee/guarantee fee) is no more than the borrowers' outside option; and the loans are paid off or defaulted at a given probability. This setting for the borrowers is apparently extremely simple and "passive", for which there are two reasons. First, our main focus is how the platform interacts with the lender under different business models of P2P lending. Considering the borrower decision problem endogenously would therefore complicate our model. Second, in reality, there are far more borrowers than lenders in P2P lending markets, given that consumers and small businesses struggle to access finance through China's state-dominated financial system. We believe it is reasonable to assume that borrower competition leads to the result that a borrower is always willing to take a loan offer as long as the total borrowing cost does not exceed her outside option.

More importantly, borrowers are assumed to have no initial wealth that can be used as acceptable collateral, and P2P lending is *unsecured* lending. This assumption is consistent with the reality that unsecured lending is a standard lending model in China's P2P lending market. By assuming that low risk borrowers are able to access sufficient collateral, Bester (1985,1987) shows different contracts can be used as a self-selection

[9] For discussion of limitation of the assumption, see section 8.3.

(screening) mechanism because low risk borrowers are more inclined to accept an increase in collateral requirements for a certain reduction in the interest rate than high risk borrowers. In this case, a separating equilibrium can be reached in which low risk borrowers choose loan contracts with high collateral and a low interest rate while high risk borrowers choose loan contracts with low collateral and a high interest rate. Since a borrower does not need to pledge collateral to obtain a P2P loan, the classic "collateral-interest rate" self-selection contract of Bester (1985,1987) is not feasible for P2P lending. Instead of designing such a self-selection contract, the platform can (imperfectly) sort borrowers by using its proprietary screening technology, as discussed above.

3.2 Structure of the lending game

3.2.1 The game structure under the non-guarantee model

Under the non-guarantee model, as mentioned previously, the platform faces an intertemporal trade-off between setting lax screening standards to increase short-term profits and honestly disclosing borrower credit risk to improve its long-term reputation. To capture the intertemporal nature, we consider a discrete time two period interaction where time is indexed $t = 0,1$. Platforms and lenders live for two periods, while borrowers only live for one period. There is only one borrower in a period. At each period, the game only looks at the interaction among a borrower, lender and platform

A. Period 0

Morning, period 0: A borrower submits an initial loan application to the platform. Only the platform can see the initial loan application. The platform *does not* publish the initial loan application and thus lenders cannot see it.

Mid-day, period 0: The platform runs a credit check on the submitted initial loan application to screen out a possible "bad" borrower. Due to the imperfection of screening technology, as shown in (1), the platform only detects bad borrowers with probability α. After (imperfectly) observing the borrower's type, the platform decides whether or not to approve the initial loan application. Specifically, the platform's screening (loan approval) strategy is characterized by the following two probability distributions:

$$prob(\tau = Approval \mid s = s_{\phi}) = 1, \; prob(\tau = Approval \mid s = s_B) = \eta_t \quad (2)$$

At period 0, this means that the platform always approves a loan application if it observes a "no-bad signal" and approves a loan application with probability $\eta_0 \in [0, \bar{\eta}]$, $\bar{\eta} \in (0,1)$ if it observes a "bad signal". In other words, the platform "lies" to lenders about borrower quality with probability η_0. $\bar{\eta}$ corresponds to the laxest screening policy available. If the platform approves the initial loan application (in the case of a "bad" signal, it approves with probability η_0), then it sets the loan rate r_0 and the transaction fee a_0 at this period. The borrower pays the transaction fee to the platform only if the loan is successfully funded later. The loan rate is paid to lenders by the borrower when the loan matures. The approved initial application becomes a loan listing, which can be viewed and bid upon by lenders on the platform's website. Again, note that lenders can only see approved initial loan applications (that is, loan listings) and *cannot* see the initial loan applications that are rejected by the platform.

Afternoon, period 0: Platforms are of two types: $\omega = \{T, O\}$, i.e. $\omega = T$ when it is truthful type; $\omega = O$ when it is opportunistic type. If a platform is the truthful type, it only approves initial loan applications with "no-bad" signals and always rejects initial loan applications with "bad" signals, i.e., chooses $\eta_0 = 0$. That a truthful platform always reports borrower credit risks honestly could be explained by the possibility that a truthful platform has a sufficiently high cost for the untruthful disclosure of information. We take such a cost is exogenous to the model, and it is not our focus. By contrast, if a platform is the opportunistic type, it strategically chooses $\eta_0 > 0$ to maximize its payoffs. That is, an opportunistic platform approves known "bad" borrowers with probability η_0. After lenders observe a loan listing, "Nature" immediately assigns a *prior* belief about the platform's type to lenders. That is, lenders have *a prior* probability assessment q_0 of the platform being the truthful type and $1 - q_0$ of the platform being of the opportunistic type. The platform knows its own type while lenders only observe a probability distribution over the platform's type. Therefore, q_0 measures the initial reputation of the platform. The setting for platform type is directly adopted from the reputation game framework in Chemmanur and Fulghieri (1994), Mathis et al. (2009) and Fulghieri et al. (2013), which are in the spirit of Kreps and Wilson (1982a) and Milgrom and Roberts' (1982) adverse selection approach.

Evening, period 0: In this stage, lenders form their beliefs about the expected return of the loan listing and then decide whether or not to finance the loan. The lenders' valuation of the loan depends not only on the platform's pricing strategy observed by the lenders (that is, the loan rate preset by the platform) but also on lender's beliefs regarding the credibility of the platform's information production (that is, the platform's reputation). Specifically, each lender computes the loan's perceived expected return in her mind based on the loan rate and the platform's reputation. Assume each lender has a willingness to lend(WTL). A lender's WTL is the lowest perceived expected return (i.e., her belief about the loan's expected return) at which she is willing to lend. A lender finances the loan if and only if the perceived expected return on the loan is greater or equal to her WTL. The details of the lenders' decision-making will be specified in section 4.1.

B. Period 1

Morning, period 1: The loan (if issued) at period 0 matures and the outcome is realized. After observing the realized loan outcome, repaid or default, which is denoted as $\upsilon_0 = RP\, or\, DF$, lenders update their beliefs about the platform's type from q_0 to q_1^X. $X = \{RP, DF\}$, which corresponds to the loan outcome. The details of the updating process will be specified in section 4.1.

Mid-day, period 1: Another borrower, either "good" or "bad", approaches the platform and submits her initial loan application. As in the period 0, the initial loan application is only visible to the platform (unless it is approved later).

Afternoon, period 1: The platform's screening ability (α) remains constant across periods. As the period 0, the platform only detects bad borrowers with probability

α .After imperfectly observing the borrower's true type, the platform chooses screening policy η_1 and sets the loan rate r_1 and the transaction fee a_1 for the approved initial loan application. The truthful platform always chooses $\eta_1 = 0$, while the opportunistic platform chooses η_1 strategically.

Evening, period 1: Similar to period 0, each lender computes the loan's perceived expected return in her mind based on the observed loan rate and the platform's *updated* reputation. A lender funds the loan if and only if the perceived expected return on the loan is greater or equal to her WTL.

Midnight, period 1: The loan (if issued) at period 1 matures, and outcome is realized, i.e. $\upsilon_1 = RP\, or\ DF$. The game concludes.

Figure 9 summarizes the timeline of main events for the lending game under the non-guarantee model and the game tree is displayed in figures 10, which will be further formalized in sections 4.1 and 4.2.

3.2.2 The game structure under the guarantee model

Under the guarantee model, the platform essentially serves as the guarantor for the repayment of the outstanding principal upon the event of default. As discussed in chapter 1, the platform is subject to the "rigid repayment" assumption in China's unique institutional environment, so we can rule out the possibility that the platform chooses strategic default and does not compensate the lender in the event of a borrower default. In this case, since the platform has enough "skin in the game", it obviously acts as a truthful type that always screens out known "bad" borrowers[10]

[10] Consider a hypothetical setting where the platform approves a known "bad" borrower with probability η and set guarantee fee as a. Denote π as the platform's payoff, on a successfully funded loan. π can be written as:

$$\pi = (a-c)(\beta + (1-\beta)(1-\alpha) + (1-\beta)\alpha\eta) - (\beta(1-p) + (1-\beta)(1-\alpha) + (1-\beta)\alpha\eta) \qquad (3)$$

$\frac{\partial \pi}{\partial \eta} = \alpha(1-\beta)(a-c-1)$. As we know $\beta < 1$ and $0 < a, c < 1$, so we have $1-\beta > 0$ and $a-c-1 < 0$. Therefore $\frac{\partial \pi}{\partial \eta} < 0$. Hence, it is optimal for the platform choosing $\eta = 0$. That is to say, the platform always acts as truthful type and rejects all known "bad" borrowers.

Time

Period 0

Morning: A borrower submits an initial loan application to the platform.

Mid-day: The platform imperfectly observes the borrower's true type and chooses screening policy η_0 and sets the loan rate r_0 and the transaction fee a_0 for the approved initial loan application.

Afternoon: "Nature" assigns a *prior* belief, q_0, about the platform's type to the lender.

Evening: The lender computes the perceived expected return of the loan based on q_0 and r_0. Then the lender decides whether or not to finance the loan based on the perceived expected return.

Period 1

Morning: The loan matures, and the outcome is realized. After observing the loan outcome, default or repaid, the lender updates her belief about the platform's type from q_0 to q_1^X.

Mid-day: Another borrower submits an initial loan application to the platform.

Afternoon: The platform imperfectly observes the borrower's true type and chooses screening policy η_1 and sets the loan rate r_1 and the transaction fee a_1 for the approved initial loan application.

Evening: The lender forms the perceived expected return on the loan based on q_1^X and r_1. Then the lender decides whether or not to finance the loan based on the perceived expected return.

Midnight: The loan matures, and the outcome is realized. The game concludes.

Figure 9 Timeline of main events: the non-guarantee model

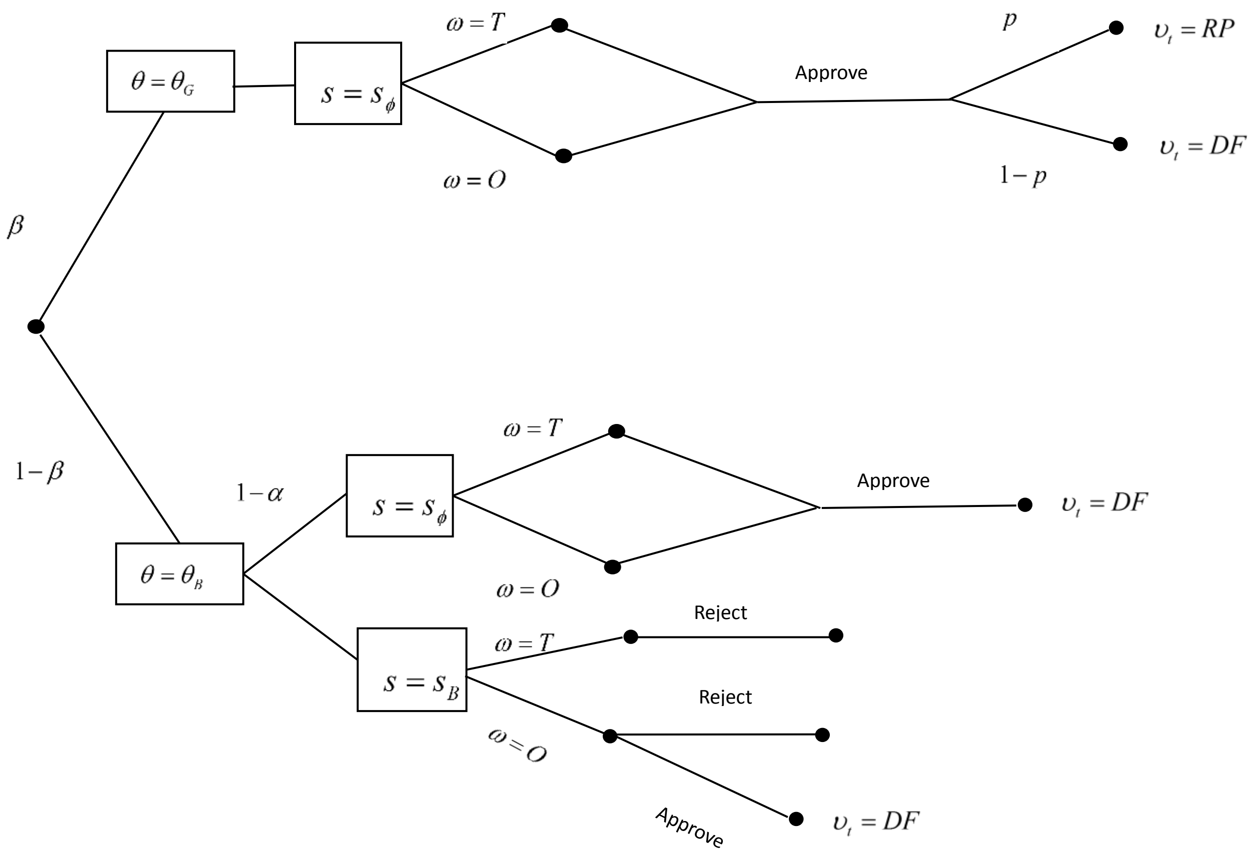

Figure 10 Game tree in the non-guarantee model

It is worth stating that lenders have rational expectations, which means that they are assumed to know the market parameters, so they can expect the platform to never "lie" under the guarantee model as we have proved. Since there are no reputation concerns under the guarantee model, the lender-platform interaction is modelled as a single-period game. The platform faces a trade-off between setting a higher guarantee fee (which implies a lower loan rate and lower lenders' expected return) or a higher loan rate (which suggests high lenders' expected return but a lower guarantee fee). Please note that, we call the fee borrowers pay to the platform under the guarantee model as guarantee fee, in order to distinguish it from the "transaction fee" in the case of the non-guarantee model. The specific sequence of events is given as follows:

Morning: A borrower approaches the platform and submits an initial loan application. As in the non-guarantee model, the platform never publishes the initial loan application and it is not visible to lenders (unless it is approved later)

Mid-day: The platform is endowed with the same screening technology as the case of the non-guarantee model. That is, the platform detects a “bad” borrower with probability α and a “good” borrower with certainty. The platform always approves the initial loan applications if it observes a “no-bad signal” and rejects *all* initial loan application if it observes a “bad signal” (that is, a known “bad” borrower). That is, the platform’s screening strategy is fixed to choosing $\eta = 0$.Then, the platform sets the loan rate r_G and the guarantee fee a_G for the approved initial loan application.

Afternoon: Because lenders have rational expectations, they can also predict that the platform acts as the truthful type under the guarantee model. Then, each lender forms the loan’s perceived expected return in her mind based on the loan rate r_G and guarantee fee a_G. The lending decision rule is the same as in the case of the non-guarantee model. A lender finances the loan if and only if her WTL is no greater than the perceived expected return on the loan.

Evening-Midnight: The loan (if issued) matures and the outcome is realized. Payoff realizes. The game concludes.

Figure 11 summarizes the sequence of main events of the lending game under the guarantee model and the game tree is displayed in figure 12, which will be formalized in sections 4.1 and 4.2.

Morning: A borrower submits an initial loan application to the platform.
Mid-day: The platform imperfectly observes the borrower’s true type and approves borrowers with a ‘no-bad’ signal and rejects borrowers with a ‘bad signal’ and sets the loan rate r_G and the guarantee fee a_G for the approved loan applications.
Afternoon: The lender forms the perceived expected return of the loan based on r_G and a_G. Then the lender decides whether or not to invest in the loan based on that perceived expected return.
Evening-Midnight: The loan matures, and the outcome is realized. The game concludes.

Figure 11 Timeline of main events: the guarantee model

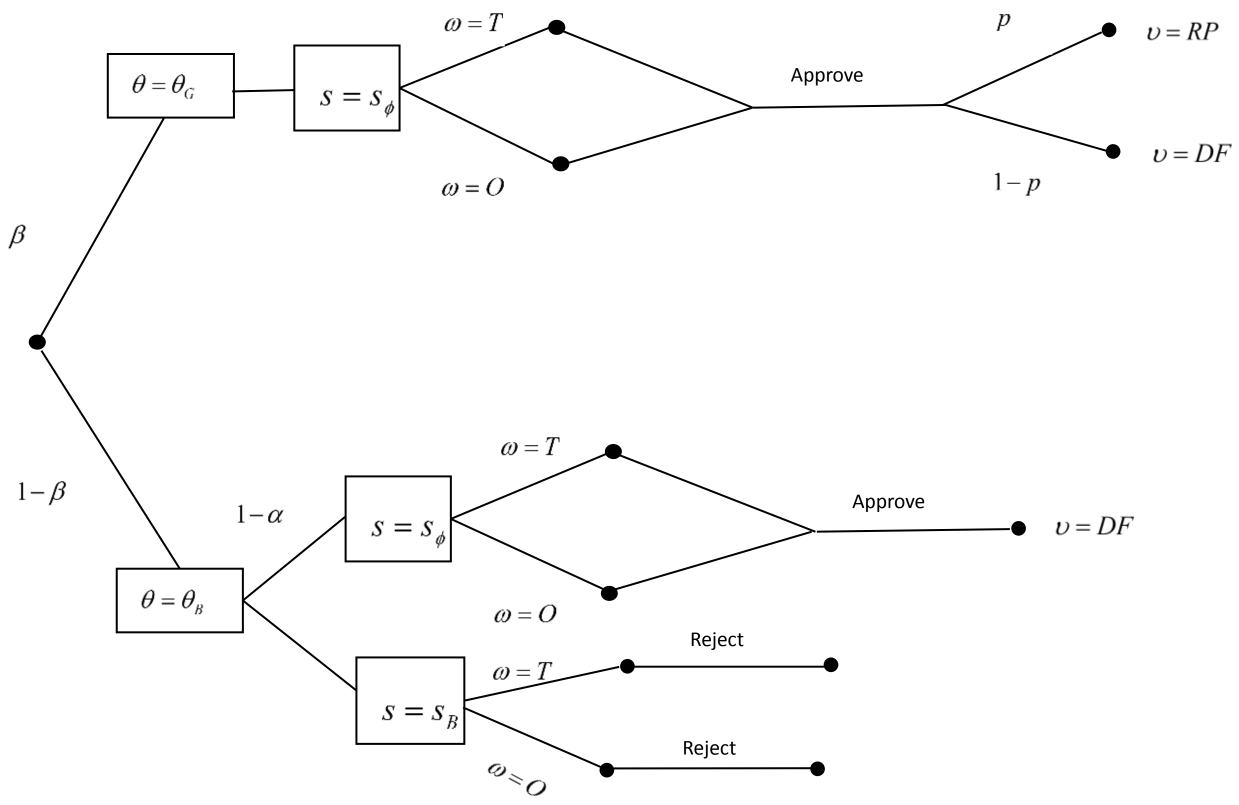

Figure 12 Game tree in the guarantee model

Chapter 4. Decision problems, optimal strategies and welfare comparison

Based on the setups given in the last chapter, this chapter derives the platform's behaviours under the non-guarantee model and guarantee model. We first characterize lenders' decision rule and platform's optimization problem. Then, we solve for platform's optimal strategies of screening and pricing. Finally, we conduct a welfare comparison for the competitive market.

4.1 Lenders' valuation and decision

4.1.1 Lenders' willingness to lend

This section characterizes lenders' valuation rule for loan listings observed on the platform and how lenders make the lending decision. First, to model lenders' lending valuation, we introduce lenders' willingness to lend (WTL), which is adopted from Wei and Lin (2016). Each loan is ￥1 and ￥ $\frac{1}{j}$ is the minimum investment amount for each loan. We assume each lender contributes at most ￥ $\frac{1}{j}$ for a loan and has a willingness to lend. A lender's WTL is the lowest perceived expected return (i.e., her belief about the loan's expected return) at which she is willing to lend. A lender will never fund a loan listing whose perceived expected return is below her WTL (WTL will be formally discussed in (7)). Although the lender is long-living in our model, for simplicity, we assume that the lender has no need for intertemporal allocation, such that she is only interested in the single-period return. In each period, after observing an approved loan listing, a lender computes the loan's perceived expected return, which is denoted as $R_t^{PER}, t = 0,1$, based on the loan rate and the platform's reputation and then makes her lending decision (as discussed later). For simplicity, we assume that each lender's WTL, denoted by W, is homogeneous and time-invariant and follows a uniform distribution on $[0,\bar{R}]$, where $\bar{R}>0$ is the highest possible expected return on the loan, which later will be specified as $\bar{R}_N$ and $\bar{R}_G$, corresponding to the non-guarantee model or guarantee model, respectively. Like Wei and Lin (2016), we assume there are always sufficient lenders to fund the loan. Given that the lender's decision-making process is homogeneous, our analysis only needs to focus on one (representative) lender (henceforth, "the lender"). Let $F(x)$ be the cumulative distribution function of uniform distribution on $\left[0,\bar{R}\right]$; now, we can derive the probability of being fully funded for an approved loan listing, $prob(funded)$:

$$prob(funded)=\begin{cases} prob(R_t^{PER}\geq W)=\dfrac{R_t^{PER}}{\bar{R}}, t=0,1 & R_t^{PER}>0 \\ 0 & R_t^{PER}\leq 0 \end{cases} \tag{4}$$

Discussion of the lender's WTL

We must acknowledge that the setting of the lender's WTL is extremely simplified. However, the basic idea of the probability of funding success is that the probability is an increasing function of the lender's perceived expected return. Obviously, (4) has such a nature because $\dfrac{\partial prob(R_t^{PER}\geq W)}{\partial R_t^{PER}}=\dfrac{1}{\bar{R}}>0$ .Additionally, by applying (4), it is convenient to obtain an analytic solution. Instead, a more realistic assumption about the lender's WTL, for example, could be:

Assume there are n lenders in the platform. Let W_i denote lender i's WTL, i=1,2,…,n, $W_1,W_2,...,W_n \overset{iid}{\sim} Unif[0,\bar{R}]$,and let $W_{(j)}$ be the j-th lowest value among $W_1,W_2,...,W_n$ and By applying order statistics distribution, the probability of being fully funded can be written as:

$$prob(R_i^{PER}\geq W_{(j)})=\int_{-\infty}^{R_i^{PER}}\frac{n!}{(j-1)!(n-j)!}\frac{1}{\bar{R}}\left(\frac{u}{\bar{R}}\right)^{j-1}\left(1-\frac{u}{\bar{R}}\right)^{n-j}du \tag{5}$$

However, it is difficult to obtain an analytic solution of a maximization problem under (5).

4.1.2 The belief update process and lending decisions under the non-guarantee model

This section derives the lender's lending decision in each period under the non-guarantee model. The core of the lender's problem is to form a belief about the platform's type and then compute the perceived expected return for the loan listing that she observes based on that belief. The lender will update her belief about the platform's type as she observes the loan performances over time.

In period 0, we assume "Nature" assigns a *prior* belief about the platform's type to the lender after she observes an approved loan listing. Denote τ_0 to be the loan approval outcome in period 0. This *prior* belief, which is denoted as q_0, can be formally characterized by the following assumption:

$$q_0 = prob(\omega = T \mid \tau_0 = approval) \qquad \text{(A4) (6)}$$

Note that the *prior* belief is characterized by a conditional probability, while the similar *prior* belief in the models of credit rating agencies, for example, in Fulghieri et al. (2013) and Mathis et al. (2009), is characterized by an *unconditional* probability. This occurs, as a standard practice in China's P2P lending, the platform *does not* publish the information about the loan listings that fail to pass its credit check and the lender can therefore only view the profiles of the approved loan applications. This means that the *prior* belief about platform type is formed in the lender's mind immediately after seeing an approved loan listing. In Lemma 3, we consider another setting where the platform reveals the rejected loan listings, and we discuss how this change affects the platform reputation-building.

As mentioned above, the lender is willing to finance the loan if and only if $R_0^{PER} \geq W$, i.e., the lender's WTL is no greater than R_0^{PER}, the perceived expected return for the loan. Denoting m_0 as the lender's actual investment in period 0, we have:

$$m_0 = \begin{cases} \dfrac{1}{j} & if\ R_0^{PER} \geq W \\ 0 & otherwise \end{cases} \qquad (7)$$

R_0^{PER}, the lender's perceived expected return on the loan, is computed by the lender from q_0, $\tilde{\eta}_0$ and r_0 ,the loan rate preset by the platform:

$$\begin{aligned} R_0^{PER} &= (1+r_0)\, prob(\theta = \theta_G \mid \tau_0 = approval)\, p - 1 \\ &= \frac{(1+r_0)\beta p}{\beta + (1-\beta)(1-\alpha) + (1-q_0)(1-\beta)\alpha\tilde{\eta}_0} - 1 \end{aligned} \tag{8}$$

where $\tilde{\eta}_0$ denotes the lender's belief about η_0, the platform's actual screening strategy in period 0. As discussed in (4), the probability of being fully funded for the loan in period 0 can be given as:

$$prob(R_0^{PER} \geq W) = \frac{R_0^{PER}}{\bar{R}_N} \tag{9}$$

where $\bar{R}_N$ is given as $\dfrac{(1+R)\beta p}{\beta + (1-\beta)(1-\alpha)} - 1$, which is the theoretical highest expected return on the loan under the non-guarantee model. By assuming that the lender's WTL is uniformly distributed on $[0, \dfrac{(1+R)\beta p}{\beta + (1-\beta)(1-\alpha)} - 1]$, the funding probability is strictly restricted to $[0,1]$. It is important to note that the funding probability is determined by the lender's belief about the platform's screening strategy $\tilde{\eta}_0$ rather than the platform's *actual* screening strategy η_0.This implies that the platform takes the lender's response as given when optimizing η_0.

If the loan has been successfully funded in period 0, the outcome of the loan, that is, whether the borrower repays the loan or defaults at the end of period 0,i.e. $\upsilon_0 = RP\, or\, DF$, becomes observable to the lender at the beginning of period 1.The lender updates the platform's reputation after observing the loan outcome using Bayes' rule. We denote this updated reputation as q_1^{RP} or q_1^{DF} , corresponding to the loan being revealed as repaid or defaulted,

$$q_1^{RP} = prob(\omega = T \mid \upsilon_0 = RP, \tau_0 = approval) = \frac{q_0\beta p}{q_0\beta p + (1-q_0)\beta p} = q_0 \tag{10}$$

$$q_1^{DF} = prob(\omega = T \mid \upsilon_0 = DF, \tau_0 = approval)$$
$$= \frac{q_0(\beta(1-p)+(1-\beta)(1-\alpha))}{\beta(1-p)+(1-\beta)(1-\alpha)+(1-q_0)(1-\beta)\alpha\tilde{\eta}_0} \quad (11)$$

$q_1^{DF} < q_0$ when $\tilde{\eta}_0 > 0$

As in period 0, in period 1, the lender is willing to finance the loan if and only if $R_1^{PER,X} \geq W$, $X = \{RP, DF\}$; denoting m_1 as the lender's actual investment, we have:

$$m_1 = \begin{cases} \frac{1}{j} & if\, R_1^{PER,X} \geq W \\ 0 & otherwise \end{cases} \quad (12)$$

Similarly, $R_1^{PER,X}$ is derived from the updated reputations, q_1^X, $X = \{RP, DF\}$, $\tilde{\eta}_1$ and r_1, the loan rate preset by the platform:

$$R_1^{PER,X} = (1+r_1)\, prob(\theta = \theta_G \mid \tau_1 = approval)\, p - 1$$
$$= \frac{(1+r_1)\beta p}{\beta+(1-\beta)(1-\alpha)+(1-q_1^X)(1-\beta)\alpha\tilde{\eta}_1} - 1 \quad (13)$$

where $\tilde{\eta}_1$ denotes the lender's belief about η_1, the platform's actual screening strategy in period 1. In addition, the probability of funding success for the loan in period 1 can be given as:

$$prob(R_1^{PER,X} \geq W) = \frac{R_1^{PER,X}}{\bar{R}} \quad (14)$$

4.1.3 Lending decisions under the guarantee model

This section discusses the lender's lending decision-making under the guarantee model. As we have proved, the platform never approves known "bad" borrowers under the guarantee model, and the lender also expects that. Then there is no "belief updating process" and we only need to consider the lending decision in a single period setting. After observing the loan rate preset by the platform, the lender computes the perceived expected return on the loan, which is given as:

$$R_G^{PER} = (1+r_G)prob(\theta=\theta_G \mid \tau=approval)p + prob(\theta=\theta_G \mid \tau=approval)(1-p) + prob(\theta=\theta_B \mid \tau=approval) - 1$$
$$= \frac{(1+r_G)\beta p + \beta(1-p) + (1-\beta)(1-\alpha)}{\beta + (1-\beta)(1-\alpha)} - 1 \tag{15}$$

Similar to the non-guarantee model, the lender is willing to finance the loan if and only if $R_G^{PER} \geq W$, i.e., the lender's WTL is no greater than the perceived expected return on the loan. Denoting m_G as the lender's actual investment, we have:

$$m_G = \begin{cases} \frac{1}{j} & if\ R_G^{PER} \geq W \\ 0 & otherwise \end{cases} \tag{16}$$

To restrict the funding probability to $[0,1]$, we assume that the lender's WTL under the guarantee model is uniformly distributed on $[0, \bar{R}_G]$. Similar to $\bar{R}_N$, $\bar{R}_G = \frac{(1+R)\beta p + \beta(1-p) + (1-\beta)(1-\alpha)}{\beta + (1-\beta)(1-\alpha)} - 1$, is highest possible expected return on the loan under the guarantee model. This is similar to that under the non-guarantee model. Then, the probability of funding success for the loan can be given as:

$$prob(R_G^{PER} \geq W) = \frac{R_G^{PER}}{\bar{R}_G} \tag{17}$$

We must note that, the lender's decision rules characterized in sections 4.1.2 and 4.1.3 imply that the lender's choice of participating on the non-guarantee model platform or the guarantee model platform is exogenous, and interactions between the two lending models are not considered in our setting. In other words, the lending decision is solely based on the expected return on one specific lending model, and the opportunity cost of choosing another lending model is not incorporated in our model.

4.2 Platform's optimization problem

Taking the lender's strategies as given, this section discusses the platform's optimization problem. First, we characterize the platform's optimization problem for the non-guarantee model under monopoly and competitive markets. Then, we do the same for the guarantee model.

4.2.1 Platform's optimization problem for the non-guarantee model

A. The monopoly case

The platform faces a dynamic decision problem under the non-guarantee model. As discussed in section 3.2.1, consider a discrete time two period interaction where time is indexed $t = 0,1$. First, we consider a *monopoly* market where the platform acts as a price-setting monopolist. Backward induction is used. The platform works backwards from the last period, choosing screening strategy η_t, and the level of the loan rate r_t and the transaction fee a_t in each period that is optimal for the remainder of the game.

Period 1

In period 1, which is also the *last* period of the game, the platform chooses η_1, r_1 and a_1 to maximize the expected payoff in that period:

$$\max_{\eta_1, a_1, r_1} \pi_1 = (a_1 - c)(\beta + (1-\beta)(1-\alpha) + (1-\beta)\alpha\eta_1)\, prob(R_1^{PER,X} \geq W) \tag{18}$$

where q_1^X and $R_1^{PER,X}$, $X = \{RP, DF\}$ are given by (10), (11) and (13).The first term, $a_1 - c$, reflects the platform's payoff on a fully funded loan; the second term, $(\beta + (1-\beta)(1-\alpha) + (1-\beta)\alpha\eta_1)$, is the probability that platform approves a loan; and $prob(R_1^{PER,X} \geq W)$ is the probability of funding.

The platform's strategy set (η_1, a_1, r_1) must satisfy the lender's and borrower's individual rationality (or participation) constraint:

$$R_1^{PER,X} = \frac{(1+r_1)\beta p}{\beta + (1-\beta)(1-\alpha) + (1-q_1^X)(1-\beta)\alpha\tilde{\eta}_1} - 1 \geq 0 \tag{19}$$

$$R - r_1 - a_1 \geq 0 \tag{20}$$

As discussed in section 3.1, a borrower is assumed to be willing to accept any loan offer whose total borrowing cost is no more than her outside option due to borrower competition.

Period 0

In period 0, the platform chooses η_0 , r_0 and a_0 to maximize the sum of the expected payoff obtained in periods 0 and 1:

$$\max_{\eta_0, a_0, r_0} \pi_{sum(0,1)} = \beta((a_0 - c) prob(R_0^{PER} \geq W) + p\pi_1(q_1^{RP}) + (1-p)\pi_1(q_1^{DF})) \\ +(1-\beta)((1-\alpha+\alpha\eta_0)((a_0 - c) prob(R_0^{PER} \geq W) + \pi_1(q_1^{DF})) + \alpha(1-\eta_0)\pi_1(q_0)) \tag{21}$$

where the first term reflects the case in which the borrower's type is "good" ($\theta = \theta_G$) in period 0. If the borrower's type is "good", the platform always approves its loan listing and thus earns a transaction fee net of the monitoring cost, $(a_0 - c) prob(R_0^{PER} \geq W)$ in period 0. The expected period 1 payoff depends on the outcome of the period 0 loan, $\pi_1(q_1^{RP})$ or $\pi_1(q_1^{DF})$, because the loan outcome affects the platform's reputation. The second term represents the case in which the borrower's type is "bad" ($\theta = \theta_B$).If the borrower's type is "bad", the platform's expected payoff depends on whether the platform approves the loan listing (with probability $1-\alpha+\alpha\eta_0$) or not (with probability $\alpha(1-\eta_0)$). In the former case, the platform earns a transaction fee net of monitor cost, $(a_0 - c) prob(R_0^{PER} \geq W)$, in period 0 and expected period 1 payoff depends on $\pi_1(q_1^{DF})$. In the latter case, the platform does not approve the loan in the period 0 and enters period 1 with a reputation of q_0. Thus, the platform's payoff is given by $\pi_1(q_0)$, the transaction fee that it earns in period 1 only. Furthermore, the platform's strategy set (η_1, a_1, r_1) must satisfy the following individual rationality constraints:

$$R_0^{PER} = \frac{(1+r_0)\beta p}{\beta + (1-\beta)(1-\alpha) + (1-q_0)(1-\beta)\alpha\tilde{\eta}_0} - 1 \geq 0 \tag{22}$$

$$R - r_0 - a_0 \geq 0 \tag{23}$$

B. The competitive case

In a *competitive* market, there exists many platforms with identical screening ability

(α) that compete for lenders. Individual platforms have no market power and takes the prices (transaction fee and loan rate) as outside their control. In this case, the platform's problem is that taking the loan rate r_t and the transaction fee a_t as given, choose screening strategy η_t in each period that is optimal for the remainder of the game.

Specifically, in period 1, the platform chooses η_1 to maximize the expected payoff in that period for a given a_1 and r_1:

$$\max_{\eta_1} \pi_1 = (a-c)(\beta+(1-\beta)(1-\alpha)+(1-\beta)\alpha\eta_1)\, prob(R_1^{PER,X} \geq W) \tag{24}$$

where q_1^X and $R_1^{PER,X}$, $X=\{RP,DF\}$ are given by (10), (11) and (13).

Similarly, the lender's and the borrower's individual rationality constraint must also hold:

$$R_1^{PER,X} = \frac{(1+r_1)\beta p}{\beta+(1-\beta)(1-\alpha)+(1-q_1^X)(1-\beta)\alpha\tilde{\eta}_1} - 1 \geq 0 \tag{25}$$

$$R - r_1 - a_1 \geq 0 \tag{26}$$

Competition among platforms generates the following zero profit condition:

$$(a_1-c)(\beta+(1-\beta)(1-\alpha)+(1-\beta)\alpha\eta_1) = 0 \tag{27}$$

Additionally, the competitive loan rate maximizes the lender's perceived expected return.

$$r_1 = \arg\max_{0<r_1\leq R-a_1} \frac{(1+r_1)\beta p}{\beta+(1-\beta)(1-\alpha)+(1-q_1^X)(1-\beta)\alpha\tilde{\eta}_1} - 1 \tag{28}$$

In period 0, the platform's problem is similar to that in period 1. The platform chooses η_0 to maximize the expected payoff in period 0 for a given a_0 and r_0:

$$\max_{\eta_0} \pi_0 = (a-c)(\beta+(1-\beta)(1-\alpha)+(1-\beta)\alpha\eta_0)\, prob(R_0^{PER} \geq W) \tag{29}$$

where R_0^{PER} is given by (8). Note that given that the platform's payoff in period 1 is strictly zero, the platform's problem is therefore to maximize the single period payoff of period 0.

As in period 1, the lender's and the borrower's individual rationality constraint must hold:

$$R_0^{PER} = \frac{(1+r_0)\beta p}{\beta+(1-\beta)(1-\alpha)+(1-q_0)(1-\beta)\alpha\tilde{\eta}_0} - 1 \geq 0 \tag{30}$$

$$R - r_0 - a_0 \geq 0 \tag{31}$$

Platform competition leads to the following zero profit condition:

$$(a_0 - c)(\beta+(1-\beta)(1-\alpha)+(1-\beta)\alpha\eta_0) = 0 \tag{32}$$

The equilibrium loan rate under perfect competition maximizes the lender's perceived expected return:

$$r_0 = \underset{0<r_0\leq R-a_0}{\arg\max} \frac{(1+r_0)\beta p}{\beta+(1-\beta)(1-\alpha)+(1-q_0)(1-\beta)\alpha\tilde{\eta}_0} - 1 \tag{33}$$

4.2.2 Platform's optimization problem for the guarantee model

In this section, we characterize the platform's problem for the guarantee model. As mentioned previously, the platform acts as the guarantor for the repayment of the outstanding principal upon the event of default. In this case, the platform screens borrowers honestly because it obviously has enough "skin in the game". That is, the platform acts as a truthful type such that choose $\eta = 0$.

A. The monopoly case

In a monopoly market, the platform faces no competition and enjoys the power of setting the price for the loans. Naturally, the guarantee fee is higher than transaction fee under the guarantee model, because as the guarantor, the platform bears the default risk of the loan listing that it approves. Part of the guarantee fee is to compensate for the future loan loss that will be covered by the platform in the event of default. Given a total borrowing cost (sum of the guarantee fee and the loan rate), a higher guarantee fee implies a lower loan rate, and thus, of course, a lower perceived expected return for the loan, which relates to a lower probability of funding success. Since the platform can pocket the guarantee fee only if the loan is successfully funded, it faces a trade-off between earning a higher guarantee fee and suffering from a lower probability of funding success caused by the lower loan rate. Then, the platform's problem is to choose the level of the guarantee fee, a_G ,and the loan rate, r_G ,to maximize its payoff:

$$\max_{a_G, r_G} \pi_G = ((a_G - c)(\beta + (1-\beta)(1-\alpha)) - \beta(1-p) - \alpha(1-\beta))\, prob(R_G^{PER} \geq W) \qquad (34)$$

The pricing strategy set (a_G, r_G) must satisfy the lender's individual rationality constraints:

$$R_G^{PER} = \frac{(1+r_G)\beta p + \beta(1-p) + (1-\beta)(1-\alpha)}{\beta + (1-\beta)(1-\alpha)} - 1 \geq 0 \qquad (35)$$

B. The competitive case

Under perfect competition, platforms compete for lenders. In this case, individual platforms have no pricing power and act as a price-taker. The competitive guarantee fee is determined by the following zero profit condition:

$$(a_G - c)(\beta + (1-\beta)(1-\alpha)) - \beta(1-p) - (1-\alpha)(1-\beta) = 0 \qquad (36)$$

This means that there is no strict incentive for platform to enter or to leave the industry in equilibrium.

As in the non-guarantee model, the competitive loan rate maximizes the lender's perceived expected return:

$$r_G = \arg\max_{0 < r_G \leq R - a_G} \frac{(1+r_G)\beta p + \beta(1-p) + (1-\beta)(1-\alpha)}{\beta + (1-\beta)(1-\alpha)} - 1 \qquad (37)$$

4.3 Equilibrium strategies of screening and pricing

4.3.1 Equilibrium strategies under the non-guarantee model

A. Definition of equilibrium

Having characterized the lender's decision rule and the platform's problem, we solve for the equilibrium of the non-guarantee model. The equilibrium concept we use is that of a Perfect Bayesian Equilibrium (PBE). Formally, a PBE of our economy consists of the platform's screening and pricing strategies (a_t, r_t, η_t) , the lender's lending decision m_t and a system of beliefs formed by the lender in response to these strategies that satisfy the following conditions:

(1) The platform's strategy profile (a_t, r_t, η_t) maximize its payoff, given the equilibrium strategies of the other agents and the set of equilibrium beliefs formed by the lender.

(2) The lender's lending decision m_t is the optimal response, given the strategies of the other agents and her beliefs.

(3) The lender updates her beliefs about the platform's type by using Bayes' rule (along the equilibrium path).

(4) The lender's belief about the platform's screening strategy, $\tilde{\eta}_t$, must correct in equilibrium. This means that, although the platform's actual screening policy, η_t, is not observable to the lender, in equilibrium, the screening policy expected by the lender has to coincide with the actual screening policy.

(5) Any deviation from equilibrium, by the platform, is met by the lender's (off-the-equilibrium path) beliefs that yield a lower expected pay-off for the platform, compared with that obtained in equilibrium.

PBE is equivalent to sequential equilibrium if each player has only two types, or there are only two periods (Fudenberg and Tirole, 1991). Kreps and Wilson (1982b) proves that for every extensive game, there exists at least one sequential equilibrium.

B. Analysis of equilibrium strategies

We define borrower surplus as the total borrowing cost minus the borrower's outside option. In the case of non-guarantee model, the total borrowing cost is the sum of the transaction fee and the loan rate. Then we have the following lemma.

Lemma 1. ***In equilibrium, the borrower surplus is zero regardless of the competition structure,*** *that is,* $r_0 + a_0 = r_1 + a_1 = R$.

Proof. First look at the monopoly case. Consider period 1, let $TB_1 = r_1 + a_1$. We have,

$\frac{\partial \pi_1}{\partial TB_1} = \frac{(a-c)(\beta+(1-\beta)(1-\alpha)+(1-\beta)\alpha\eta_1)\beta p}{(\beta+(1-\beta)(1-\alpha)+(1-q_1^X)(1-\beta)\alpha\tilde{\eta}_1)\bar{R}_N} > 0$, therefore the platform maximizes its payoff in period 1 by setting $TB_1 = R$. Similarly, in period 0, let $TB_0 = r_0 + a_0$ we have,

$$\frac{\partial \pi_{sum(0,1)}}{\partial TB_0} = \beta((a_0-c)\frac{\beta p}{\bar{R}_N(\beta+(1-\beta)(1-\alpha)+(1-q_0)(1-\beta)\alpha\tilde{\eta}_0)}) + (1-\beta)((1-\alpha+\alpha\eta_0)((a_0-c)\frac{\beta p}{\bar{R}_N(\beta+(1-\beta)(1-\alpha)+(1-q_0)(1-\beta)\alpha\tilde{\eta}_0)}) > 0$$

, therefore the platform maximizes $\pi_{sum(0,1)}$ by setting $TB_0 = R$.

In the case of perfect competition, because the competitive loan rate maximizes the lender's perceived expected return, the competitive loan rate then reaches its upper bound, that is, $r_1 = R - a_1$. **Q.E.D.**

This result means that the individual rationality constraints for borrowers are binding under either a monopoly or competitive market. All borrower surplus is extracted by the platform and the lender. The rationale behind this is straightforward. First, as discussed above, due to borrower competition, a borrower is willing take a loan offer as long as the total borrowing cost is no more than R. The platform has all the bargaining power and can make a "take it or leave it" offer to borrowers who compete for loans. This defines borrowers' individual rationality constraint. Under a monopoly, as a price-setting monopolist, it's optimal for the platform to set the highest possible loan rate given the transaction fee, since it maximizes the likelihood of funding success. Under perfect competition, platforms compete for lenders ex ante on the loan rate; therefore, the equilibrium loan rate is the highest loan rate such that it attracts the most lenders.

Denote a_{Mt}^*, r_{Mt}^* and a_{Ct}^*, r_{Ct}^* as the platform's optimal transaction fee and loan rate in the monopoly and competitive markets at period t, respectively. We have:

Proposition 1. ***Regardless of the competition structure, the opportunistic platform always chooses the same pricing strategy as the truthful platform.***

Monopoly pricing

$$a_{M0}^{*}=a_{M1}^{*}=\frac{1}{2}\frac{R\beta p+\beta cp-\alpha\beta+\beta p+\alpha-1}{\beta p}, r_{M0}^{*}=r_{M1}^{*}=\frac{1}{2}\frac{R\beta p-\beta cp+\alpha\beta-\beta p-\alpha+1}{\beta p}.$$

Competitive pricing

$$a_{C0}^{*}=a_{C1}^{*}=c \quad, r_{C0}^{*}=r_{C1}^{*}=R-c \quad .$$

This is supported by the lender's off-the-equilibrium path beliefs that the lender sets $prob(\omega=T \mid \tau_t=approval)=0, \tilde{\eta}_t=1$ ***in response to any pricing strategy other than that characterized above.***

Proof. Consider the problem of the truthful platform under monopoly. Since the truthful platform always rejects known bad borrowers, we only need to solve its pricing strategy. Specifically, its problem is to choose loan rate and transaction fee to maximize its (single period) payoff:

$$\max_{r,a} \pi_t=(a-c)(\beta+(1-\beta)(1-\alpha))prob(R_t^{PER}\geq W)$$

$$s.t.\begin{cases} R=a+r \ (According\ to\ Lemma\ 1) \\ \dfrac{(1+r)\beta p}{\beta+(1-\beta)(1-\alpha)}-1\geq 0 \\ a-c\geq 0 \end{cases}$$

We initially ignore the constraints and solve for the "less-constrained" problem. Then we verify this solution satisfies the constraints. By substituting $r=R-a$ and applying first order condition $\frac{\partial \pi_t}{\partial a}=0$, we have:

$$a_{Mt}^{*}=\frac{1}{2}\frac{R\beta p+\beta cp-\alpha\beta+\beta p+\alpha-1}{\beta p}, r_{Mt}^{*}=\frac{1}{2}\frac{R\beta p-\beta cp+\alpha\beta-\beta p-\alpha+1}{\beta p}.$$

To ensure a_{Mt}^{*} is a maximiser, we check second order condition:

$$\frac{\partial^2\pi_t}{\partial a_{Mt}^{*\,2}}=-\frac{2\beta p}{\dfrac{(1+R)\beta p}{\beta+(1-\beta)(1-\alpha)}-1}$$

$\dfrac{(1+R)\beta p}{\beta+(1-\beta)(1-\alpha)}-1>0$ is equivalent to $\dfrac{R\beta p+\beta \mathrm{p}-1}{-1+\beta}<\alpha$

Because $\alpha>\dfrac{R\beta p+\beta p-c-1}{\beta c+\beta-c-1}$ (A3) and $\dfrac{R\beta p+\beta p-c-1}{\beta c+\beta-c-1}>\dfrac{R\beta p+\beta \mathrm{p}-1}{-1+\beta}$,

$\frac{R\beta p+\beta \mathrm{p}-1}{-1+\beta}<\alpha$ holds. So $\frac{\partial^2 \pi_t}{\partial a^2}<0$.

Now we verify $\frac{(1+r)\beta p}{\beta+(1-\beta)(1-\alpha)}-1>0$.

Solve $\frac{(1+r)\beta p}{\beta+(1-\beta)(1-\alpha)}-1>0$ for α, we have $\alpha>\frac{R\beta p-\beta cp+\beta p-1}{\beta-1}$,which holds because $\frac{R\beta p-\beta cp+\beta p-1}{\beta c+\beta-c-1}-\frac{R\beta p-\beta cp+\beta p-1}{\beta-1}=\frac{(R-c)\beta pc}{(1+c)(1-\beta)}>0$

Then we prove that given the lender's out-of-equilibrium beliefs, it is not optimal for the opportunistic platform to deviate from the pricing strategy above.

If the platform chooses $a^{'} \neq a^{*}$ or $r^{'} \neq r^{*}$, after observing this, the lender sets her beliefs about the platform' type and screening strategy as $prob(\omega=T \mid \tau_t=approval)=0, \tilde{\eta}_t=1$. Then the lender's perceived expected return becomes $(1+R-a')\times\beta\times p-c-1$. From (A1), we immediately have $(1+R-a')\times\beta\times p-c-1<0$. Since the lender never invests in a loan with negative *ex-ante* return, the platform earns zero transaction fee when deviating from the pricing strategy of the truthful platform. Therefore, it is optimal for the opportunistic platform to stick to the pricing strategy of the truthful platform in order to obtain a non-zero transaction fee.

Now consider the competitive market. If the platform is the truthful type, the competitive loan rate and transaction fee solves,

$$(a-c)(\beta+(1-\beta)(1-\alpha))=0$$

$$r=\underset{0<r\leq R-a}{\arg\max}\frac{(1+r)\beta p}{\beta+(1-\beta)(1-\alpha)}-1$$

Then the "truthful" competitive pricing is given as:

$a_{Ct}^{*}=c$, $r_{Ct}^{*}=R-c$.

If the platform deviates from the above pricing strategy, after observing that, the lender sets her beliefs about the platform' type and screening strategy as

$prob(\omega = T \mid \tau_t = approval) = 0, \tilde{\eta}_t = 1$. Then the lender's perceived expected return is negative and the likelihood of funding success is zero as the case of monopoly. Since the deviation generates no greater pay-off, platforms have no incentive to do so and thus stick to "truthful" competitive pricing.

Q.E.D.

While the platform's actual screening strategy is not observable, the lender can see the pricing scheme released by the platform, i.e., how the platform sets the loan rate and transaction fee. Since R , β , p and α are common knowledge to both the lender and the platform, the lender can compute the pricing structure for the truthful platform. Then, the lender can compare the actual pricing structure she observed with the "truthful pricing structure" computed in her mind. For any pricing structures that deviate from the "truthful pricing structure", the rational lender infers that the platform that sets this pricing structure is a truthful type with probability *zero*. In other words, upon observing any "*non-truthful pricing structure*", the lender immediately infers that the platform is an opportunistic type with probability *one* and that the platform approves known bad borrowers with probability *one*. In this case, the lender only obtains a negative perceived expected return as shown in the proof of Proposition 1, and therefore the lender chooses *not to* invest in the platform. Since the transaction fee is paid to the platform only when the loan is successfully funded, it earns zero payoff if the lender does not bid on the loan it issued. Consequently, under a monopoly, in order to gain a positive payoff, the opportunistic platform mimics the truthful type's pricing strategy. Under perfect competition, platforms have no incentive to deviate from the "truthful pricing strategy" because the platforms will not be strictly better off by doing so.

The core of the platform-lender game concerns how the platform signals its creditability and how the lender responds to these signals. Specifically, the platform's signals include its choice of pricing and screening strategy. The lender can perfectly observe the platform's pricing strategy but can only detect an imperfect signal of the platform's screening strategy (that is, the platform's type). This may give the platform an incentive to stick to the pricing strategy of the truthful type but to strategically choose its screening policy, which causes platform moral hazard. It is worth noting that the signalling mechanism in P2P lending described above is different from that in models that characterize the interactions between an credit rating agency and investors or between an investment bank and investors in which the credit rating agency/ investment bank signals their type *only* through their information disclosure strategy (e.g., Chemmanur and Fulghieri, 1994; Mathis et al., 2009; and Fulghieri et al., 2013).

We now proceed to find the (opportunistic) platform's equilibrium screening strategy.

Proposition 2: ***Under either a monopoly or competitive market,*** $\eta_0^* = \eta_1^* = \bar{\eta}$ ***.The platform approves a known bad borrower (a loan application with "bad" signal) with probability*** $\bar{\eta}$ ***in each period. In other words, the platform chooses the loosest screening strategy and lies to the lender about borrower credit quality with probability*** $\bar{\eta}$ ***.***

This is supported by the lender's off-the-equilibrium path beliefs that the platform sets $prob(\omega = T \mid \tau_t = approval) = 0, \tilde{\eta}_t = 1$ ***in response to any screening strategy other than that characterized above.***

Proof. First consider the monopoly case. Since we have proved that the opportunistic platform always adopts the "truthful pricing strategy" as the truthful type, the platform's problem is therefore about the choice of its screening policy η. Specifically, in period 1, the platform chooses $\eta_1 \in [0, \bar{\eta}]$ to maximize her payoff at that period. The upper bound of η , which is $\bar{\eta}$, ensures the perceived expected return at any period is positive. This means, in equilibrium, the lender expects a positive perceived return by investing in a loan listing approved by the platform. So, the lender invests in the loan with a positive probability. The platform's payoff in period 1 is written as:

$$\pi_1 = (a_{M1}^* - c)\frac{\dfrac{(1+r_{M1}^*)\beta p}{\beta + (1-\beta)(1-\alpha) + (1-q_1^X)(1-\beta)\alpha\tilde{\eta}_1} - 1}{\dfrac{(1+R)\beta p}{\beta + (1-\beta)(1-\alpha)} - 1}(\beta + (1-\beta)(1-\alpha) + (1-\beta)\alpha\eta_1)$$

(P1)

$$\frac{\partial \pi_1}{\partial \eta_1} = (a_{M1}^* - c)\frac{\frac{(1+r_{M1}^*)\beta p}{\beta+(1-\beta)(1-\alpha)+(1-q_1^X)(1-\beta)\alpha\tilde{\eta}_1}-1}{\frac{(1+R)\beta p}{\beta+(1-\beta)(1-\alpha)}-1}(1-\beta)\alpha \tag{P2}$$

Because $\bar{\eta}$ ensures $\frac{\frac{(1+r_{M1}^*)\beta p}{\beta+(1-\beta)(1-\alpha)+(1-q_1^X)(1-\beta)\alpha\tilde{\eta}_1}-1}{\frac{(1+R)\beta p}{\beta+(1-\beta)(1-\alpha)}-1} > 0$, we have $\frac{\partial \pi_1}{\partial \eta_1} > 0$.

Because $\frac{\partial \pi_1^2}{\partial^2 \eta_1} = 0$, π_1 linearly depends on η_1.

Given $\frac{\partial \pi_1}{\partial \eta_1} > 0$, apparently π_1 reaches maximum at $\eta_1 = \bar{\eta}$. So $\eta_1^* = \bar{\eta}$.

In period 0, the platform chooses $\eta_0 \in [0, \bar{\eta}]$ to maximize the sum of expected payoff obtained in period 0 and 1:

$$\pi_{sum(0,1)} = \beta(\frac{R_0^{PER}}{R_{\max}}(a_{M1}^* - c) + p\pi(q_1^{RP}) + (1-p)\pi(q_1^{DF})) + (1-\beta)((1-\alpha+\alpha\eta_0)(\frac{R_0^{PER}}{R_{\max}}(a_{M1}^* - c) + \pi(q_1^{DF})) + \alpha\left(1-\eta_0\right)\pi(q_0))$$

(P3)

$$\text{where } R_0^{PER} = \frac{(1+r_{M0}^*)\beta p}{\beta+(1-\beta)(1-\alpha)+(1-q_0)(1-\beta)\alpha\tilde{\eta}_0} - 1, \tag{P4}$$

$$R_{\max} = \frac{(1+R)\beta p}{\beta+(1-\beta)(1-\alpha)} - 1, \tag{P5}$$

$$\pi(q_1^{DF}) = (a_{M1}^* - c)(\beta+(1-\beta)(1-\alpha)+(1-\beta)\alpha\eta_1^*)\frac{\frac{(1+r_{M1}^*)\beta p}{\beta+(1-\beta)(1-\alpha)+(1-q_1^D)(1-\beta)\alpha\eta_1^*}-1}{R_{\max}} \tag{P6}$$

$$\pi(q_1^{RP}) = \pi(q_0) = (a_{M1}^* - c)(\beta+(1-\beta)\times(1-\alpha)+(1-\beta)\alpha\eta_1^*)\frac{\frac{(1+r_{M1}^*)\beta p}{\beta+(1-\beta)(1-\alpha)+(1-q_0)(1-\beta)\alpha\eta_1^*}-1}{R_{\max}} \tag{P7}$$

$$\frac{\partial \pi_{sum(0,1)}}{\partial \eta_0} = \alpha(1-\beta)(\frac{R_0^{PER}(a_{M0}^* - c)}{R_{\max}} + \pi(q_1^{DF}) - \pi(q_0)) \tag{P8}$$

Because $\eta_1^* < 1$, we have $a_{M1}^* - c > (a_{M1}^* - c)(\beta+(1-\beta)(1-\alpha)+(1-\beta)\alpha\eta_1^*)$

Also, because $\tilde{\eta}_0 \le \eta_1^*$, we have

$$\frac{(1+r_{M0}^*)\beta p}{\beta+(1-\beta)(1-\alpha)+(1-q_0)(1-\beta)\alpha\tilde{\eta}_0}-1 \ge \frac{(1+r_{M1}^*)\beta p}{\beta+(1-\beta)(1-\alpha)+(1-q_0)(1-\beta)\alpha\eta_1^*}-1$$

Taken together, immediately we have $\frac{R_0^{PER}(a_{M0}^*-c)}{R_{\max}} > \pi(q_0)$

Therefore, we have $\frac{\partial \pi_{sum(0,1)}}{\partial \eta_0} > 0.$

Because $\frac{\partial \pi^2_{sum(0,1)}}{\partial^2 \eta_0} = 0$, $\pi_{sum(0,1)}$ linearly depends on η_0.

Given $\frac{\partial \pi_{sum(0,1)}}{\partial \eta_0} > 0$, apparently $\pi_{sum(0,1)}$ reaches maximum at $\eta_0 = \bar{\eta}$. So $\eta_0^* = \bar{\eta}$.

Then we consider the competitive case. At period 1, the platform's problem is to choose $\eta \in [0, \bar{\eta}]$ to maximize her payoff at that period, take the loan rate and guarantee fee as given:

$$\max_{\eta_1} \pi_1 = (a_{C1}^*-c)\frac{\frac{(1+r_{C1}^*)\beta p}{\beta+(1-\beta)(1-\alpha)+(1-q_1^X)(1-\beta)\alpha\tilde{\eta}_1}-1}{\frac{(1+R)\beta p}{\beta+(1-\beta)(1-\alpha)}-1}(\beta+(1-\beta)(1-\alpha)+(1-\beta)\alpha\eta_1)$$

(P9)

$$\frac{\partial \pi_1}{\partial \eta_1} = (a_{C1}^*-c)\frac{\frac{(1+r_{C1}^*)\beta p}{\beta+(1-\beta)(1-\alpha)+(1-q_1^X)(1-\beta)\alpha\tilde{\eta}_1}-1}{\frac{(1+R)\beta p}{\beta+(1-\beta)(1-\alpha)}-1}(1-\beta)\alpha \quad \text{(P10)}$$

We know $\tilde{\eta}_1$ and r_{C1}^* ensures $\frac{(1+r_{C1}^*)\beta p}{\beta+(1-\beta)(1-\alpha)+(1-q_1^X)(1-\beta)\alpha\tilde{\eta}_1}-1>0$,

and $a_{C1}^*-c \ge 0$.

Therefore $\frac{\partial \pi_1}{\partial \eta_1} \ge 0$.

Because $\frac{\partial \pi_1^2}{\partial^2 \eta_1} = 0$, π_1 linearly depends on η_1.

Given $\frac{\partial \pi_1}{\partial \eta_1} \geq 0$, apparently π_1 reaches maximum at $\eta_1 = \bar{\eta}$. So $\eta_1^* = \bar{\eta}$.

Now move to period 0. At period 0, the platform chooses $\eta_0 \in [0, \bar{\eta}]$ to maximize the sum of expected payoff obtained in period 0 and 1:

$$\pi_{sum(0,1)} = \beta(\frac{R_0^{PER}}{R_{\max}}(a_{C0}^* - c) + p\pi(q_1^{RP}) + (1-p)\pi(q_1^{DF})) + (1-\beta)((1-\alpha+\alpha\eta_0)(\frac{R_0^{PER}}{R_{\max}}(a_{C0}^* - c) + \pi(q_1^{DF})) + \alpha\left(1-\eta_0\right)\pi(q_0)) \tag{P11}$$

Because $\pi(q_1^{DF}) = \pi(q_0) = \pi(q_1^{RP}) = 0$ under perfect competition, the $\pi_{sum(0,1)}$ is simplified to

$$\pi_{sum(0,1)} = (a_{C0}^* - c)\frac{\frac{(1+r_{C0}^*)\beta p}{\beta + (1-\beta)(1-\alpha) + (1-q_0)(1-\beta)\alpha\tilde{\eta}_0} - 1}{\frac{(1+R)\beta p}{\beta + (1-\beta)(1-\alpha)} - 1}(\beta + (1-\beta)(1-\alpha) + (1-\beta)\alpha\eta_0) \tag{P12}$$

Similar to the period 1, we have

$$\frac{\partial \pi_{sum(0,1)}}{\partial \eta_0} = (a_{C0}^* - c)\frac{\frac{(1+r_{C0}^*)\beta p}{\beta + (1-\beta)(1-\alpha) + (1-q_0)(1-\beta)\alpha\tilde{\eta}_0} - 1}{\frac{(1+R)\beta p}{\beta + (1-\beta)(1-\alpha)} - 1}(1-\beta)\alpha \geq 0 \tag{P13}$$

And $\frac{\partial \pi^2_{sum(0,1)}}{\partial^2 \eta_0} = 0$.

So $\pi_{sum(0,1)}$ linearly depends on η_0.

Given $\frac{\partial \pi_{sum(0,1)}}{\partial \eta_0} > 0$, apparently $\pi_{sum(0,1)}$ reaches maximum at $\eta_0 = \bar{\eta}$. So $\eta_0^* = \bar{\eta}$.

Q.E.D.

In period 1, the last period of the game, the platform has no incentive to maintain its reputation in the eye of the lender. Thus, the platform finds that choosing the laxest screening policy by setting $\eta_1^* = \bar{\eta}$ is optimal. In period 0, the platform faces a dynamic trade-off between current payoff and long-term reputation (which relates to the expected long-term payoff). The benefit of approving a known bad borrower is that the platform can pocket a transaction fee of a_0. The cost of this is a lower payoff in period 1 due to reputation loss. Specifically, deliberately approving a known application that doomed to default in the future reduces the platform's reputation from q_0 to $\frac{q_0(1-\beta)(1-\alpha)}{(1-\beta)(1-\alpha)+(1-q_0)(1-\beta)\alpha\tilde{\eta}_0} < q_0$. A reduced reputation lowers the lender's perceived expected return and thus her likelihood to invest, which eventually diminishes the platform's payoff in period 1. However, we can prove that the marginal benefit of "lying" to the lender (giving a green light to a known bad borrower to raise fund on the platform) is strictly positive. That is, the benefit of "lying" outweighs its cost, thus, the disciplining effect of the reputation concerns is simply not large enough to induce the platform to report borrower quality honestly.

Then, what is responsible for the "failure" of reputation? First, the *ex post* non-verifiability of the platform's screening effort confines the disciplining effect of reputation concerns. Specifically, a reputation mechanism is perfectly effective for curbing the platform from untruthfully disclosing borrower quality only if the lender is able to unambiguously attribute a bad loan to the platform's opportunistic behaviour. However, this is unlikely to happen. A bad loan can be caused by one of the three following cases: (1) the platform's honest screening error. That is, the platform fails to observe a "bad" signal and mistakenly assigns a "no-bad" signal to a "bad" borrower with probability $1-\alpha$; (2) "bad luck", that is, a "good" borrower, who is approved by the platform and successfully funded by the lender, fails to repay the loan with probability $1-p$;or (3) the platform's opportunistic behaviour, that is, deliberately giving a green light to a known "bad" borrower to post her loan request on the platform. The lender can only observe the loan outcome but not the real cause behind a bad loan; thus, she cannot perfectly infer that a bad loan is due to an honest screening mistake, "bad luck" or a "bad platform". Instead, as discussed in section 4.1.2, after observing a realized bad loan, the lender can only form a conditional probability that characterizes how likely it is that the bad loan is due to the platform's opportunistic behaviour. If in an economy, the good borrower's repayment probability and/or the platform's screening precision are relatively small, the rational lender will expect that a bad loan is more likely to be triggered by the platform's honest screening error or the borrower's bad luck. This weakens the effectiveness of reputation to prompt the platform's truthful information disclosure. This is consistent with the findings of Fulghieri et al. (2013). They find that in a solicited-only credit rating system, the reputation concerns are not powerful enough to discipline the credit rating agencies. They blame this result on "the imperfect (ex post) observability of a firm's project quality by investors essentially limits the effectiveness of reputation as a disciplining device".

Following this logic, improvement of such ex post observability would strengthen the disciplining effect of reputation concerns. Intuitively, all else being equal, reputation concerns can better discipline a platform if the platform has greater screening precision α, because, in this case, the lender can infer that a bad loan is more likely to be due to the platform's moral hazard rather than an honest screening error; or simply speaking, the disciplining effect is enhanced by the augmented reputation cost. Lemma 3 formalizes this intuition.

Lemma 2. The *reputation cost of the platform increases with the platform's screening ability* α.

Proof. The reputation cost can be straightforwardly defined as the reputation loss from q_0 to q_1^{DF}, $q_{loss} = q_0 - \dfrac{q_0(\beta(1-p)+(1-\beta)(1-\alpha))}{\beta(1-p)+(1-\beta)(1-\alpha)+(1-q_0)(1-\beta)\alpha\tilde{\eta}_0}$.

q_{loss} increases in α immediately follows the fact that

$$\frac{\partial q_{loss}}{\partial \alpha} = \frac{q_0\tilde{\eta}_0(-1+q_0)(-1+\beta)(1-\beta p)}{\left(-(-1+\beta)\left(1+(-1+q_0)\tilde{\eta}_0\right)\alpha+\beta p-1\right)^2} > 0$$

Q.E.D.

The reputation's disciplining effect is also weakened by the practice that the platform does not publish the information about rejected loan listings (that is, those initial loan applications that are identified as "bad" credit risks and are not approved by the platform), and thus only approved loan listings can be viewed by the lender. Consider a hypothetical setting where the platform is required to reveal information about *all* (approved and rejected) loan listings. Thus, the lender's *prior* probability regarding the platform's type (the platform's initial reputation) is characterized by the unconditional probability $q_0 = prob(\omega = T)$ instead of the conditional probability $q_0 = prob(\omega = T \mid \tau_0 = approval)$ that is specified in our model. This setting changes the lender's belief updating process and thus the platform's reputation building.

Lemma 3. ***When the platform is required to publish the profiles of all approved and rejected loan listings, being observed a loan approval lowers the platform's reputation, while a loan rejection increases the platform's reputation.***

Proof. After observing an approved loan listing, the lender uses Bayes' rule to update her belief about the platform's type-the platform's reputation:

$$q_0^A = prob(\omega = T \mid \tau_0 = approval) = \frac{q_0(\beta + (1-\beta)(1-\alpha))}{\beta + (1-\beta)(1-\alpha) + (1-q_0)(1-\beta)\alpha\tilde{\eta}_0}$$

Apparently, $q_0^A < q_0$ because $(1-q_0)(1-\beta)\alpha\tilde{\eta}_0 > 0$. Therefore, a loan approval reduces the platform's reputation.

If the lender observes a loan rejection, the platform' reputation will be restored to

$$q_0^\phi : \quad q_0^\phi = prob(\omega = T \mid \tau_0 = rejection) = \frac{q_0 \times (1-\beta)\alpha}{q_0(1-\beta)\alpha + (1-q_0)(1-\beta)\alpha(1-\tilde{\eta}_0)}$$

It is easy to verify $q_0^\phi > q_0$ because $q_0(1-\beta)\alpha + (1-q_0)(1-\beta)\alpha(1-\eta_0) < (1-\beta)\alpha$.

Thus, a loan rejection actually leads to a rise in reputation.

Q.E.D.

If the lender can see the platform rejecting an initial loan application, this increases the probability of the platform being truthful in the lender's eyes, because a loan rejection is more likely to occur when the platform is the truthful type. Then, a natural question to ask is: if the platform is required to publish its rejected loan listings, does that induce the platform to screen borrowers honestly? Because the platform's optimal screening strategy depends on the cost and benefit of truthful information production, specifically, in period 0, the marginal benefit of approving a known "bad" borrower is

$$\alpha(1-\beta)(\frac{R_0^{PER}(q_0^A)}{\bar{R}}(a_0-c)+\pi_1(q_1^{DF})-\pi_1(q_0^{\phi}))$$

Where $R_0^{PER}(q_0^A)=\dfrac{(1+R-a_0)\beta p}{\beta+(1-\beta)(1-\alpha)+(1-q_0^A)(1-\beta)\alpha\tilde{\eta}_0}-1$,

$$\pi_1(q_1^{DF})=(a_1-c)(\beta+(1-\beta)(1-\alpha)+(1-\beta)\alpha\eta_1)\frac{\dfrac{(1+R-a_1)\beta p}{\beta+(1-\beta)(1-\alpha)+(1-q_1^{DF})(1-\beta)\alpha\eta_1}-1}{\bar{R}}$$

$$\pi_1(q_0^{\phi})=(a_1-c)(\beta+(1-\beta)(1-\alpha)+(1-\beta)\alpha\eta_1)\frac{\dfrac{(1+R-a_1)\beta p}{\beta+(1-\beta)(1-\alpha)+(1-q_0^{\phi})(1-\beta)\alpha\eta_1}-1}{\bar{R}}$$

The platform only finds that a truthful screening strategy is optimal when the marginal benefit of approving a known "bad" loan applicant is strictly negative. So, if q_0^{ϕ} is sufficiently large and/or q_0^A and q_1^{DF} sufficiently small, rejecting all known "bad" borrower may be optimal for the platform.

Unfortunately, we are unable to rigorously prove the existence of such a truth-telling solution, so this is only a conjecture. However, what we can see is that disclosing rejected loan listings would increase the benefit of rejecting a known "bad" borrower. Consequently, the platform has more incentive to act as a truthful type. However, in reality, platforms are not required to do so, and not disclosing the information about rejected loan applications seems a standard practice in China's P2P lending industry. This practice lowers the benefit of being a truthful platform and thus gives platforms less incentive to honestly screen borrowers.

4.3.2 Equilibrium strategies under the guarantee model

Under the guarantee model, the platform has no reputation concerns and always screens out borrowers with observed "bad" signals. As discussed in section 3.2.2, the lender-platform interaction is modelled as a single-period game. We use the Nash Equilibrium(NE) to characterize the equilibrium. In the monopoly market, given the lender's decision rule, an equilibrium pricing strategy maximizes the platform's payoff. In a competitive market, the competitive guarantee fee satisfies the platform's zero profit condition, and the competitive loan rate maximizes the lender's perceived expected return. Platforms have no strict incentive to deviate from such competitive pricing.

First, we look at the total borrowing cost in the equilibrium.

Lemma 4 ***Either in a monopoly or competitive market, the borrower surplus is pushed to zero, that is,*** $r_G + a_G = R$**.**

Proof. Consider the monopoly case. Let $TB_G = r_G + a_G$ .Obviously, $\frac{\partial \pi_G}{\partial TB_G} > 0$, therefore the platform payoff reaches maximum at $TB_G = R$. Next consider the competitive case. Because platform competition maximizes the lender's perceived expected return, the competitive loan rate then reaches its upper bound, that is, $r_G = R - a_G$.

Q.E.D.

This means that regardless of the competition structure, the participation constraints for borrowers are binding under the guarantee model. This is consistent with the finding for the non-guarantee model as described in Lemma 1. This is not surprising, because under either the non-guarantee or the guarantee model, borrowers have no bargaining power and the platform can make "take it or leave it" offer to borrowers. Especially under a monopoly, all else being equal, the platform's payoff strictly increases with the loan rate and the guarantee fee, and it is optimal for the platform to maximize the sum of the loan rate and guarantee fee. The pricing strategy for the guarantee model reflects how the borrower surplus is shared between the platform and the lender.

Now we look at the pricing strategy from another angle. Under the guarantee model, the lender undertakes the risk of interest loss while the platform bears the risk of repaying the outstanding principal. If we take the borrowing cost (loan rate plus guarantee fee) as given, the platform's pricing strategy, more precisely, how to split the total borrowing cost into the loan rate and guarantee fee, can be viewed as a risk-sharing arrangement between the platform and the lender. By solving the platform problem, we have the platform's optimal pricing strategy:

Proposition 3: ***The platform's optimal pricing strategy under the guarantee model is characterized as:***

Monopoly:

$$a^*_{G,M} = \frac{1}{2}\frac{\alpha(\beta-1)(R+c+1)-\beta p+R+c+1}{\alpha\beta-\alpha+1} \quad r^*_{G,M} = \frac{1}{2}\frac{\alpha(\beta-1)(R-c-1)+\beta p+R-c-1}{\alpha\beta-\alpha+1}$$

Competitive*:*

$$a^*_{G,C} = \frac{\alpha\beta \mathrm{c}+\alpha\beta-\alpha \mathrm{c}-\beta \mathrm{p}-\alpha+c+1}{\alpha\beta-\alpha+1}, \quad r^*_{G,C} = R-\frac{\alpha\beta \mathrm{c}+\alpha\beta-\alpha \mathrm{c}-\beta \mathrm{p}-\alpha+c+1}{\alpha\beta-\alpha+1}$$

Proof. First consider the monopoly case. Under the guarantee model, the platform's problem is only about price-setting. The platform maximizes her payoff by choosing $a_{G,M}$ and $r_{G,M}$:

$$\max_{a_{G,M},r_{G,M}} \pi_{G,M} = ((a_{G,M}-c)(\beta+(1-\beta)(1-\alpha))-\beta(1-p)-\alpha(1-\beta))\frac{\dfrac{(1+r_{G,M})\beta p+\beta(1-p)+(1-\beta)(1-\alpha)}{\beta+(1-\beta)(1-\alpha)}-1}{\dfrac{(1+R)\beta p+\beta(1-p)+(1-\beta)(1-\alpha)}{\beta+(1-\beta)(1-\alpha)}-1}$$

$$\begin{aligned} s.t.\ & R^{PER}_{G,M} = \frac{(1+r_{G,M})\beta p+\beta(1-p)+(1-\beta)(1-\alpha)}{\beta+(1-\beta)(1-\alpha)}-1>0 \\ & (a_{G,M}-c)(\beta+(1-\beta)(1-\alpha))-\beta(1-p)-\alpha(1-\beta)\geq 0 \\ & R = a_{G,M}+r_{G,M} \end{aligned}$$

As in the proof of Proposition 1, we initially ignore the constraints and solve for the "less-constrained" problem. Then we verify this solution satisfies the constraints. By substituting $r_{G,M} = R - a_{G,M}$ and applying first order condition $\frac{\partial \pi_G}{\partial a_G} = 0$, we have

$$a_{G,M}^{*} = \frac{1}{2}\frac{\alpha(\beta-1)(R+c+1)-\beta p+R+c+1}{\alpha\beta-\alpha+1} \quad .$$

Then we verify $(a_{G,M}^{*}-c)(\beta+(1-\beta)(1-\alpha))-\beta(1-p)-\alpha(1-\beta)\geq 0$ .This inequality can be rewritten as $-\frac{\beta p+R-c-1}{(\beta-1)(R-c-1)}<\alpha$.

$\frac{R\beta p+\beta p-c-1}{\beta c+\beta-c-1}>-\frac{\beta p+R-c-1}{(\beta-1)(R-c-1)}$ is equivalent to $\frac{\beta pR(R-c)}{(\beta-1)(1+c)(R-c-1)}>0$, which apparently holds.

Together with assumption (A1), we have $\alpha>\frac{R\beta p+\beta p-c-1}{\beta c+\beta-c-1}>-\frac{\beta p+R-c-1}{(\beta-1)(R-c-1)}$.

So $(a_{G,M}^{*}-c)(\beta+(1-\beta)(1-\alpha))-\beta(1-p)-\alpha(1-\beta)\geq 0$.

Next, we verify $R_{G,M}^{PER}=\frac{(1+R-a_{G,M}^{*})\beta p+\beta(1-p)+(1-\beta)(1-\alpha)}{\beta+(1-\beta)(1-\alpha)}-1>0$ .By substituting $a_{G,M}^{*}=\frac{1}{2}\frac{\alpha(\beta-1)(R+c+1)-\beta p+R+c+1}{\alpha\beta-\alpha+1}$, this inequality is equivalent to $-\frac{\beta p+R-c-1}{(\beta-1)(R-c-1)}<\alpha$, which is proved to hold as above.

Now we consider the competitive case. To reach the equilibrium, it is necessary that the optimal $a_{G,C}^{*}$ to be such

$$(a_{G,C}^{*}-c)(\beta+(1-\beta)(1-\alpha))-\beta(1-p)-\alpha(1-\beta)=0$$

This zero-profit condition means there is no strict incentive for platforms to enter or to leave the industry. Solving the zero-profit condition, we have $a_{G,C}^{*}=\frac{\alpha\beta\mathrm{c}+\alpha\beta-\alpha\mathrm{c}-\beta\mathrm{p}-\alpha+c+1}{\alpha\beta-\alpha+1}$,

Also, immediately we have $r_{G,C}^{*}=R-a_{G,C}^{*}=R-\frac{\alpha\beta\mathrm{c}+\alpha\beta-\alpha\mathrm{c}-\beta\mathrm{p}-\alpha+c+1}{\alpha\beta-\alpha+1}$.

Q.E.D.

Now we examine the relationship between the loan rate, the guarantee fee and the borrower's *ex-ante* risk. The welfare implication will be discussed in the next section. First, the borrower's *ex-ante* risk is defined as $\delta = prob(default \mid approval)$, which is the default probability conditional on the loan listing being approved by the platform. By using Bayes' rule, δ is given as:

$$\delta = prob(default \mid approval) = \frac{\beta(1-p)+(1-\beta)(1-\alpha)}{\beta+(1-\beta)(1-\alpha)} \tag{38}$$

By substituting $\delta = \frac{\beta(1-p)+(1-\beta)(1-\alpha)}{\beta+(1-\beta)(1-\alpha)}$, $a^*_{G,M} / a^*_{G,C}$ and $r^*_{G,M} / r^*_{G,C}$ can be rewritten as:

$$a^*_{G,M} = \frac{1}{2}(R+c+\delta) \ , \ r^*_{G,M} = \frac{1}{2}(R-c-\delta) \ ; \tag{39}$$

$$a^*_{G,C} = \delta + c \, , \ r^*_{G,C} = R - \delta - c \, . \tag{40}$$

Obviously, we have $\frac{\partial a^*_{G,M}}{\partial \delta}, \frac{\partial a^*_{G,C}}{\partial \delta} > 0$ and $\frac{\partial r^*_{G,M}}{\partial \delta}, \frac{\partial r^*_{G,C}}{\partial \delta} < 0$ which confirms our intuitions. That is, all else being equal, the guarantee fee is positively associated with the borrower's *ex-ante* risk, while the loan rate is negatively correlated with the borrower's *ex-ante* risk under either competition structure.

Similarly, we rewrite the loan rate and transaction fee under the non-guarantee model, by substituting $\delta = \frac{\beta(1-p)+(1-\beta)(1-\alpha)}{\beta+(1-\beta)(1-\alpha)}$, and we have $a^*_{Mt} = \frac{1}{2}\frac{(R+c+1)\delta - R - c}{\delta - 1}$, $r^*_{Mt} = \frac{1}{2}\frac{(R-c-1)\delta - R + c}{\delta - 1}$. Then, we immediately have $\frac{\partial a^*_{Mt}}{\partial \delta} = -\frac{1}{2(\delta-1)^2} < 0$, $\frac{r^*_{Mt}}{\partial \delta} = \frac{1}{2(\delta-1)^2} > 0$. That is, all else being equal, under a monopoly, the transaction fee is negatively associated with borrower's *ex-ante* risk, whereas the loan rate is positively correlated with the borrower's *ex-ante* risk, which is contrary to the guarantee model. However, under perfect competition, the pricing strategy is independent of the borrower's *ex-ante* risk, since $a^*_{Ct} = c$, $r^*_{Ct} = R - c$.

4.4 Welfare comparison

Under the non-guarantee model, we find that the opportunistic platform always mimics the pricing strategy of the truthful platform; that is, the loan rate and transaction fee set by the opportunistic platform are identical to those set by the truthful platform. This occurs because if the platform deviates from the "truthful pricing strategy", the lender immediately infers that the platform is an opportunistic type after observing any pricing strategies other than the "truthful pricing strategy". However, reputation concerns are not enough to discipline the platform in the sense of screening out known "bad" borrowers. The platform chooses the loosest screening strategy by approving a known "bad" borrower with the highest possible probability. The explanation for "the failure" of reputation concern is that the lender is unable to perfectly attribute a bad loan to the platform's opportunistic behaviour because a bad loan can also be caused by the platform's honest screen error due to the platform's imperfect screening technology or "bad luck" due to the "good" borrower's default. Therefore, under certain conditions, the benefit of overstating borrower quality outweighs the punishment from "voting with the lender's feet" (reputation cost). Under the guarantee model, the platform always acts as a truthful type by screening out known "bad" borrowers. This occurs simply because the platform has enough "skin in the game" and the marginal benefit of giving green light to a known "bad" borrower is strictly negative. Overall, in the sense of prompting the platform to conduct honest screening, it seems that a risk-sharing mechanism (the guarantee model) is more powerful than reputation acquisition (the non-guarantee model) in the disciplining platform.

A natural and important follow-up question is which lending model is more socially desirable? To answer this question, this section discusses the comparative welfare implications under the two P2P lending models in a competitive market. Consider the total *ex-ante* surplus of the platform, the lender and the borrower. As both the borrower's and platform's surplus in a competitive market is pushed to zero, the overall *ex-ante* social welfare can be derived from the lender's expected return. Under the non-guarantee model, the *ex-ante* social welfare is given as

$$TS_N = (1 + r_{Ct})\beta p - \beta - (1-\beta)(1-\alpha+\alpha\overline{\eta}) \tag{41}$$

Similarly, under the non-guarantee model, the *ex-ante* social welfare is given as:

$$TS_G = (1+r_{G,C})\beta p + \beta(1-p) + (1-\beta)(1-\alpha) - \beta - (1-\beta)(1-\alpha) \quad (42)$$

Proposition 4: $TS_G > TS_N$.***The guarantee model generates greater social welfare than the non-guarantee model in a competitive market.***

Proof. Let $TS'_N = (1+r_N)\beta p - \beta - (1-\beta)(1-\alpha)$, which is the lender surplus when the platform acts as a truthful type. We first prove $TS_G > TS'_N$.

By substituting $r_{G,C} = R - \dfrac{\alpha\beta\mathrm{c} + \alpha\beta - \alpha\mathrm{c} - \beta\mathrm{p} - \alpha + c + 1}{\alpha\beta - \alpha + 1}$, $r_{Ct} = R - c$ into TS_G and TS'_N , respectively, we have

$$TS_G - TS'_N = \frac{((1-\beta)\alpha + \beta p - 1)^2}{1+(\beta-1)\alpha} \geq 0 .$$

$TS_G = TS'_N$ if and only if $(1-\beta)\alpha + \beta p - 1 = 0$, i.e. $\alpha = \dfrac{1-\beta p}{1-\beta}$.

However, since $\dfrac{1-\beta p}{1-\beta} > 1$ and $\alpha < 1$, the above equality never holds.

Therefore, $TS_G - TS'_N = \dfrac{((1-\beta)\alpha + \beta p - 1)^2}{(1+(\beta-1)\alpha)^2} > 0$.

Apparently, $TS'_N > TS_N$, then immediately we have $TS_G > TS_N$

Q.E.D.

The guarantee model may create efficiency gains in two respects. In terms of screening efficiency, the efficiency gains are created by financing high quality borrowers. By contrast, the social welfare is destroyed by lending to low quality borrowers who are *ex-ante* inefficient. Under the non-guarantee model, the lessened screening incentive creates a welfare loss of $-\alpha(1-\beta)\overline{\eta}$. That is, by approving known "bad" borrowers, the platform's dishonest screening behaviour imposes a deadweight loss on the lender. Therefore, the guarantee model is welfare-enhancing because of its efficient screening policy.

The guarantee model also creates efficiency gains in terms of pricing. As mentioned previously, the pricing strategy reflects a risk-sharing arrangement between the platform and the lender. Under the guarantee model, the range of the platform's payoff is $[-1, a_{G,C}^*]$, and for the lender it is $[0, r_{G,C}^*]$. In terms of pricing efficiency, if we take the total borrowing cost as given, an *ex-ante* riskier borrower "should pay" more to the platform and less to the lender because the platform has more "skin in the game" as a guarantor. By contrast, an observably less risky borrower "should pay" less to the platform and more to the lender. Consequently, all else being equal, efficient pricing should imply that the loan rate decreases with the borrower's *ex-ante* risk, whereas the guarantee fee increases with the borrower's *ex-ante* risk. As shown in section 4.3.2, $\frac{\partial a_{G,C}^*}{\partial \delta} > 0$ and $\frac{\partial r_{G,C}^*}{\partial \delta} < 0$, which suggests that the guarantee fee is positively correlated with borrower's *ex-ante* risk whereas the loan rate is negatively associated with borrower's *ex-ante* risk. This result is consistent with the implications of efficient pricing. Under the non-guarantee model, the range of the platform's payoff is $[0, a_{Ct}^*]$, and for the lender it is $[-1, r_{Ct}^*]$. Following similar logic, efficient pricing under the non-guarantee model should mean that the loan rate increases with the borrower's *ex-ante* risk whereas transaction fee decreases with the borrower's *ex-ante* risk. However, the section 4.3.2 shows that the pricing strategy of the non-guarantee model is unrelated to the borrower's *ex-ante* risk since $a_{Ct}^* = c$, $r_{Ct}^* = R - c$. This means that the pricing strategy under the non-guarantee model is inefficient.

Chapter 5. The dark side of the guarantee model: overconfident platform and welfare losses

In the previous analysis, we assume that the platform is always well-calibrated. That is, it has *unbiased beliefs* about the risk parameters: the screening ability α, *ex-ante* fraction of "good" borrowers β and repayment probability p. Apparently, this assumption is a standard setting for most of the economic models. Specifically, assuming that all defaulted loans have zero recovery value, the *ex-ante* loss for a given loan is therefore $\delta = \frac{\beta(1-p)+(1-\beta)(1-\alpha)}{\beta+(1-\beta)(1-\alpha)}$. If the platform's beliefs about the risk parameters are correct, its *ex-ante* prediction of future loan losses, δ, would converge to the actual loan losses. In other words, on average, the predicted loan losses would equal the actual loan losses. Under the guarantee model, since the guarantee fees are set based on the platform's prediction of future loan losses, on average, the guarantee fee should be enough to compensate the potential loan losses if the platform is well-calibrated.

However, in reality, newly established, inexperienced platforms may have difficulty forming unbiased beliefs about the risk parameters. That is, the platform may be not well-calibrated. In this case, the platform would misunderstand and misprice the borrower risk. For example, if the platform overestimates its screening ability α, it will underestimate the *ex-ante* loan loss δ because $\frac{\partial\delta}{\partial\alpha} = \frac{\left(-1+\beta\right)\beta p}{\left(1+\left(-1+\beta\right)\alpha\right)^2} < 0$. Then, in turn, the platform will underprice the borrower risk, which means that, the guarantee fees preset by the platform cannot fully cover the potential loan losses (this will be proved later). It's difficult to deny that the platform's tendency to underprice risk increases its probability of insolvency. This in turn would harm the welfare benefits of the guarantee model shown in section 4.4.

Therefore, in this chapter, we first weaken the assumption of perfect rationality and allow incorrect beliefs, then we analyse how this affects the platform's choice of strategies and thus social welfare in a competitive market. Without loss generality, we only consider the case where the platform has incorrect beliefs about its screening precision α .Specifically, we assume that the platform is overconfident and overestimates its screening ability, where the level of overconfidence is given by the parameter λ . Then, the perceived screening precision is $\hat{\alpha}=\lambda\alpha$, where α is the platform's actual screening precision. That is, the platform believes its screening precision of α to be $\lambda\alpha$. The case $\lambda=1$ represents the benchmark rationality, and we focus our analysis on the case $\lambda>1$, where the platform is overconfident. To avoid further complicating our analysis, we assume that the lender shares the same (incorrect) belief about screening precision as the platform. This implies that, in the lender's mind, the platform's screening is $\lambda\alpha$, instead of α . In what follows, we first illustrate the overconfident platform's choice of strategies under the non-guarantee model, and then we discuss the effect of overconfidence on the platform's choice of strategies and social welfare under the guarantee model.

5.1 The overconfident platform's strategies under the non-guarantee model

In this section, we illustrate that, in the case of the non-guarantee model, the platform's strategies remain substantially unchanged under the overconfidence assumption. We first look at the platform's screening strategy. In period 1, as in the case when the platform is well-calibrated, the platform chooses $\eta_1 \in [0,\bar{\eta}']$ to maximize its payoff in that period given a_M^* and r_M^* . The upper bound of η, which is $\bar{\eta}'$, ensures that the perceived expected return at any period is positive. Plugging $\hat{\alpha}=\lambda\alpha$ into $\frac{\partial \pi_1}{\partial \eta_1}$, the marginal benefit of approving a known bad borrower under the overconfidence assumption is given as:

$$\frac{\partial \pi_1}{\partial \eta_1}=(a_{C1}^*-c)\frac{\dfrac{(1+r_{C1}^*)\beta p}{\beta+(1-\beta)(1-\lambda\alpha)+(1-q_1^X)(1-\beta)\lambda\alpha\tilde{\eta}_1}-1}{\dfrac{(1+R)\beta p}{\beta+(1-\beta)(1-\lambda\alpha)}-1}(1-\beta)\lambda\alpha\eta_1 \tag{43}$$

We know that $\tilde{\eta}_1$ and r_{C1}^* ensure $\frac{(1+r_{C1}^*)\beta p}{\beta+(1-\beta)(1-\lambda\alpha)+(1-q_1^X)(1-\beta)\lambda\alpha\tilde{\eta}_1}-1>0$, and $a_{C1}^*-c\geq 0$. Therefore, $\frac{\partial \pi_1}{\partial \eta_1}\geq 0$, and the platform chooses $\eta_1^*=\overline{\eta}'$. In period 0, similar to the proof of proposition 2, we can also prove that $\eta_0^*=\overline{\eta}'$. That is, if the platform is overconfident about its screening precision, it still chooses the loosest screening policy and lies to the lender with probability $\overline{\eta}'$ about the borrower risk in each period, as the well-calibrated platform does. Although $\overline{\eta}'$ may be different from $\overline{\eta}$, overconfidence does not essentially change the platform's screening decision.

Now we move to the platform's pricing strategy under the overconfidence assumption. By simply inspecting the Proposition 1, note that $a_{Ct}^*=c$, $r_{Ct}^*=R-c$, then apparently a_{Ct}^* and r_{Ct}^* are independent of the overconfident parameter λ. This suggests that the platform's pricing strategy under the non-guarantee model is not dependent on the platform's level of overconfidence. As a consequence, the overconfident platform chooses the same pricing strategy as the well-calibrated platform. In sum, overconfidence *does not* essentially modify the platform's strategies under the non-guarantee model.

5.2 The welfare cost of overconfidence under the guarantee model

This section analyses the effect of overconfidence on social welfare under the guarantee model. First, we look at how overconfidence affects the platform's pricing strategy. By observing the platform's pricing strategy in Proposition 3, we note that the optimal guarantee fee is a function of the platform's screening precision. Because the platform's pricing strategy is based on its perceived screening precision $\hat{\alpha}$, *not* the actual screening precision α, intuitively, the overconfident platform tends to under-appreciate the borrower's *ex-ante* risk and thus to underprice such risk. This intuition is verified in the following proposition.

Proposition 5: ***Under the guarantee model, if the platform is overconfident, i.e.,*** $\hat{\alpha} > \alpha$ ***, the platform will underprice the borrower's ex-ante risk.***

Proof. The platform forms its assessment about the borrower *ex-ante* risk based on its perceived screening precision $\hat{\alpha}$. Then the perceived *ex-ante* borrower risk $\hat{\delta}$ is given as:

$$\hat{\delta} = \frac{\beta(1-p)+(1-\beta)(1-\hat{\alpha})}{\beta+(1-\beta)(1-\hat{\alpha})}$$

Because $\frac{\partial \hat{\delta}}{\partial \hat{\alpha}} = -\frac{(1-\beta)\beta p}{(1+(\beta-1)\alpha)^2} < 0$, It is obvious that if the platform is overconfident, i.e., $\hat{\alpha} > \alpha$, we have $\delta > \hat{\delta}$. That is, the perceived *ex-ante* risk $\hat{\delta}$ (the platform's belief about the actual *ex-ante* risk δ) is smaller than actual *ex-ante* risk δ . So the platform under-appreciates the borrower *ex-ante* risk.

The guarantee fee, which is set by the platform based on the perceived risk parameters, can be given as:

$$\hat{a}^*_{G,C} = \frac{\hat{\alpha}\beta c + \hat{\alpha}\beta - \hat{\alpha}\mathrm{c} - \beta p - \hat{\alpha} + c + 1}{\hat{\alpha}\beta - \hat{\alpha} + 1}$$

By substituting $\hat{\delta} = \frac{\beta(1-p)+(1-\beta)(1-\hat{\alpha})}{\beta+(1-\beta)(1-\hat{\alpha})}$, $\hat{a}^*_{G,C}$ can be re-written as $\hat{a}^*_{G,C} = \hat{\delta} + c$.

Therefore, if $\delta > \hat{\delta}$,we have $\hat{a}^*_{G,C} < a^*_{G,C}$. That is, the actual guarantee fee is smaller than the break-even guarantee fee. So, the *ex-ante* borrower risk is underpriced by the overconfident platform.

Q.E.D.

The platform's underpricing of risk means that the guarantee fees are not sufficient to cover the potential loan losses, and in this case, the platform suffers *ex-ante* losses. To analytically illustrate this, plugging $\hat{\alpha} = \lambda\alpha$ into the platform's payoff function, the payoff function can be rewritten as $\pi^{'}_G = \frac{\alpha\beta(\lambda-1)(\beta-1)}{1+\alpha(\beta-1)\lambda}$. In the case of overconfidence ($\lambda > 1$), we apparently have $\pi_G^{'} < 0$.

Naturally, such underpricing of risk could increase platforms' bankruptcy probability. Until August of 2016 when Chinese regulators issued the first comprehensive framework for monitoring the P2P lending business, there was no general regulation tailored to P2P lending. Therefore, no capital requirement or other entry barriers encouraged many overconfident platforms to enter the P2P lending industry. As a result, the industry has witnessed widespread platform collapse. Figure 11 reports the number of problematic platforms since 2010 in China. At the end of 2016, 1,741 out of 2,448 platforms had run into difficulties, which can include halted operations, frozen withdrawals or even runaway bosses.

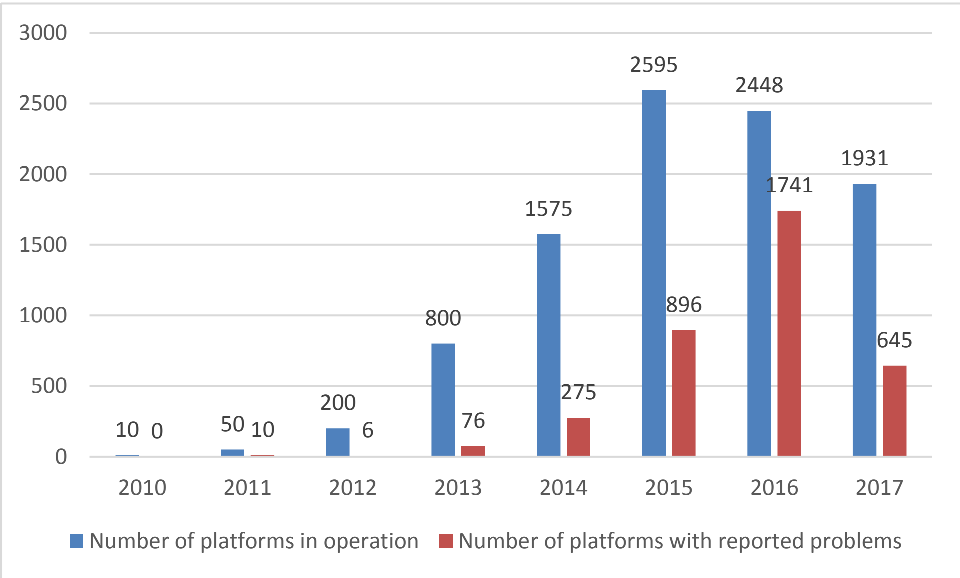

Figure 13 Number of problematic platforms and normal platforms

Source: wdzj.com

Although we do not have platform-level data to properly test for causality between the level of the risk premium (guarantee fee) and the likelihood of platform failure, we can observe the high loan rates (implying a low risk premium) in those potential bankrupt platforms. As shown in the Figure 12, in the early years of China's P2P lending industry, 65% of the problematic platforms set their annualized loan rates above 30%. Although, platform fraudsters intentionally set high loan rates to attract the naïve lenders in some cases, such fraudsters will clearly face criminal investigations.

Therefore, it's reasonable to state that such unusually high loan rates (low guarantee fees) are not only fraud-driven but also due to the platform's underpricing of borrower risk.

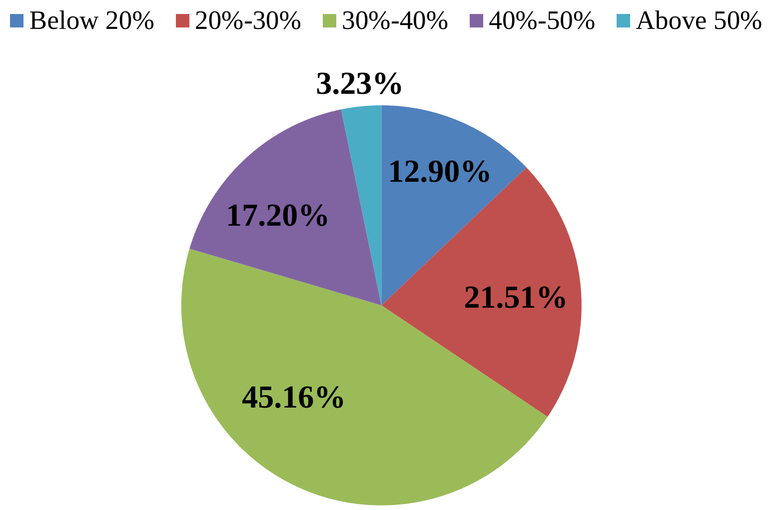

Figure 14 Loan rate distribution among problematic platforms

Source: Sohu Finance (www.sohu.com/a/8049208_11559)

Nevertheless, it is still worthwhile to note that although the underpricing of risk makes platforms vulnerable to collapse, it does not mean that all platform failures are due to platforms' overconfidence. Under certain circumstances, even well-calibrated platforms are susceptible to collapse. Well-calibrated platforms have unbiased predictions about the loan losses, but they still experience unexpected losses in certain periods. Specifically, *expected losses* (ELs) refer to the predicted average level of loan losses that the platform is expected to experience, and losses above the expected level are usually referred as *unexpected losses* (ULs)**.** The concepts of expected losses and unexpected losses used here are similar to those in the banking industry (for example, see Basel Committee on Banking Supervision, 2005). For a well-calibrated platform, although its average long term expected losses will converge to the actual losses, it may suffer substantial unexpected losses in a short time, that may greatly increase its probability of bankruptcy. Moreover, the nature of online lending incurs an additional operational risk for platforms. Driven by anonymity and dependency on information technologies, platforms are more susceptible to cyber-attacks and hacking-related fraud risks.

Having characterized the pricing strategy, we can analytically discuss the impact of overconfidence on social welfare under the guarantee model. To this end, we first rewrite the social welfare function by incorporating the platform's overconfidence and the probability of platform failure. For simplicity, we do not explicitly model the platform's failure process, instead, we assume that the platform goes bankrupt with probability $\mu(\lambda)$, which is an increasing function of the platform's level of overconfidence ($\frac{\partial \mu(\lambda)}{\partial \lambda} > 0, \mu(1) = 0, \lambda \geq 1$). We also assume that the platform always chooses to repay the loan principal to the lender in the event of borrower default, and that the platform is able to do so. The logic behind this assumption is that although lenders have no residual claims on the platform, the platform will suffer huge reputation costs if it chooses not to compensate the lender under the "rigid repayment" expectation, as discussed in chapter 1. In other words, in practice, the platform's claimholders give up their claims and compensate lenders first in the case of failure.

Specifically, the *ex-ante* social welfare under the guarantee model consists of two components: 1) the lender's expected return from the loan; and 2) the expected social cost of overconfidence. The first part of social welfare function is given by:

$$(1+\hat{r}_{G,C})\beta p + \beta(1-p) + (1-\beta)(1-\alpha) - \beta - (1-\beta)(1-\alpha) \tag{44}$$

where $\hat{r}_{G,C}$ is the loan rate that is set by the overconfident platform. Because $\hat{r}_{G,C} = R - \hat{a}_{G,C}$ and as proved in Proposition 5, $\hat{a}_{G,C} < a_{G,C}$, we have $\hat{r}_{G,C} > r_{G,C}$. This means that when the platform is overconfident, the lender actually enjoys higher expected returns than in the case when the platform is well-calibrated.

The second part of the social welfare function, which is the *ex-ante* social cost of overconfidence, can be given by:

$$(\hat{a}_{G,C} - c)(\beta + (1-\beta)(1-\alpha)) - \beta(1-p) - (1-\alpha)(1-\beta) - \mu(\lambda)c_p \tag{45}$$

where $(\hat{a}_{G,C} - c)(\beta + (1-\beta)(1-\alpha)) - \beta(1-p) - (1-\alpha)(1-\beta) = \frac{\alpha\beta(\lambda-1)(\beta-1)}{1+\alpha(\beta-1)\lambda} < 0$ is the platform's *ex-ante* loss under overconfidence, c_P is assumed to be the additional public cost incurred by the platform's failure. Then, the *ex-ante* social cost under the overconfidence assumption is:

$$TS_G = \frac{\alpha\beta(\lambda-1)(\beta-1)}{1+\alpha(\beta-1)\lambda} - \mu(\lambda)c_P \tag{46}$$

By taking the derivative of TS_G with respect to the platform's overconfidence level λ, we find that overconfidence has adverse effect on the social welfare. The proposition below provides a formal proof of this.

Proposition 6 $\frac{\partial TS_G}{\partial \lambda} < 0$**.** ***The platform's overconfidence reduces the ex-ante social welfare****.*

Proof. By substituting $\hat{r}_{G,C} = R - \frac{\lambda\alpha\beta c + \lambda\alpha\beta - \lambda\alpha c - \beta p - \lambda\alpha + c + 1}{\lambda\alpha\beta - \lambda\alpha + 1}$, $\frac{\partial TS_G}{\partial \lambda}$ is given as:

$$\frac{\partial TS_G}{\partial \lambda} = -\frac{\beta\left(\alpha(1-\beta)+\beta p-1\right)(\beta-1)\alpha p}{\left(1+\alpha(\beta-1)\lambda\right)^2} - \frac{\partial \mu(\lambda)}{\partial \lambda}c_P$$

$\alpha(1-\beta)+\beta p-1<0$ is equivalent to $\alpha < \frac{\beta p-1}{\beta-1}$, which immediately holds given $\frac{\beta p-1}{\beta-1} > 1$ and $\alpha < 1$. So $-\frac{\beta\left(\alpha(1-\beta)+\beta p-1\right)(\beta-1)\alpha p}{\left(1+\alpha(\beta-1)\lambda\right)^2} < 0$.

And $\frac{\partial \mu(\lambda)}{\partial \lambda} > 0$, apparently, we have $\frac{\partial TS_G}{\partial \lambda} < 0$.

Q.E.D.

From the above proof, we know that despite the fact that platform's overconfidence increases the lender's expected return, the platform's *ex-ante* loss triggered by the underpricing of risk outweighs the lender's incremental gains. This alone unconditionally reduces social welfare. Moreover, in practice, greater welfare losses may come from the public costs of the platform's failure. Specifically, first, when a large platform collapses, retail investors who have little financial sophistication and lose their savings could take to the streets to protest, which may spill over into social unrest[11]. Additionally, as in Käfer (2016), the failure of a well-known platform can shake lenders' confidence in other platforms. This loss of investor confidence may lead to a dramatic drop in the platforms' fee-based revenues. In an extreme condition, additional platform failure may result. In this sense, platform failure is socially undesirable because it has potential to be contagious. Therefore, the presence of a platform's overconfidence challenges welfare-improving characteristics of the guarantee model presented in a fully rational economy, which is characterized in Proposition 4. A natural and important follow-up question is whether the platform is truly overconfident in its screening precision. This question has important policy implications because it concerns social welfare, and we empirically investigate it in the next chapter.

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[11] The collapse of Ezubao(E 租宝) is a typical example, where many of 230,000 investors, mainly senior whom invested their life savings in the platform.
https://www.ft.com/content/bed7bf3a-df8f-11e5-b072-006d8d362ba3

Chapter 6. Does the platform underprice risk: data and empirical strategy

In the last chapter, we relax the standard assumption of perfect rationality and allow the platform to be overconfident and to overestimate its screening ability. In this case, under the guarantee model, the overconfident platform tends to underestimate and underprice credit risk, which creates welfare losses. The platform's under-appreciation of risk also increases its probability of failure, which further generates greater social costs. An important empirical question is whether the platform is truly overconfident. Ideally, a straightforward way to answer this question is to directly assess the difference between the actual screening precision and the platform's perceived screening precision. However, such a direct assessment cannot be implemented, since both the perceived and actual screening precision are unobservable to us. Fortunately, Proposition 5 provides a testable implication of this issue. That is, if the platform underprices the loan risk it has to bear, that is, the guarantee fees are not enough to cover the potential loan losses, it may suggest that the platform is overconfident.

We use loan-level data from a Chinese P2P lending platform to perform the "underpricing tests". Specifically, in this chapter, we develop an empirical procedure to test whether the credit risk of P2P loans is underpriced in *ex-post* and *ex-ante* senses by the platform. That is, whether the guarantee fees are sufficient to cover the *ex-post* realized loan losses and the *ex-ante* predictable loan losses. In the following sections, we first describe how the platform works (the research context) and the dataset. Then, we outline the empirical strategy. The *ex-post* test examines whether the actual loan losses can be compensated by the guarantee fees, whereas the *ex-ante* test examines whether the guarantee fees are enough to absorb the *ex-ante* predictable loan losses.

6.1 Context and data

The loan-level data for the empirical analysis are obtained from renrendai.com (人人贷), one of China's earliest P2P lending platforms. As of 31 August 2017, renrendai had 517,608 lenders and 471,139 borrowers, and by 2 October 2017, it had facilitated over ¥37.8 billion (£4.16 billion) in funded loans since its launch in 2010. In this section, we provide a brief outline of the funding procedure on renrendai and then describe our sample.

6.1.1 Credit review and loan listing

To post a loan request on renrendai, borrowers must first go through a credit review process. Currently, there is no nationwide, widely recognized credit bureau in China, so the credit review process is mainly run through renrendai's proprietary methodology. Specifically, a borrower first fills out an initial loan application to specify the desired loan amount, loan term and loan purpose. Then, the borrower is required to submit various types of personal information to renrendai for the credit review, including copies of her national identification card, educational qualifications, an employment letter, bank statements, property ownership certificate, marriage certificate, cell phone number, and online video, among others. Renrendai verifies these pieces of information and based on its analysis, it assigns a credit grade to the borrower, and presets an interest rate for the loan listing. Renrendai's credit grades go as follows, from lower risk to higher risk: AA, A, B, C, D, E and HR.

After passing the credit review, a final loan listing for bidding is created on renrendai (that is, after the initial loan application has been approved by the platform), that indicates the desired loan amount, loan term, loan rate, a text description of the loan purpose and optionally includes the borrower's image(the loan amount and term could be different from the initial loan application based on result of credit review). A listing is open for several days. Lenders can view the progress of each listing, information about the listing and the borrower, and their entire bidding history.

6.1.2 Bidding, fees and (implicit) loan guarantee

To bid on a listing, lenders must transfer sufficient funds to their noninterest-bearing renrendai accounts. The minimum bid amount is ¥50. Renrendai encourages lenders to bid in small amounts to diversify risk. Listings on renrendai are funded as closed auctions. In this closed format, the auctions are set to terminate as soon as the total bid amount reaches the amount sought at the preset loan rate.

Once a loan listing is fully funded, the borrower is charged a guarantee fee, which equals 0%-5% of the principal, according to her credit grade. In particular, 0% for AA, 1% for A, 2% for B, 2.5% for C, 3% for D, 4% for E, and 5% for HR. All guarantee fees go to the provision fund, which is the fund used to repay the outstanding principal when a loan becomes delinquent. After a loan is issued, the borrower pays both the principal and the interest in equal instalments monthly. The principal guarantee provided by renrendai works as follows: if the loan is 30+ days overdue, renrendai will repay the outstanding principal to the lenders, and the ownership of the loan will be transferred to renrendai. Renrendai and its partner institution will then attempt further debt collection. However, in case where the provision fund for loan guarantees become exhausted, renrendai does not have to continue to provide loan guarantees. That is, offering loan guarantees is not a strictly legal obligation for renrendai.

6.1.3 Data and variables

Our dataset consists of funded loan listing that were created on renrendai.com from 1 January to 20 June 2015. The data were collected in early April of 2017 using a computer program. Renrendai had been adjusting its lending or application procedure during the early years of operation. There is no significant operational change during the chosen sample period, which ensures our data is consistent.

There are several types of loan listings on renrendai, but our dataset only contains one particular type of loan listing, “unsecured loan listings”. We are only interested in “unsecured loan listings” because 1) “unsecured loan listings” are unsecured loans, collateral or personal guarantees are not required to apply this type of loan; and 2) the loan payments are “guaranteed” only by renrendai’s provision fund. That is, the risks of principal loss is entirely borne by renrendai. In our dataset, most borrowers are rated in among one of the lowest three credit grades-D, E or HR-while only a tiny fraction of borrowers are rated with higher credit grades-AA, A, B or C. We drop loan listings with AA, A, B or C credit grades from our dataset, given that the average predicted losses for AA, A, B or C loans, cannot be estimated properly due to such small number of observations. Thus, our final sample covers 5,594 loans, all of which are rated D, E or HR.

In our sample, each loan has one of three repayment statuses: defaulted, paid off (including paid off on time and paid off early) and repaying. A loan is classified as defaulted if it is 30+ days overdue, because renrendai repays the outstanding principal to lenders through its provision fund when the loan is 30+ days overdue. Although "30+ days overdue" does not seem to be a "normal" standard for default, as the usual rule is 90 days of non-payment, renrendai does suffer an actual loss when the loan payments are 30+ days late under the aforementioned principal guarantee mechanism. To measure renrendai's loss given default (LGD), we construct the variable, LGD, which is the ratio of renrendai's real loss to the loan amount on a defaulted loan, in which the real loss is calculated as the present value of the outstanding principal (that is, the amount that renrendai repays to the lenders) minus the present value of the recovered amount. We use the day when the loan is issued as the "present day" when calculating present values.

Table 2 Variables and summary statistics

Variables	Description	All loans No. of Obs.=5,594		Defaulted loans No. of Obs.=1,026	
		Mean	**S.D**	**Mean**	**S.D**
Default indicator and LGD					
Default	Equals 1 if the loan is 30+ days overdue and 0 otherwise	0.1834			
LGD	Loss-given-default			0.6037	0.2733
Credit grade	Set of dummy variables indicating borrower's credit grade (AA, A, B, C,D, E, HR).HR is used as the reference group				
Credit grade-D		0.222		0.0194	
Credit grade-E		0.325		0.052	
Credit grade-HR		0.452		0.930	
Loan characteristics					
Loan Amount	Loan amount requested by borrower in 1000RMB	21.083	17.055	23.267	17.649
Loan Rate	Annual contractual loan rate	11.818	1.042	12.312	0.860
Term	Number of months between loan origination and maturity	13.925	7.375	17.392	7.102
Origination time	Set of month dummy variables controlling for the time of loan origination				
January		0.295		0.325	
February		0.117		0.114	
March		0.175		0.175	
April		0.162		0.151	

May		0.143		0.130	
June		0.108		0..105	
No. of bids	Total number of bids received	22.120		23.626	
Borrower characteristics					
Basic information					
Age	Borrower's age at the data collection time	33.194	6.398	34.451	7.033
Male	Equals 1 if the borrower is male and 0 otherwise	0.868		0.865	
Marital status	Equals 1 if current marital status is married and 0 otherwise	0.579	0.494	0.603	0.489
Business owner	Equals 1 if the borrower is a business owner and 0 otherwise	0.169	0.374	0.274	0.446
Working class	Equals 1 if the borrower is working class and 0 otherwise	0.691	0.462	0.624	0.485
Online seller	Equals 1 if the borrower is an online seller and 0 otherwise	0.140	0.347	0.102	0.303
Active days	time span between borrower's registration date and loan origination or initiation date	4.818	8.3134	4.114	7.751
Education	Set of dummy variables indicating borrower’s highest qualification (High school or below, Associate degree, Bachelor, Master or above)."High school or below "is used as the reference group.				
High school or below		0.237		0.335	
Associate degree		0.403		0.474	
Bachelor		0.326		0.183	
Master or above		0.034		0.008	
Lending history					
No. of funding success	Number of previous funding success	0.314	0.723	0.209	0.611
Amount raised	Total amount of previous funded loans (in 1000RMB)	6.531	32.310	6.331	39.848
Previous overdue	Equals 1 if there are previous late payment histories, and 0 otherwise	0..0486	0.215	0.070	0.256
Asset information					
Property ownership	Equals 1 if the borrower owns a property or more and 0 otherwise.	0.518		0.521	
Mortgage	Equals 1 if the borrower has mortgage to pay off and 0 otherwise	0.225		0.171	
Vehicle ownership	Equals 1 if the borrower owns a vehicle or more and 0 otherwise.	0.343		0.306	
vehicle loan	Equals 1 if the borrower has vehicle loan to pay off and 0 otherwise	0.090		0.087	
Income Level	Set of dummy variables indicating the borrower's monthly income range.				

Income<5000RMB		0.347		0.312	
5000RMB=<Income<=10000RMB		0.320		0.320	
10000RMB<Income<=20000RMB		0.143		0.126	
20000RMB<Income<50000RMB		0.114		0.120	
Income>=50000RMB		0.077		0.123	
Loan purposes	Set of dummy variables indicating the borrower's purposes for applying loans				
Home decoration	Equals 1 if the loan purpose is for home decoration and 0 otherwise	0.228		0.241	
Property purchase	Equals 1 if the loan purpose is for property purchase and 0 otherwise	0.034		0.302	
Investment	Equals 1 if the loan purpose is for investment and 0 otherwise	0.130		0.135	
Personal consumption	Equals 1 if the loan purpose is for personal consumption and 0 otherwise	0.123		0.147	
Working capital	Equals 1 if the loan is applied as a working capital loan	0.407		0.384	
Other purposes	Equals 1 if the loan is applied for other purposes other than below	0.076		0.060	
Job information					
Years at current job	Set of dummy variables indicating number of years worked at current job.				
Year<1		0.091		0.084	
1<Years<=3		0.396		0.441	
3<Years<=5		0.210		0.188	
Years>5		0.304		0.287	
No. of employee	Set of dummy variables indicating number of employee of the borrower's current company.				
No. of employee<10		0.227		0.259	
10<No. of employee<=100		0.322		0.379	
100<No. of employee<500		0.170		0.128	
No. of employee>=500		0.281		0.234	

Table 2 lists the variable descriptions and provides summary statistics for our sample. For each loan, we have loan characteristic information (loan amount, term, loan rate, etc.), basic information about the borrower (gender, age , educational qualifications, etc), borrower credit information(credit grade, lending history, etc), borrower asset information(income level, property ownership, car ownership, etc.), borrower employment information (length of employment , firm size, etc.), and monthly repayment data.

The loan sample reveals that 1,026 out of 5,594 loans end up in default. That is, 18% of the loans are 30 days or more delinquent, and renrendai repaid the outstanding principals of these loans to the lenders. Approximately 93% of defaulted loans are credit grade HR, while only 5% and 2% are credit grades D and E, respectively. The sample also suggests that most of defaulted borrowers (approximately 81%) have below a bachelor's degree. The average term of defaulted loans is 17.4 months, which is longer than that for all loans (14 months). The average LGD for the 1,026 defaulted loans is 60.37%; that is, renrendai's average loss per defaulted loan is 60.37% of the loan amount.

6.2 Empirical strategy

6.2.1 *Ex-post* test: the guarantee fees and actual losses

We first look at the underpricing of risk from an *ex-post* perspective. Although we cannot observe the platforms' perceived borrower *ex-ante* risk, we do observe the guarantee fees set by the platform. In the case of renrendai, the provision fund is used to cover potential loan losses and is financed by the guarantee fees paid by the borrowers. Since the guarantee fees are the only source to cover the loan losses, it is reasonable to assume that, for a given loan, renrendai sets the guarantee fee based on the loan's predicted loss, as suggested by Proposition 3. That is, mathematically, a loan's guarantee fee should at least equal the platform's prediction of the loan's future loss.

If the platform is well-calibrated, it can make an unbiased prediction of future loan losses. Thus, the guarantee fees should be an unbiased predictor of the actual loan losses. In this sense, the difference between the guarantee fees and the actual loan losses should be zero on average. More precisely, this difference, as a prediction error, should be unforecastable white noise, that have zero mean. We use the Mincer-Zarnowitz regression to test whether the platform's prediction errors have this property, as suggested by Lopez and Saidenberg (2000). Specifically, we estimate the following linear regression:

$$AL_i = \alpha + \beta GF_i + \varepsilon_i \tag{47}$$

where AL_i is the actual loss rate on loan i, GF_i is the guarantee fee rate for loan i

and ε_i is an error term. Then, we can test the joint hypothesis $\alpha = 0$ and $\beta = 1$. If the estimated coefficients are different, it indicates that there is systematic bias in the platform's predictions. Specifically, if the estimated β is significantly greater than one, it would suggest that he guarantee fees are underpriced.

6.2.2 *Ex-ante* test: the guarantee fees and predictable losses

This section examines the platform's underpricing of risk from an *ex-ante* perspective. That is, instead of looking at the difference between the guarantee fees and the *ex-post* actual loan losses, as in the above *ex-post* test, we examine whether the guarantee fees can cover the *ex-ante* predictable loan losses. Given that the guarantee fee rates are mapped to credit grades on renrendai, we specifically focus on testing whether predictable losses based on credit grade levels can be covered by the corresponding guarantee fee rates. If the preset guarantee fee rates are not enough to compensate the predictable losses at the corresponding credit grade levels, it would suggest that the loans' risk is underpriced in an *ex-ante* sense.

A. Overview

Before formally introducing the details of the test, we provide an overview to describe how the test works in a general sense. Specifically, the test contains two steps. The first step is to generate predictable losses for each credit grade from historical data. Then, the second step is to test whether the guarantee fee rates for the corresponding credit grades can cover the predictable losses. Given that the second step can be performed in straightforward manner by using the standard regression technique, we only discuss the first step here.

To better illustrate the rationale of the generation process of predictable losses, we first consider the following abstract and hypothetical example. We use a three-period setting in which time is indexed as $t = 0,1,2$. Loans last for one period. Since the guarantee fee rates are mapped to credit grades, without loss of generality, we assume that all loans have an identical credit grade, so they are charged at an identical guarantee fee rate. We are particularly interested in examining whether the guarantee fee rate for loans issued at $t = 2$ are sufficient to absorb the predictable losses. To this end, we develop a procedure to generate the expected loan losses based on information available when loans are issued at $t = 2$. We use the generated expected losses as an approximation of the predictable losses. Specifically, the general generation process can be described as follows:

(1) Using default predictors(loan characteristics, borrower characteristics, etc.) for loans issued at $t = 0$ and their realized loan outcomes(default or not), which are available at $t = 1$, as inputs, we estimate our default prediction model and the loss given default (LGD).

(2) We use the estimated default prediction model and the loss given default in (1) to calculate the expected losses for loans issued at $t = 1$.

(3) We assess the prediction accuracy of our model by comparing the realized loan outcomes and actual loan loss rate for loans issued at $t = 1$ (which are available at $t = 2$) with the predicted default probabilities and the expected losses. If our model shows reasonably good predictive power, the average generated expected losses for each credit grade for loans issued at $t = 1$, is used as the predictable losses on credit grade levels for loans issued at $t = 2$; that is, an *ex-ante* prediction of the loan losses for loans issued at $t = 2$. Importantly, the expected losses are predictable losses, because the information needed to generate the loss prediction is already available when the loans are issued.

Now we specify the procedure in relation to our dataset. Specifically, our goal is to estimate the predictable losses for credit grades D, E and HR. Based the above rationale, we divide our dataset into two subsets: the training dataset and the validation dataset.
The training dataset is used to estimate the model parameters. The validation dataset is used to perform an out-of-sample test of the predictive power of the default prediction model that is built on the training dataset. It means to withhold some of the data from the model estimation process, then use the estimated model to make prediction for hold-out data to see the model's predication accuracy. Specifically, the training dataset contains the data on the default predictors (loan characteristics, borrower characteristics, etc.) and realized loan outcomes (default or not) for loans issued during

1/1/2015-16/3/2015. We use the training dataset to estimate and calibrate our default prediction model and the LGD. The rest of the data, that is, the default predictors and realized loan outcomes for loans issued during 17/3/2015-20/6/2015, forms the validation dataset, which has no overlap with the training dataset.

If the estimated default prediction model presents reasonably good out-of-sample default prediction accuracy, then we can use the model to generate predictable loan losses on credit grade levels. That is, the average expected losses for the loans with a given credit grade are the predictable losses for that credit grade.

The rest of the section outlines the *ex-ante* test in more detail. Section B describes the generation process of the expected losses on individual loan level. Sections C explains why we do not model unexpected losses. Subsequently, in section D, the loss coverage ratio test is developed to test whether the predictable losses at each credit grade level can be covered by the corresponding guarantee fee rate.

B. The modelling process of the expected losses

The modelling of expected losses is a two-stage process. In the first stage, we model the *probability of default (PD).* That is, given the predictor variables, how likely is it for a given loan to end in default? In the second stage, we estimate the *loss given default (LGD)*. LGD is a widely used parameter in credit risk management in the banking industry; it refers to the bank's percentage of exposure to loss in case the loan defaults. In this study, LGD is defined as the percentage of the original loan amount that the platform might lose if the borrower defaults. Thus, the platform's expected loss (EL) on a given loan, expressed as a percentage of the original loan amount, is written as:

$$EL = PD * LGD \tag{48}$$

The details of the two-stage process are given as follows:

Stage 1: Estimate conditional probability of default for individual loans.

Specifically, we look to estimate:

$$P(Outcome = default \mid \boldsymbol{X} = \boldsymbol{x}) \tag{49}$$

This is the probability of default, conditional on the loan and borrower characteristics

$\mathbf{x}=(x_1, x_2, ...x_m)$. We use logistic regression to implement such an estimation. An event of loan default is indexed as $Y=1$, while full payment or still in payoff is indexed as $Y=0$. A logistic regression model of default prediction is then written as:

$$P(Y=1 \mid \boldsymbol{X}=\boldsymbol{x}) = f_L(\boldsymbol{\beta x}) \tag{50}$$

where f_L is the logistic link function, and $f_L(s)=\dfrac{1}{1+e^{-s}}$. $\mathbf{x}$ is the vector of predictor variables, which includes loan characteristics (loan amount, term, loan rate, etc.), and, borrower characteristics (credit grade, personal details, etc.). Maximum likelihood estimation(MLE) is used to find the estimates of $\hat{\boldsymbol{\beta}}$ of the parameters $\boldsymbol{\beta}$. The reasons we use logistic regression for default prediction is because of logistic regression is the most commonly used method for building credit scorecards in consumer finance, and it also has "a strong theoretical underpinning in that it gives rise directly to an additive log odds score which is a weighted linear sum of attribute values"[12] (Thomas, 2009, p79).

After estimating the parameters, we can obtain the probability of a positive outcome, in our case loan default, by using the estimated model. That is, for a specific loan i, given the predictor variables, $\mathbf{x}_i=(x_{i1}, x_{i2}, ...x_{im})$, predicted probability of default is calculated as:

$$\hat{P}_i(Y=1 \mid \boldsymbol{X}=\boldsymbol{x}_i) = 1 \big/ 1+e^{-\hat{\boldsymbol{\beta}}\mathbf{x}_i} \tag{51}$$

Stage 2: Estimating the platform's predictable LGD

LGD is usually defined from the lender's perspective, which is obvious since the lender bears the loan's default risk in standard lending. In contrast to that, in this study, LGD is defined from the platform's perspective instead of the lender's, because under the guarantee model, the platform must bear the default risk of the loan as the platform repays the outstanding principal to the lender once a default event has occurred. In addition, our interest is to investigate, from an *ex-ante* perspective, whether the

[12] We are aware that if instead we use the duration models, such as cox proportional hazards model, the right censoring problem (i.e. loans may default after the date of last observation in the sample) may be dealt and information of the dataset can be fully exploited. However, the post estimation test shows that hazard ratio is not constant over time, which means this model is not appropriate for the dataset, as the model assumes there is a baseline hazards and the default risk increase proportionally over time

principal losses that the platform undertakes to pay can be compensated by guarantee fees. Note that the ownership of a defaulted loan is transferred to the platform after the outstanding principal is paid to the lender(s) and the platform engages in further debt collection, so the platform's actual loss on a defaulted loan is the outstanding principal minus the amount recovered from the defaulted loan. The platform's LGD is therefore:

$$LGD = \frac{outstanding\ principal - amount\ recovered}{principal} \tag{52}$$

LGD is a random variable. Unfortunately, LGD is not well-understood and properly modelling LGD is currently changeling. According to Li et al. (2016), the reasons for this difficulty includes 1) data limitations and a lack of risk drivers; and 2) the unusual distribution of LGD. Consequently, LGD is relatively understudied, although the numbers of LGD studies has been increasing in recent years (Qi and Zhao,2011). However, among these works, little attention has been paid to modelling LGD for consumer loans. One exception is Leow et al.(2014).

Given that there are no standard tools for modelling LGD, and our focus is not on developing models of it, in this study, LGD is simplified to constant for all loans. Therefore, we straightforwardly use the average historical LGD of the training dataset as the predictable LGD.

After estimating the default probability, PD_i, and LGD, the expected loss for a specific given loan can then be calculated as:

$$EL_i = PD_i * LGD \tag{53}$$

where PD_i is the predicted probability of default that obtains from (51).

C. Unexpected losses and default correlation

Of course, statistical-based models cannot capture all the risk, and the actual loan losses that occur can be higher than expected. Losses above the expected level are unexpected losses, as mentioned in section 5.2. Figure 13 is drawn from Basel Committee on Banking Supervision (2005), and it shows probability distribution of losses to an institution's credit portfolio. Estimating the loss distribution is central to an institution's portfolio risk management, because it answers the question "what is the size of the loss for a given confidence level" (CSFB,1997). The loss distribution can be generated by an institution's internal approach and/or well-known credit risk models, such as KMV(Moody's), CreditRisk+(CSFB) or CreditMetrics(JP Morgan). In practice, banks' expected losses are generally covered through the pricing of credit and credit provisions. So-called "economic capital" is needed for absorbing unexpected losses. Interest rates may absorb some parts of unexpected losses, but setting prices high enough to cover all unexpected losses is unrealistic, since such high prices are not supported by the market (Basel Committee on Banking Supervision, 2005).

Although estimating unexpected losses is certainly important for financial institutions' credit risk management, we *do not* model unexpected losses in this study. In other words, in the *ex-ante* test, predictable losses only refer to the expected losses, although unexpected losses are not unpredictable. There are three reasons for this approach. First, the most straightforward reason is that the guarantee fees should at least cover the expected losses if they are not underpriced in an *ex-ante* sense. Second, it is difficult to determine the precise proportion of unexpected losses a platform wishes to cover. Specifically, platforms face a trade-off between setting higher guarantee fee rates to cover more unexpected losses and lowering their guarantee fee rates so that they can increase their loan rates and attract more lenders. However, it is difficult for us to guess a platform's mindset in such trade-off, given that different platforms have different marketing strategies, time horizons and risk management practices, etc. Finally, China's highly competitive P2P lending business environment, is likely to drive the guarantee fee rates to a relatively low level that is just enough to cover all of the expected losses and a very small portion of the unexpected losses. In other words, the actual guarantee fee rates may be very close to break-even fee rates that just sufficient to cover the expected losses.

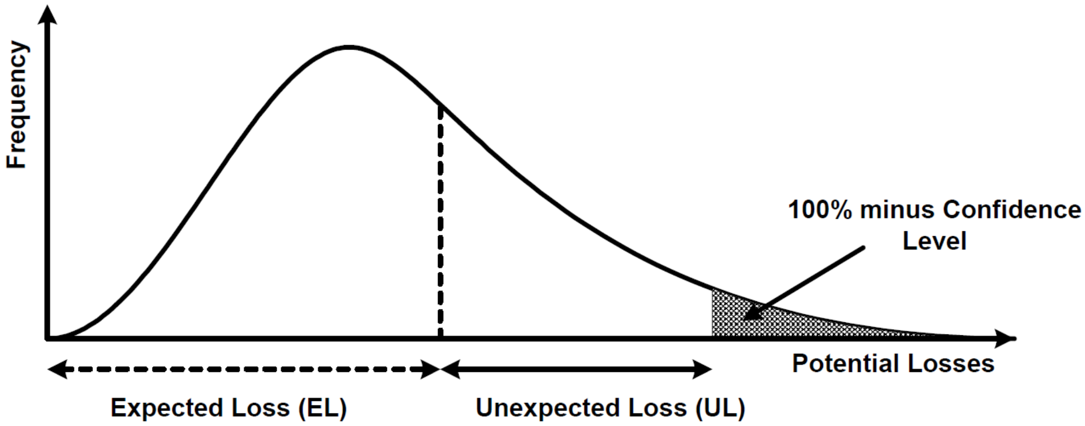

Figure 15 Expected loss and unexpected loss

Source: Basel Committee on Banking Supervision (2005)

One more aspect is worth noting here. Loan defaults can be correlated. However, the rationale behind default correlation is complicated and not well understood. An intuitive rationalization of default correlation could be that all borrowers are affected by common, systemic factors such as macroeconomic conditions. To model the aforementioned default loss distribution, default correlation needs to be considered; otherwise, unexpected losses will be underestimated. That is, with or without incorporating default correlation, *both loss distributions have the same level of expected losses,* but the loss distribution with default correlation has fatter tails (more chances of suffering extreme losses) (CSFB,1997). This argument can be proven on the linearity of expectation operator, that is, $E(X+Y)=E(X)+E(Y)$, where X and Y are arbitrary random variables, without regard to whether they are independent or correlated.

D. The loss coverage ratio test

After obtaining the expected losses, which are used as the predictable losses for the future loans, we can proceed to test whether the guarantee fee rates are properly set according to the predictable losses. First, we introduce the *loss coverage ratio* (LCR). For a given loan i whose credit grade is j, LCR_i is calculated as:

$$LCR_i = \frac{EL_i}{Guarantee\ fee\ rate_j} \tag{54}$$

where EL_i is loan i 's expected loss that is generated by the process in section B, and $Guarantee\ fee\ rate_j$ corresponds to the *latest* guarantee fee rate for credit grade j. To be more specific, $Guarantee\ fee\ rate_j$ is *not* the actual guarantee fee rate charged for loan i (credit grade j) when the loan is issued, but is the latest guarantee fee rate for credit grade j that we can observe at the time of data collection. $Guarantee\ fee\ rate_j$ may be different from the actual guarantee fee rate for credit grade j, because a platform may update its risk predictions and adjust its guarantee fee rates based on the most recent information. In this sense, LCR_i actually characterizes the extent to which the *ex-ante*, predictable losses for future loans are covered by the guarantee fee rate set for these loans. Obviously, if LCR_i is greater than one, then the guarantee fee charged on a given loan is not enough to cover the loan's predictable loss. Therefore, to formally test whether LCR_i is statistically greater than one, we use a simple linear regression:

$$LCR_i = \beta_1 x_{1i} + \beta_2 x_{2i} + ... + \beta_j x_{ji} + \varepsilon_i \tag{55}$$

where x_{ji} is a dummy variables that equals one if credit grade for loan i is j and zero otherwise**.** If $\hat{\beta}_j$ is significantly greater than one, it means that the guarantee fee rate for credit grade j are not sufficient to cover the predictable losses. That is, the guarantee fee rate is underpriced for credit grade j, given that the guarantee fee rate should be at least cover the losses that can be predicted. However, if $\hat{\beta}_j$ is significantly less than one, we cannot infer that the guarantee fee rate for credit grade j is overpriced in an *ex-ante* sense, because the guarantee fee may be used not only to cover the expected losses but also the aforementioned *unexpected losses***.** In this case, we can only infer that the guarantee fee is *not* underpriced in an *ex-ante* sense.

Chapter 7. Empirical results, discussion, and policy implications

This chapter first discusses the empirical results, and then policy implications by combing the theoretical and empirical findings. We start from the *ex-post* test in which we straightforwardly examine whether the actual loan losses can be absorbed by the preset guarantee fees.

7.1 The *ex-post* test result: Mincer-Zarnowitz regression

Let us first look at the result of the *ex-post* test. Table 3 reports the result of the Mincer-Zarnowitz regression as discussed in section 6.2.1, which we used to testing whether the guarantee fee is an unbiased predictor of the *ex-post* realized loan losses. The regression result shows that the joint hypothesis of a zero intercept and an estimated coefficient of 1 is rejected. This means that the guarantee fee is a biased predictor of the actual loan losses. More precisely, the estimated coefficient is significantly greater than one, which suggests that the guarantee fee is underpriced in an *ex-post* sense. That is, on average, the guarantee fees charged by renendai are not enough to compensate the real loan losses that the platform suffers. Such underpricing can be evidence of platform's overconfidence. The logic behind this is that the platform sets the guarantee fees based on its assessment of borrower risk. If that assessment is biased, specifically, downward-biased, the platform will underprice the loans' credit risk accordingly. Therefore, from an *ex-post* perspective, we can observe that the guarantee fees are not sufficient to cover the platform's actual loan losses.

Table 3 Mincer-Zarnowitz regression

The table reports OLS regression for actual loan loss rate. Standard errors are robust heteroskedasticity consistent and clustered at the loan level.

Actual loss rate	Coef.	Std. Err.	P Value
Guarantee fee rate	12.550	0.395	0.000
Constant	-0.420	0.014	0.000
N.of obs		5,594	
Prob > chi2		0.000	
R-squared		0.143	

Wald Test: H_0: Guarantee fee rate=1, Constant=0
F(2, 5593) = 464.71
Prob > F = 0.0000

However, we must admit that we may still find the evidence of the presence of such underpricing of the loans' risk even if the platform is not overconfident. This is because, as discussed in section 6.2.2, a well-calibrated platform's average expected losses converge to the real losses over the long term, but the platform may experience substantial, unpredicted losses over short period. Specifically, as shown in Figure 14, which is derived from Basel Committee on Banking Supervision (2005), the actual loan losses that occur may be higher than the expected level at some points. Such losses above expected level are so-called unexpected losses. In reality, as in the case of banking industry (Basel Committee on Banking Supervision, 2005), the platform may reasonably predict the average level of loan losses over long term, but it is never possible for it to know in advance the actual losses in a particular period. Although our sample size is reasonably large, the time span of the sample period is relatively short. Therefore, the presence of underpricing of risk in an *ex-post* sense may be due to not only to the platform's overconfidence but also to the unexpected losses that the platform suffered during the sample period.

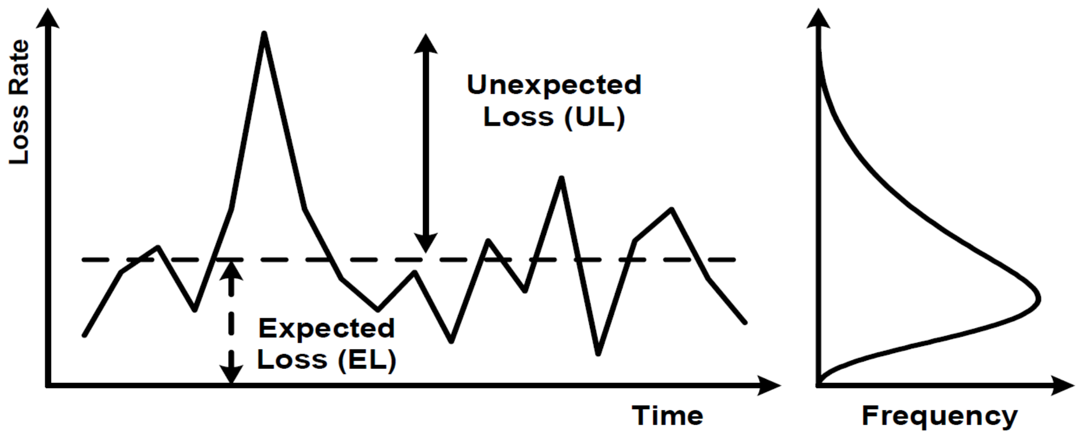

Figure 16 Expected loss and actual loss

Source：Basel Committee on Banking Supervision (2005)

7.2 Generating predictable loan losses: estimation, diagnostics and model selection

Now we move on the *ex-ante* test to find out whether the guarantee fees can cover the expected losses that can be predicted *ex-ante*. As discussed in section 6.2.2, the first step is to estimate the predictable loan losses from historical loan transaction and outcome data. To this end, this section estimates the logistic regression models for default prediction as outlined in section 6.2.2 by using the training dataset. Then, some postestimation diagnostics tests are performed to see if the estimated model fits the data well. Finally, we further check whether the estimated model presents reasonably good out-of-sample prediction accuracy by using the validation dataset.

In what follows, we start with the full specification, and then consider improving our model by using backward-stepwise elimination.

7.2.1 Default prediction model I: full specification

A. Estimation

Table 4 reports the results of the logistic default prediction model with the full specification using the training dataset. The estimated coefficients illustrate how loan and borrower characteristics affect the likelihood of default. All being else equal, younger borrowers, borrowers who have higher credit ratings and higher education levels, and borrowers who are mortgage payers are less likely to default; conversely, borrowers who chooses longer loan term and borrowers who have a previous late payment history are associated with a higher default probability. Personal characteristics, gender and marital status are not associated with default probability after controlling for the other factors. Surprisingly, borrower lending history, including the number of previous times the borrower had funding success and the total amount the borrower raised are not significantly associated with default, which seems to be counter-intuitive. Default rates vary across loan purposes, but borrowers who are applying for loans for investment and personal consumption purposes are more likely to default than otherwise similar borrowers. We also find that borrowers who are registered as private business owners have a higher default rate than working class borrowers. Borrowers' employer firm size and length of employment have no predictive power for default[13].

Table 4 Logistic estimates for default prediction: model I

This table reports maximum likelihood estimates for logistic regression in full specification. Standard errors are robust heteroskedasticity consistent and clustered at the loan level. For credit grade dummies, "HR" is used as the reference group. For loan purposes dummies, "other purposes" is used as the reference group. For loan origination month, "March" is used as the reference group. For education level, No. of employee, Years at current job and income level, "High school or below", "No. of employee<10", " Years<1" and " Income<5000RMB" are used as the reference groups, respectively.

Default	Coef.	Std. Err.	P value
Credit grade dummies			
Credit grade D	-3.911	0.314	0.000
Credit grade E	-3.242	0.237	0.000
Loan characteristics			
Loan rate	-0.199	0.182	0.276
Term	0.109	0.022	0.000
Loan amount	0.007	0.007	0.326
No.of bids	-0.005	0.005	0.347
Loan purposes			
Home decoration	0.483	0.282	0.086
Property purchase	0.273	0.467	0.559
Investment	0.619	0.300	0.039
Personal consumption	0.588	0.299	0.049
Working capital	0.214	0.266	0.421
Loan origination month			
January	0.000	0.159	0.999
February	0.067	0.176	0.702
Borrower basic information			
Male	0.102	0.181	0.572
Age	0.064	0.011	0.000
Marital status	-0.011	0.136	0.936
Business owner	0.707	0.280	0.012
Online seller	-0.399	0.343	0.245
Active days	0.005	0.009	0.560
Borrower lending histories			
No. of funding success	-0.094	0.193	0.626
Amount raised	0.003	0.004	0.412
Previous overdue	0.752	0.358	0.036

13 Despite Petersen and Rajan(1997)'s findings of firm age's non-linear effect in terms of financing, we do not expect borrower's age would have non-linear effect on default probability. Therefore the age squared is not included in the model. The borrower photo is also not included due to the data collection programme is unable to obtain such data, although Duarte et al. (2012) found using borrower photo may improve default prediction.

Borrower asset information			
Property ownership	-0.236	0.153	0.124
Mortgage	-0.371	0.182	0.042
Vehicle ownership	-0.316	0.162	0.051
vehicle loan	0.230	0.263	0.383
Borrower education level			
Associate degree	-0.193	0.145	0.183
Bachelor degree	-0.963	0.183	0.000
Master or above	-2.479	0.720	0.001
Borrower job information			
No. of employee			
10<Number of employee<=100	-0.185	0.238	0.437
100<Number of employee<500	-0.486	0.295	0.099
Number of employee>=500	-0.358	0.282	0.204
Years at current job			
1<Years<=3	0.002	0.223	0.991
3<Years<=5	-0.160	0.245	0.512
Years>5	-0.396	0.251	0.115
Borrower income level			
5000RMB=<Income<=10000RMB	-0.116	0.160	0.469
10000RMB<Income<=20000RMB	-0.110	0.221	0.619
20000RMB<Income<50000RMB	0.083	0.268	0.756
Income>=50000RMB	0.449	0.313	0.151
No. of obs.		2,785	
Pseudo R2		0.358	

B. Diagnostic tests

Rather than evaluating the relationships between default likelihood and the predictive variables, we are more interested in using the estimated logistic model to generate predicted default probabilities. Therefore, before we can use our model for default prediction, we need to check that the estimated model fits the data sufficiently. We begin with the link test of Pregibon (1979). The link test examines whether the model is specified correctly. After estimating the logistic model, the link test uses the prediction and prediction squared to rebuild the model. If the model is correctly specified, the prediction squared should have no explanatory power. Table 5 reports the results of the link test, which is another logistic specification. The results reveal the prediction squared is not a statistically significant predictor; thus then we can state that our model is specified properly and we have not omitted relevant variable(s)

Table 5 Link test results for model I

π is the predicted probability from model I.

Default	Coef.	Std. Err.	P value
π	0.946	0.075	0.000
π^2	-0.021	0.023	0.367
No. of obs.		2,785	
Pseudo R2		0.3578	

Table 6 Hosmer–Lemeshow goodness-of-fit test results for model I

No.of obs.	2,785
No. of groups	10
Hosmer-Lemeshow chi2(8)	2.63
Prob > chi2	0.9555

Next, we turn to assess the goodness of fit of the estimated logistic model. For a linear model, the most common measure of goodness of fit is R^2, but it is less useful with logistic regression. A better way of evaluating the goodness of fit of a logistic model is the Hosmer–Lemeshow goodness-of-fit test (Hosmer and Lemeshow,1980). The Hosmer–Lemeshow test compares the observed versus predicted frequency for different subgroup of the data. If the fit is good, the difference between the observed and predicted frequency should be sufficiently small. The Hosmer–Lemeshow test statistic is a distributed chi-square. Table 6 reports the result of the Hosmer–Lemeshow test. With p-value of 0.96, we cannot reject the null hypothesis that there is no difference between the observed and predicted frequency. Thus, the model fit is considered to be adequate.

Now we evaluate the model's power for default predicting, which is our major concern. Specifically, we focus on the model's out-of-sample prediction accuracy by using the validation dataset. There are two reasons for this approach. First, the model is designed to predict the default probability of future loans, so it would not make sense if we only measured the model's in-sample prediction performance. Second, the in-sample prediction accuracy is likely to overstate the model's true prediction power.

In practice, the decision making of approving/rejecting loan applicants using logistic model is based on the threshold probabilities. That is, the platform chooses a particular probability, for example 0.5, as the threshold. Then, the platform rejects all loan applicants whose predicted probability of default is below the chosen threshold probability. In this sense, default prediction actually becomes a classification problem. For a given threshold probability, an intuitive way to assess the classification power is to determine what fraction of true default cases are correctly classified *(sensitivity)* and what fraction of true no-default cases are correctly classified *(specificity)*. The model's sensitivity and specificity vary across threshold probabilities. Receiver operating characteristic (ROC) curve provides a comprehensive framework to characterizes classification accuracy; that is, the ROC curve measures the sensitivity and specificity at every possible threshold. Figures 15 and 16 report the in-sample and out-of-sample ROC curves, respectively. The ROC curves show the trade-off between sensitivity and specificity. That is, the probability of correctly detecting a default (true positive rate) increases with the probability of erroneously classifying a no-default as default (false positive rate). This suggests if the platform chooses a rigorous screening standard, i.e., a lower threshold that corresponds to a higher false positive rate, then it will it obviously enjoy higher sensitivity. However, in this case, more "good" applicants will be incorrectly rejected.

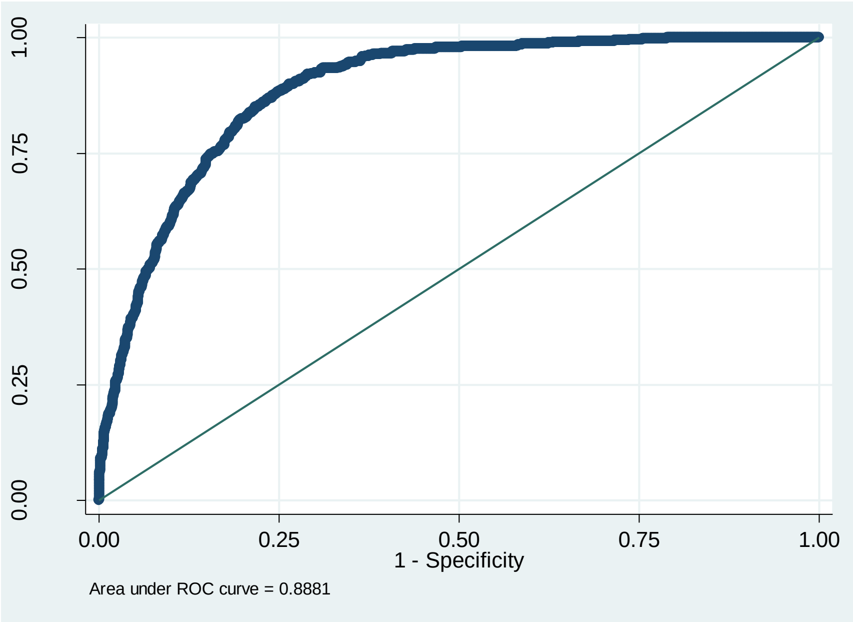

Figure 17 ROC curve for the training dataset (in-sample ROC curve)

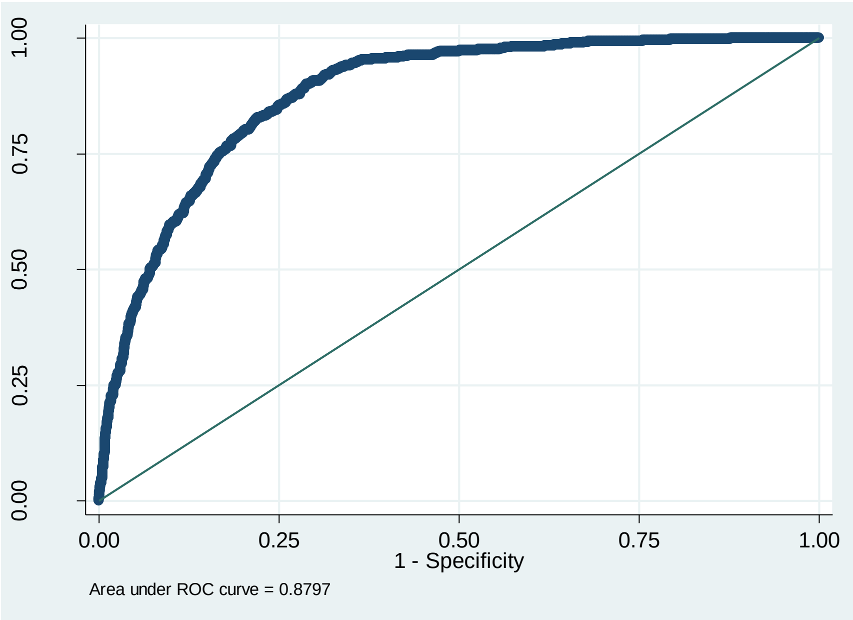

Figure 18 ROC curve for the validation dataset (out-of-sample ROC curve)

A simple but useful measure of discrimination accuracy can be computed from the ROC curves: the area under the ROC curve (AUC). The AUC can be interpreted as the probability that, if one defaulting borrower and one no-default borrower are randomly selected, the defaulting borrower has a higher predicted probability of default than the no-default probability. The in-sample and out-of-sample AUCs for our model are 0.8881 and 0.8797, respectively. These results indicate that the probability of a borrower being "correctly" classified by our model are 0.8881 in the training dataset and 0.8797 in the validation dataset. Although there is no "magic" number regarding the value of AUC that universally defines a good classification, under rule of thumb suggested by Hosmer Jr. et al. (2013), an AUC between 0.8 and 0.9 is considered to be excellent classification, while above 0.9 is considered to be outstanding. On this basis, we can state that our model provides reasonably good in-sample and out-of-sample predictive power. Moreover, because the in-sample and out-of-sample AUCs are very close to each other, our model has little issue with overfitting.

We also check the multicollinearity of model I. The result of multicollinearity test shows the average Variance Inflation Factors (VIF) for all variables is 2.47 and none of VIFs exceeding 10 (see appendix A for details), which are signs of serious multicollinearity requiring correction, according to the general rule of thumb. However, the VIFs for the term and loan rate exceed 5, which implies the presence of relatively mild multicollinearity. This result is likely due to the possibility that the "loan term" is one factor affects renrendai's loan pricing. In the next section, we improve the model by using stepwise elimination.

7.2.2 Default prediction model II: backward stepwise elimination

A. Model estimation and diagnosis

Although above the diagnostics checks show in general model I fits the data well and has good predictive power, we re-estimate our model by using backward stepwise logistic regression. We do so because backward stepwise elimination can overcome the mild multicollinearity problem presented in model I, by removing the predictors whose loss provides the most statistically insignificant deterioration of the model fit, in a stepwise manner. Also, stepwise elimination is often used for cutting down the number of default predictors to build a robust credit scorecard (Thomas, 2009). Therefore, we expect the default prediction model produced by backward stepwise logistic regression (model II) to have similar goodness of fit and predictive power but less of a multicollinearity problem compared with model I.

The parameter estimation and diagnostic tests of model II are reported in Table 7. The remaining predictor variables, including credit grade, loan term, and the education dummies are all highly significant. It does not surprise us that the loan rate is dropped by the backward elimination, given that the correlation between the loan rate and the loan term, and more importantly, the loan rate has little predictive power after controlling the total borrowing cost.

Table 7 Backward stepwise logistic estimates for default prediction: model II

This table reports maximum likelihood estimates for backward stepwise logistic regression. Standard errors are robust heteroskedasticity consistent and clustered at the loan level. The significance level at which variables can enter the model is set at 0.05.

Default	Coef.	Std. Err.	P value
Credit grade dummies			
Credit grade D	-3.742	0.309	0.000
Credit grade E	-3.168	0.231	0.000
Loan characteristics			
Term	0.090	0.008	0.000
Borrower basic information			
Age	0.059	0.010	0.000
Business owner	0.864	0.161	0.000
Borrower lending histories			
Previous overdue	0.754	0.273	0.006
Borrower asset information			
Mortgage	-0.478	0.155	0.002
Borrower education level			
Master or above	-2.337	0.695	0.001
Bachelor degree	-0.855	0.148	0.000
Borrower income level			
Income>=50000RMB	0.452	0.219	0.039
Borrower job information			
Years>5	-0.407	0.153	0.008
No. of obs.		2,785	
Pseudo R2		0.3466	

The multicollinearity test for model II indicates that multicollinearity problem is no longer be a concern, given that average VIF is 1.14 and all VIFs are less than 2 (see appendix B for details). To check model II's specification error, goodness of fit and predictive power/classification accuracy, we use the link test, Hosmer–Lemeshow goodness-of-fit test and ROC analysis as in model I. Model II passes the link test and the Hosmer–Lemeshow test, confirming that model II has no specification problem and provide a reasonably good fit to the data. Figures 17 and 18 show both in-sample and out-of-sample ROC curves for model II, respectively. The area under the out-of-sample ROC curve (AUC) is 0.8776, meaning that 87.76% of the borrowers are classified "correctly". This predictive power/classification accuracy is as good as that of model I.

Table 8 Link test results for model II

π is the predicted probability from model II

Default	Coef.	Std. Err.	P value
π	0.920	0.076	0.000
π^2	-0.031	0.024	0.195
No. of obs.	2,785		
Pseudo R2	0.3472		

Table 9 Hosmer–Lemeshow goodness-of-fit test results for model II

No. of obs.	2785
No. of groups	10
Hosmer-Lemeshow chi2(8)	4.77
Prob > chi2	0.782

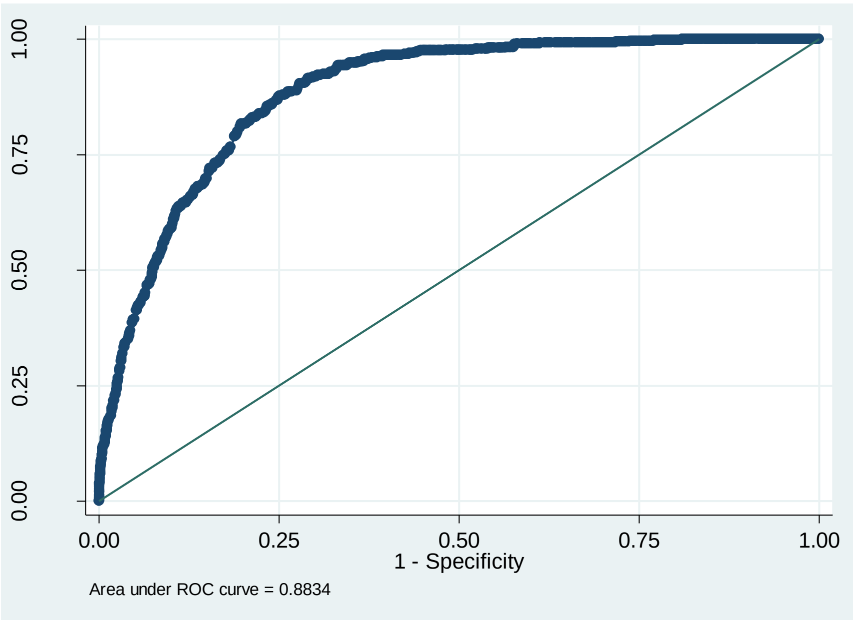

Figure 19 ROC curve for the training dataset (in-sample ROC curve): model II

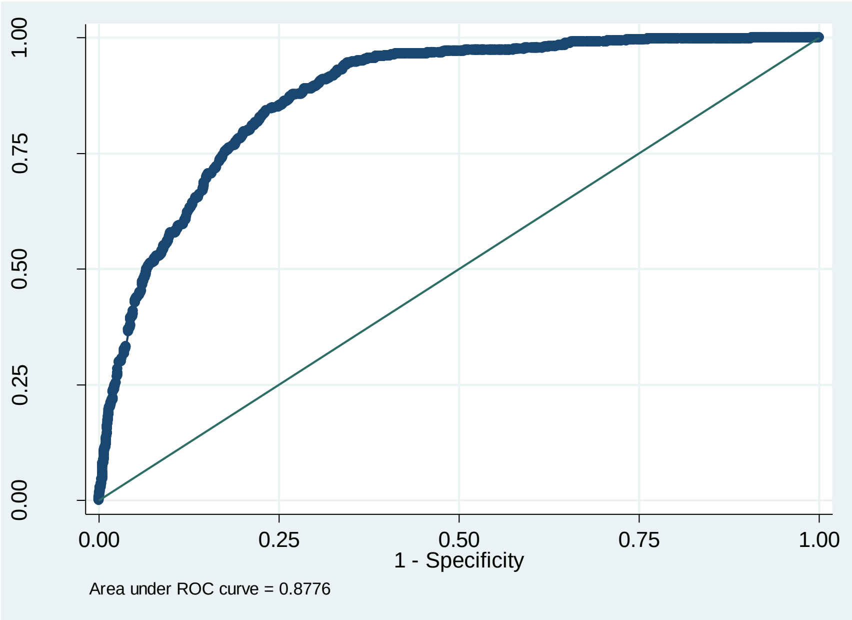

Figure 20 ROC curve for the validation dataset (out-of-sample ROC curve): model II

B. The excepted losses

Now we can produce the expected loss for an individual loan. To do so, we first generate the predicted probability of default, PD_i for each loan in the validation dataset based on Model II. Note that the model is estimated by using data from the training dataset, so the predicted default probabilities, PD_i, are out-of-sample predictions. Next, the expected losses are computed as $EL_i = PD_i * LGD$, where LGD is the average loss given default in the training dataset (as shown in Table 10). Figure 19 reports the density distribution of the generated expected losses.

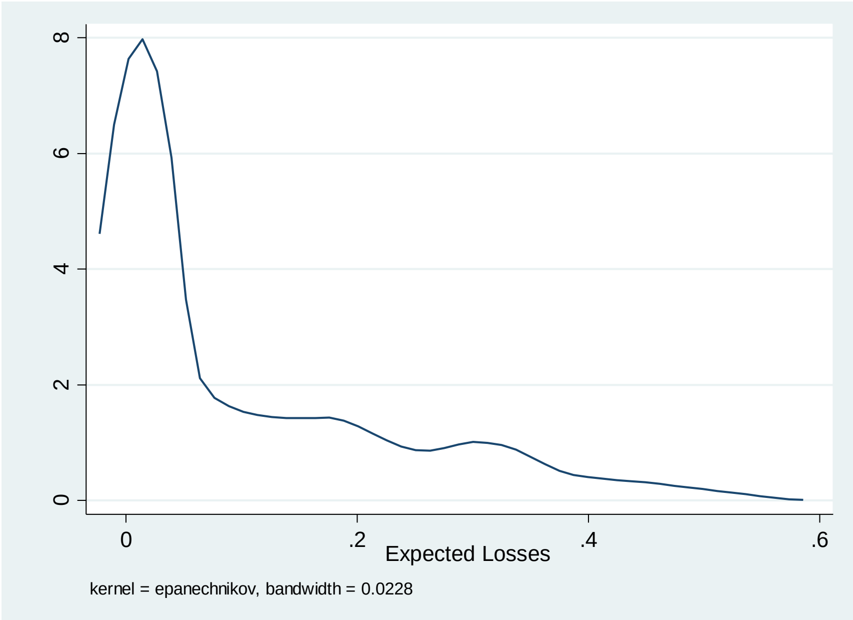

Figure 21 The distribution of the generated expected loan losses (predictable loan losses)

Although Model II has robust out-of-sample predictive power, the average historical LGD from the training dataset may not be an unbiased prediction of the LGD for loans in the validation dataset. Specifically, we must admit that the average historical LGD may be a downward-biased estimator of LGD (Frye,2004). The most important reason for that is average historical LGD may not reflect adverse economic scenarios, as the severity of loss on defaulted loans during an economic downturn is likely to be higher than under normal economic conditions (Basel Committee on Banking Supervision, 2005). To detect a potential issue with underestimating LGD, we further check if the average generated expected losses, which are calculated using average historical LGD are close to the actual average losses. Fortunately, as shown in Table 10, we find they are close to each other, which suggests that the issue is not troublesome. The difference between the expected losses and actual losses can be understood as the unexpected losses, which is the risk that cannot be captured by our statistical based model.

Table 10 Predicted losses and actual losses

	No. of obs.	Mean	Std. Dev.
Expected losses	2,809	0.1008	0.1288
Actual losses	2,809	0.1093	0.2633
LGD in the training dataset	530	0.5895	0.2686

In actual practice, in addition to the average historical LGD, a more conservative and robust LGD can be used. In the absence of relevant data to estimate the effect of downturn conditions on the LGD of P2P lending and given the fact that P2P lending is unsecured lending where no collateral or personal guarantee is required, it is reasonable to use 100% as a conservative LGD. The Bank of England (2017) also recommends using 100% as LGD for similar cases. However, in this study, we do not use this conservative LGD in order to avoid overstating it.

7.3 The loss coverage ratio test results

Now we implement the loss coverage ratio regression as described in section 6.2.2.D. The regression results are shown in Table 11. We first examine the results for credit grade D and E. The estimated coefficients for credit grade D and E are smaller than one and the Wald tests reject the null hypothesis that estimated coefficients equal one. Therefore, we *cannot* infer that the guarantee rates credit grades D and E are underpriced. Specifically, the estimated coefficient for credit grade D is 0.3492. That is, on average, every ¥1 of expected loss is covered by ¥2.86(1/0.3218) of guarantee fees. Similar interpretations applied to the estimated coefficient for credit grade E. Although the average loss coverage ratios for credit grades D and E are less than one, we cannot conclude that their credit risks are overpriced, because the "excessive part" of the guarantee fee can be used to absorb the unexpected losses, as discussed in section 6.2.2.C. Thus, again, we can only safely state that the guarantee fees for credit grades D and E are not underpriced, given that they can fully cover the loans' expected losses.

However, the results for the riskiest loans tell a different story. The estimated coefficient for the lowest credit grade HR are greater than one and the null hypothesis that it equals one is also rejected by the Wald test, which suggests that the guarantee fee rate for HR loans is underpriced. Specifically, the average loss coverage ratio for credit grade HR is 4.2847, meaning that on average, the guarantee fee charged for these loans can only cover 22.33% (1/4.2847) of their expected losses.

Table 11 Loss coverage ratio analysis

Panel A reports OLS regression results for loss coverage ratio and Wald test results for estimated coefficients. Standard errors are robust heteroskedasticity consistent and clustered at the loan level. The regression is without constant. Panel B reports one sided t test result for loss coverage ratio.

Panel A

Loss coverage ratio	Coef.	Std. Err.	P value
Credit grade D	0.349	0.022	0.000
Credit grade E	0.349	0.013	0.000
Credit grade HR	4.285	0.069	0.000
No. of obs.		2,809	
Adj-R2		0.750	

Wald test:

Ho: Credit grade D=1	Ho: Credit grade E=1	Ho: Credit grade HR=1
F(1, 2808) = 862.23	F(1, 2808) = 2430.84	F(1, 2808) = 2248.52
Prob > F = 0.0000	Prob > F = 0.0000	Prob > F = 0.0000

Panel B

	No. of Obs.	Mean	Std. Err.	Std. Dev.
Loss coverage ratio	2,809	2.069468	0.0481421	2.551532
Ho: mean = 1				
Ha: mean > 1				
Pr(T > t) = 0.0000				

One might argue that the difference in the loss coverage ratios indicates the presence of a cross subsidy; that is, the "overestimated" guarantee fees for credit grade D and E subsidies the underestimated guarantee fees for credit grade HR. However, we find no such evidence, since the univariate test shows that the overall average loss coverage ratio for all loans is significantly greater than one. Specifically, the overall average loss coverage ratio is 2.0695, which means that overall, the guarantee fees only cover 48.32% of the expected losses.

Taken together, these findings suggest that renrendai underprices the loans' risks in an *ex-ante* sense, given that the preset guarantee fees are not sufficient to cover the predictable loan losses. These results provide evidence of the platform's overconfidence. The rationale behind this is formalized in our theoretical model. That is, if the platform's beliefs about its risk parameters (for example, its screening ability), upon which its risk assessments are based, are downward biased, it will underprice borrower risk *ex-ante*.

We conjecture that the most important reason behind such an under-appreciation of risk is that the newly established, inexperienced platforms often lack adequate risk management systems. Specifically, as reported by Sohu Finance, most of the medium and small P2P platforms with monthly loan transaction volume below ¥ 1 billion lack effective and independent risk management systems; In addition, for a minority of the large platforms, although they have their independent risk management systems and professional risk officers, their systems are insufficient for novel lending models such as P2P lending. Moreover, what makes a bad situation worse is that China currently lacks a nationwide, mature consumer rating agency or credit bureau, like FICO, to help platforms to calibrate the relevant risk parameters for default prediction, and platforms therefore rely heavily on their own proprietary risk assessment systems. Finally, there are general concern regarding the quality of credit risk models in P2P lending because these models are untested through stressed economic cycles (FSB and BIS ,2017).

However, we must acknowledge that in addition to the platform's overconfidence, there are two other reasons that could contribute to the finding or occurrence of *ex-ante* underpricing of risk. The first is related to our sample period and size. Our default prediction model is estimated using data on loans that issued from 1 January to16 March in 2015 (i.e., the training dataset). Although our model showed reasonably good out-of-sample prediction accuracy for the validation dataset, renrendai can use a longer and bigger sample to calibrate and validate its own default prediction model, which may generate different expected losses from our model. In such case, the platform may not be overconfident, given a different information set. The second reason is that the guarantee fees may be strategically underpriced by the platform. That is, the platform may use a loss leader pricing strategy to gain market share. Therefore, the *ex-ante* underpricing that we observe would not be due to the platform's overconfidence.

7.4 To guarantee or not to guarantee: risks and benefits of the two lending models and policy implications

As shown in section 4.4, the welfare comparison under perfect rationality indicates that the guarantee model can generate greater social welfare than the non-guarantee model. Nevertheless, the welfare-enhancement of the guarantee model can be jeopardized by a platform's under-appreciation of risk. In this section, we discuss the risks and benefits of the different lending models and their implications for policymakers.

7.4.1 Risks and benefits of the guarantee model and the non-guarantee model

Let us first look at the guarantee model. As revealed by our theoretical analysis, the guarantee model creates a more efficient allocation of credit compared with the non-guarantee model. That is, "good" borrowers who are worth being financed should obtains loans, whereas "bad" borrowers with low credit quality should be declined credit. This improved screening efficiency comes from the fact that the guarantee model can incentivize the platforms to honestly screen loan applicants, given that the platforms have enough skin in the game.

However, the prevalence of the guarantee model can also generate a risk of financial instability. First, under the guarantee model, the platforms actually accumulate credit risks by bearing the default losses of the loans they facilitate, and they cannot offset these risks by spreading them to lenders, which is what platforms do under the non-guarantee model. Although the loan guarantees are voluntarily offered by the platforms through provision funds, platforms that fail to deliver on the loan guarantees face huge reputation costs based on investors' "rigid repayment" expectation in China's unique institutional background. In other words, strategical default is not a rational option for the platforms. In this case, the platforms entail bank-like credit risk, but they are not as rigorously regulated as banks. This makes the platforms particularly susceptible to failure. Therefore, given the rapid growth of P2P facilitated-credit in China, the prevalence of the guarantee model could pose systemic risk in the future.

Second, in the earlier sections, we found evidence that the platform underprices the credit risk that it has to bear under the guarantee model. This may arise due to the platform's inadequate risk management. This underpricing of risk will reduce the platforms' profitability and increase the chance of platform failure, which can in turn exacerbate financial instability. Moreover, the magnitude of the underpricing of risk could be greater than we estimate, since the credit risk models in P2P lending have not yet been tested through a full credit cycle. In sum, under the guarantee model, the greater screening efficiency is accompanied by greater financial instability.

Now we turn to the non-guarantee model. Under the non-guarantee model, the platforms do not take on the credit risk on their own, and lenders on the platforms absorb loan losses directly. In this sense, the non-guarantee model poses much less prudential and systemic risk, because it can spread the credit risk across lenders, and the credit risk does not be accumulated in the platforms. However, the non-guarantee model has a downside, which is the potential for platform moral hazard. That is, the platforms have incentives to boost their loan origination volume for transaction fees, regardless of loan quality. This distortion of incentives stems from the fact under the non-guarantee model, the platforms have little skin in the game because they do not bear the credit risk of the loans they facilitate. The presence of this platform moral hazard lowers the screening efficiency to allow some bad borrowers, who should have been rejected, to be granted credit instead. More importantly, as illustrated by our theoretical analysis, the platform's tendency to overstate borrower credit quality cannot be effectively reduced through reputation concerns because a bad loan cannot be unambiguously attributed to the bad behaviour of the platform as the platform's screening effort is not *ex-post* verifiable. Therefore, the non-guarantee model could lead to a reduction in lending standards while improving access to credit. Overall, under the non-guarantee model, the lower prudential and systemic risk is accompanied by less efficient credit allocation.

7.4.2 Policy implications

Given the different risks and benefits presented under the different lending models, policymakers are confronted with a trade-off between financial stability and efficiency when they clarify the role of P2P platforms. If a platform guarantee is allowed, regardless whether it is direct or indirect, then policymakers will be acknowledging that platform play the role of a credit intermediary. However, this increases the chance for potential of financial instability in the system. If, by contrast, the guarantee model is banned, and platforms are only allowed to facilitate loans under the non-guarantee model, it means that the platforms can only serve as information intermediaries. This could cause a reduction in screening efficiency as shown in our theoretical analysis. Therefore, when the regulators define the roles and functions of P2P platforms, they should strike a balance between financial stability and screening efficiency.

China's first comprehensive framework for monitoring the P2P sector actually reflects such a balance. The regulation, issued in August of 2016, forbids platforms from directly or indirectly guaranteeing the principal or interest on loans they facilitate[14]. Thus, the regulation prioritizes financial stability, instead of screening efficiency, by prohibiting the guarantee model. The reason for this approach is straightforward. Given the remarkable size and growth rate of China's P2P lending sector as well as the frequency with which platform failure has occurred, the common use of the guarantee model would have the potential to threaten China's financial stability in the future. Therefore, reducing the systematic risk of the P2P sector is the current regulatory imperative.

By contrast, rather than playing a prudential role as Chinese regulators, regulators in developed economies mainly focus on how to ensure that the platforms act as honest brokers and that the lending process is fair and transparent (Lenz,2016). They take this approach because the platforms in these countries generally operate under the non-guarantee model and when they provide investment protection through provision funds, they do not face hard constraints such as the "rigid repayment" expectation as that their Chinese counterparts confront. Under such circumstances, credit risk does not accumulate in the platforms and they are less vulnerable to collapse. Therefore, the regulators pay more attention addressing misaligned incentives and investor protection in P2P lending.

Another regulatory implication is related to the information disclosure requirements

[14] The regulation gives P2P platforms one year grace period to rectify their businesses.

in China's recent P2P regulation. Under the regulation, although the platforms are required to disclose data regarding their borrowers, the loans, and the risk assessments, among others, these requirements are quite general and fail to provide specifics. This vagueness gives the platforms an incentive to manipulate their information disclosure. The platforms can cherry pick their reported information by hiding unfavourable data in order to increase their loan origination volume. Therefore, more specific information disclosure requirements can reduce the platforms' tendency to engage in information manipulation. Moreover, the source of platform moral hazard is the opaqueness of the platforms' risk and screening algorithms. Although it is unrealistic to ask the platforms to disclose the details of their proprietary algorithms, something can still be done to mitigate the platform's moral hazard. For example, as we rationalized in Lemma 3, disclosing the data about both approved and rejected loan applicants would increase the transparency of screening process and encourage the platforms to reject borrowers who are known as bad credit risks.

Chapter 8. Conclusion

The rapidly and significantly growing market for P2P lending in China, in which individual lenders directly finance consumers or small businesses without intermediation of traditional credit institutions, is expanding access to credit by providing loans to certain borrowers who might not otherwise have received capital. There are two basic models for P2P lending in China: the non-guarantee model and the guarantee model. Under the non-guarantee model, the platforms only serve as information producers that screen borrowers but do not bear the risk of bad loans. By contrast, under the guarantee model, the platforms play a more active role in the transaction process, in the form of providing loan guarantee. The different lending models give the platforms different incentives when screening borrowers and pricing the loans, which affects the transaction outcomes and overall social welfare. A comparison of the two lending models from theoretical and empirical perspectives provide insights into the fundamental question "which P2P lending model produces the most socially desirable outcome?"

8.1 Summary of the findings

8.1.1 Can reputation concerns prompt the platform's truthful screening?

We first develop game-theoretic models of lending processes to derive the platforms' screening and pricing strategies under the two lending models. For the non-guarantee model, the theoretical analysis focused on whether reputation concerns, as a disciplinary device can induce platform's truthful information production. We find that the opportunistic platforms always mimic the pricing strategy of the truthful platform. That is, there only exists "truthful pricing" in the economy. The intuition behind this result is straightforward. Based on public information, a rational lender can form loan rates and transaction fees that are set by the truthful platform, i.e., the "truthful pricing structure", in her mind. Once the lender observes any pricing structures that deviate from that of the truthful one, her belief about the platform's type will be updated immediately; that is, she will infer that the platform is the opportunistic type. On the basis of this belief, it is optimal for her not to invest finance in any loans on that platform. Given the lender's response, the platform's optimal action is to copycat the pricing strategy of the truthful type.

In this sense, the reputation mechanism disciplines the platform with regard to pricing, because the pricing structure revealed by the platform is a perfect signal of the platform's type, as both the actual pricing strategy and the truthful pricing strategy are observable to the lender. This incentivizes the platform to act as the truthful type in pricing.

Given the platform's pricing strategy, we then look at the platform's screening strategy, which is characterized by the probability of approving a known "bad" borrower. The lending game unfolds in a dynamic setting in which the platform's optimal screening strategy must balance higher short-term profits from misreporting borrower credit risk against higher long-term profits from improved reputation for honestly reporting borrower credit risk. We find that, despite the presence of such trade-off, under our parameter space, the platform will still approve a known "bad" borrower with the highest possible probability. In other words, the platform will choose the loosest screening strategy and lies to the lender about borrower credit quality with a certain probability. This means that the reputation concerns fail to discipline the platform. The root cause of the failure of the reputation mechanism to prevent the platform from dishonestly revealing borrower credit quality is that the lender cannot attribute a bad loan to the platform's opportunistic behaviour. In addition to the platform's untruthful information disclosure, there may be two other explanation for the occurrence of a bad loan. First, the platform's could have made an honest screening error due to the imperfection of the screening technology, and second ,based on "bad luck", even "good" borrowers who are *ex-ante* worthing financing, may still end up in default. Therefore, if the "good" borrower's repayment probability or the platform's screening precision are relatively low, in the lender's mind, the occurrence of a bad loan is more likely due to one of these two causes other than the platform's information manipulation. This *ex-post* non-verifiability of the platforms' screening effort actually limits the disciplinary effect of the reputation mechanism, especially when the benefits of "lying" outweigh the costs.

8.1.2 Is the guarantee model more socially desirable than the non-guarantee model?

Next, to perform the welfare comparison of the two lending models, we model the platform's behaviours under the guarantee model using a similar framework. Since the platform has enough "skin in the game" under the guarantee model, it's optimal for it to act as the truthful type and reject all known "bad" borrowers. Thus, we solve for the platform's optimal pricing strategy, which is an outcome of the trade-off between a higher a guarantee fee or a higher loan rate. We find that the optimal pricing strategy can be viewed as a risk-sharing arrangement between the platform and the lender. That is, all else being equal, the guarantee fee is positively associated with the borrower's *ex-ante* risk, while the loan rate is negatively correlated with the borrower's *ex-ante* risk.

Having characterized the platform's equilibrium strategies under the two lending models, we conduct a comparative welfare analysis under the competitive setting. We find that the guarantee model produces greater overall social welfare. The increased welfare can be explained by the higher screening and pricing efficiency of the guarantee model. Specifically, with regard to screening efficiency, the platform always screens borrowers honestly under the guarantee model given it has enough "skin in the game". In contrast, under the non-guarantee model, the platform approves known "bad" borrowers who are inefficient to finance *ex-ante*, with a certain probability, therefore the lender will suffer welfare loss in the sense of screening efficiency. With regard to pricing efficiency, the pricing structure under the guarantee model is *ex-ante* efficient, because the loan rate increases with the borrower's *ex-ante* risk, whereas the guarantee fee decreases in borrower's *ex-ante* risk. But the platform's competitive pricing strategy under the non-guarantee model can be viewed as inefficient, since it is independent of the borrower's *ex-ante* risk and thus does not reflect the aforementioned risk-reward balance.

However, the welfare-enhancing property of the guarantee model is challenged when we relax the assumption that the platform is well-calibrated. We find that when the platform is overconfident about its screening ability, it will underprice the loan risk. It means that the guarantee fees are not sufficient to cover the potential loan losses, because the platform sets the guarantee fees based on its perceived screening precision, not its actual screening precision. When considering the presence of the platform's overconfidence and probability of platform failure in the social welfare function, we find that under the guarantee model, the *ex-ante* social welfare decreases with the platform's level of overconfidence. This reduction in social welfare is the result of the platform's *ex-ante* loss due to the underpricing of risk and the public cost of platform failure.

8.1.3 Does the platform underprice risk?

By using loan-level data from a Chinese P2P lending platform that uses the guarantee model, we empirically examine whether the loans' credit risk is underpriced by the platform. Our results show that the platform underprices the guarantee fees in both an *ex-post* and *ex-ante* sense. Specifically, we first test the relationship between the guarantee fees and actual loan losses. We find that, the guarantee fees that set by the platform are not enough to cover the actual loan losses, which suggests that the guarantee fees are underpriced in an *ex-post* sense. This *ex-post* underpricing provides an evidence that the platform is overconfident, because the guarantee fees, which reflect the platform's expectation of future loan losses, should be an unbiased predictor of the actual loan losses, if the platform is well-calibrated. Statistically, in this case, the prediction errors, the difference between the guarantee fees and the actual losses, should be zero on average.

To look at the underpricing problem from an *ex-ante* perspective, we develop a procedure to generate expected loan losses from historical loan data. We use the generated expected losses as *ex-ante*, predictable loan losses. We find that the preset guarantee fees are also not sufficient to absorb such predictable loan losses, which means that the guarantee fees are underepriced in an *ex-ante* sense. In particular, the guarantee fees charged for HR loans can only cover 22.33% of their predictable losses. These findings also provide evidence of the presence of the platform's overconfidence because the overconfident platform will underprice the borrower's *ex-ante* risk given its biased belief about screening precision.

8.2 Contribution

This study contributes to the growing literature on P2P lending by modelling the behaviours of two alternative types of P2P platforms. Previous research implicitly assume P2P platforms are honest information producers and their roles in information transmission are not considered. The literature thus mainly analyses the effects of different mechanisms in mitigating information problems during borrower-lender interactions. In contrast, this study focuses on platform-lender interactions. Specifically, we develop theoretical models that characterize a P2P platform's information disclosure and loan pricing strategies. The platform's tendency to overstate borrower quality (dishonest information disclosure) and reputation concerns are both incorporated into our model.

This work complements the literature on reputation models in game theory by providing an analysis in the context of P2P lending. The theoretical results show that reputational concerns may not be sufficient to induce fully truthful information disclosure of P2P platforms, when the platform's screening technique is imperfect. That is, since a bad loan can be caused not only by the platform's deliberately lax screening standards but also the platform's honest screening errors or bad lucks, the lender may not unambiguously attribute a bad loan to the platform's opportunistic behaviour. This intuition is consistent with cases in credit rating agencies and investment banks (Chemmanur and Fulghieri, 1994; Mathis et al., 2009, and; Fulghieri et al., 2013) in which the credit rating agencies or investment banks are only able to imperfectly observe asset quality.

We provide empirical evidence relating to regulatory concerns about the impact of P2P platforms on financial stability. Specifically, we develop an empirical procedure to test whether the platform underprices the loans' risk in both *ex-ante* and *ex-post* sense.

The results support the untested conjecture in the prior literature that the platforms are likely to under-appreciate borrower risk. The results also offer an explanation for the phenomenon of widespread platform collapse in China's P2P lending market. In addition, given the generality of the empirical procedure, it has potential to be used as a standard framework for platform underpricing test.

To the best of our knowledge, this research is the first study that analytically compares the two models of P2P lending in China. This comparison provides important practical insights. Our analysis shows that the different lending models have different risks and benefits. Specifically, the non-guarantee model creates less risk of financial instability but has lower screening efficiency and could potentially lead to deterioration of lending standards, while the guarantee model generates efficiency in credit allocation but creates systemic and prudential risk. On this basis, regulations that define the role and function of P2P lending platforms, should balance financial stability against screening efficiency. This provides a rationale for China's recent P2P regulations, in which the guarantee model is banned, and platforms can only act as information intermediaries, because the risk of financial instability brought about by the prevalence of the guarantee model outweighs the consequent improvement in screening efficiency given the status quo in the P2P lending sector in China. Moreover, our analysis suggests that under the non-guarantee model, the platforms' motives of information manipulation can be weakened by more detailed information disclosure policy. Specifically, the mandatory disclosure information on all approved and rejected loan applicants can incentivize the platforms to act as honest brokers by making them decline known "bad" borrowers, which will improve their reputation in the lenders' minds.

8.3 Limitations and future research

"All models are wrong; some models are useful."

—George E. P. Box, British statistician

Throughout the process of theoretical modelling, we are always confronted with a trade-off between the generality of the model assumptions and the model's computational complexity. In some cases, we have to make some seemingly "unrealistic" assumptions not only to (greatly) simplify the model's structure but also to set the model's boundaries. We believe that "the risks and benefits" of these assumptions have been carefully evaluated, but relaxing and generalizing some of these assumptions can improve this work and will among our future research interests.

First, the platform's screening precision or ability α is assumed to remain constant and the screening cost per loan applicant is assumed to be zero. This assumption does not take into account the platform's strategic information acquisition problem (for example, as Hauswald and Marquez (2006) discussed in banking), in which the screening effort is assumed to be costly and the screening precision is a function of the screening effort. The platform therefore faces a trade-off between the screening cost and screening precision. Our simplified specification allows us to focus on the platform's information manipulation decision under a given screening parameter rather than the platform's choice of screening precision, which is beyond the scope of this paper.

Second, in chapter 5, we allow the platform to be overconfident about its screening parameter α. In the platform-lender game, the core setting is that the lender can update her belief about the platform's type based on the observed loan outcome. Following this logic, leaves an open question; that is, do platforms "learn" their own screening abilities dynamically through the realized loan outcomes they observe? If so, the platforms' beliefs about their own screening precisions may converge towards the actual values overtime. This question may be worth empirically testing in the future. Specifically, Figure 20 reports the monthly dynamics of the average loan rate for China's P2P lending sector since 2014. As the figure shows, there has been a steady decrease in the loan rate, from 21.63% in the early 2014 to 9.21% in May 2017. The gradually decline in the loan rate might suggest that the platforms are updating their beliefs about their own screening ability and adjusting their overpriced loan rates and underpriced guarantee fees to an appropriate level. However, the P2P loan rates are also affected by general credit conditions, so the decline in the P2P loan rate may just be a result of loose credit environment. Therefore, further examination is required to isolate the effects of credit market tightness on the P2P loan rates and to extract the idiosyncratic variation, which is the component driven by platforms' learning curves.

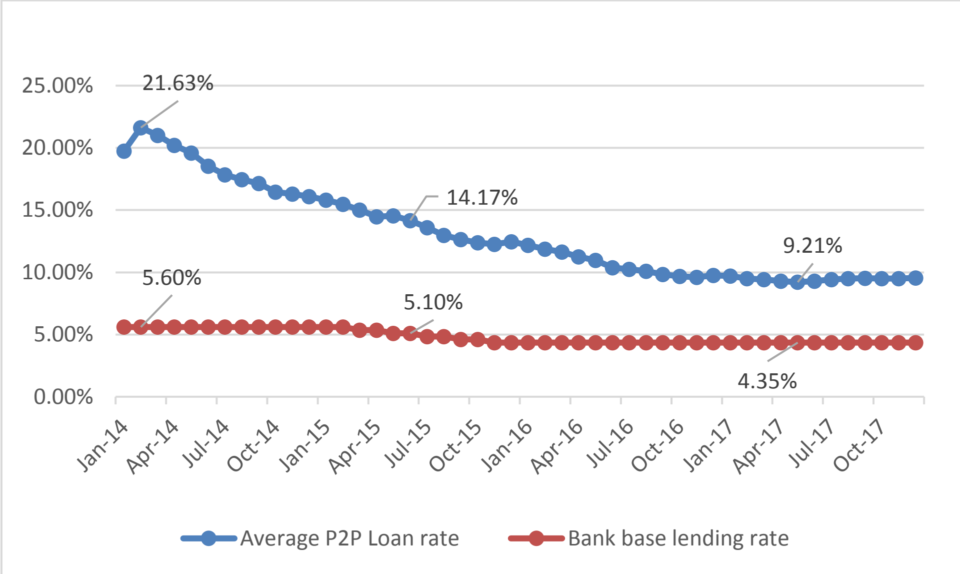

Figure 22 The average P2P loan rate and bank base lending rate in China

Source: wdzj.com, People's Bank of China

Third, as mentioned in section 4.1.1, lenders are assumed to be homogeneous and their willingness to lend (WTL)follows an identical distribution. Although this setting is extremely simplified, it is sufficient to characterize the intuition that funding probability is an increasing function of the lender's perceived expected return, which is our major concern. Modelling heterogenous lenders may lead to additional insights, but we have to leave it to our future research due to the challenges in solving such models.

With respect to our empirical analysis, unfortunately, it's difficult to examine the theoretical predictions under the non-guarantee model. Specifically, an ideal setting to examine a platform's reduced screening incentive requires the platform to facilitate both guaranteed loans and non-guaranteed loans. Under this setting, we may able to examine the difference in the platform's screening efforts the across guaranteed and non-guaranteed loans if we are able to isolate other factors that affect loan quality. However, this test is unlikely to be implemented by us, given the data accessibility problem regarding the candidate platforms. However, because the new regulation on China's P2P lending forbids platform guarantees, it may provide us a chance to examine a platform's screening efforts under different lending models by evaluating the effects of the policy change on loan quality.

Besides, the default prediction model is estimated using pooled data (all ages combined, all men and women combined, etc). The pooled analysis might be misleading when there is effect modification. In the future, stratified analysis may be conducted when sample size for each stratum is adequate.

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Appendices

A. Collinearity Diagnostics for Model I

Variable		VIF
Credit grade dummies		
	Credit grade D	1.36
	Credit grade E	1.22
Loan characteristics		
	Loan rate	6.92
	Term	6.56
	Loan amount	3.39
	No.of bids	2.20
	Loan purposes	
	Home decoration	3.18
	Property purchase	1.43
	Investment	2.36
	Personal consumption	2.40
	Working capital	3.97
	Loan origination month	
	January	1.21
	February	1.25
Borrower basic information		
	Male	1.04
	Age	1.53
	Marital status	1.27
	Business owner	3.25
	Online seller	4.08
	Active days	1.46
Borrower lending histories		
	No. of funding success	2.45
	Amount raised	2.50
	Previous overdue	1.30
Borrower asset information		
	Property ownership	1.68
	Mortgage	1.42
	Vehicle ownership	1.47
	vehicle loan	1.27
Borrower education level		
	Associate degree	1.65
	Bachelor degree	1.82
	Master or above	1.20
Borrower job information		

No. of employee	
10<Number of employee<=100	3.81
100<Number of employee<500	3.60
Number of employee>=500	2.16
Years at current job	
1<Years<=3	3.47
3<Years<=5	2.82
Years>5	3.64
Borrower income level	
5000RMB=<Income<=10000RMB	1.49
10000RMB<Income<=20000RMB	1.70
20000RMB<Income<50000RMB	2.06
Income>=50000RMB	2.16
Mean VIF	2.47

B. Collinearity Diagnostics for Model II

Variable	VIF
Credit grade dummies	
Credit grade D	1.18
Credit grade E	1.19
Loan characteristics	
Term	1.04
Borrower basic information	
Age	1.33
Business owner	1.22
Borrower lending histories	
Previous overdue	1.01
Borrower asset information	
Mortgage	1.04
Borrower education level	
Master or above	1.04
Bachelor degree	1.08
Borrower income level	
Income>=50000RMB	1.16
Borrower job information	
Years>5	1.27
Mean VIF	1.14