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Like a Moth to a Flame: Does the Stock Market Exacerbate Credit Risks of Peer-to-Peer (P2P) Lending?

Xin Liu
University of Macau

Xiaoran Ni
Central University of Finance and Economics (CUFE)

Zhigang Qiu
Renmin University of China

Kailun Zhang
The Chinese University of Hong Kong (CUHK)

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Abstract

In this paper, we reveal the link between the stock market and the Peer-to-Peer (P2P) lending market by exploring information of more than 450 thousand loans on Renrendai.com, a leading Chinese P2P crowd lending platform. Based on the fact that retail investors exhibit a disproportional level of attention when the Shanghai Stock Exchange (SSE) composite index is above the 3,500 threshold, we find that both the default rate and the degree of delinquency have a disproportional jump for loans borrowed above the 3,500 threshold of the SSE composite index. This effect is more pronounced when loan quality is lower and investors are more overconfident. Furthermore, when the SSE composite index exceeds 3,500, the overall creditworthiness of borrowers disproportionally becomes worse, indicated by higher interest rate, longer fulfill time needed to achieve the target borrowing amount, lower credit scores, and lower loan amounts. Overall, our paper establishes a direct link between stock market indexes and credit risks of the P2P lending market, and reveals a specific channel through which the development of FinTech could amplify financial risks.

JEL Classification: G33; G21; G10

Keywords: Peer-to-peer (P2P) lending; Shanghai Stock Exchange (SSE) composite index; Credit risk; Retail investor

1. Introduction

The development of information technology and digital finance has changed the traditional financial lending business and it gave birth to various Fintech forms. One representative Fintech form is Peer-to-Peer (P2P) lending, the practice of directly matching lenders and borrowers through online services based on financial intermediary platforms on the Internet. The P2P market acts as an important alternative funding source for small firms and individuals that are lacking of sufficient hard information and collaterals (Wang, Yu, Yang, and Zhang, 2021). Although P2P lending could foster entrepreneurship and small business development by providing a flexible alternative to traditional banking, at least to some extent, it gradually becomes new intermediaries, which creates financial risks and even social problems (He and Li, 2021; Hua and Huang, 2021). Several recent studies explore how the P2P lending market is related with the bank loan market (e.g. Cole, Cumming, and Taylor, 2019; Tang, 2019; Erel and Liebersohn, 2020; De Roure, Pelizzon, and Thakor, 2021). By comparison, evidence on how the P2P lending market is related with the stock market is relatively rare. In this paper, we contribute to the literature by filling this gap.

In particular, we focus on the link between P2P practices and the stock market in China by exploring information of more than 450 thousand loans on Renrendai.com, a leading Chinese P2P crowd lending platform. Although China is not the only setting for this research question, our setting is worth noticing for at least three reasons. First, China's P2P industry, the world's largest, is one of the riskiest and least-regulated slices of the nation's sprawling shadow-banking system.[1] As obtaining credit from brokerage firms is tightly regulated by the China Securities Regulatory Commission (henceforth CSRC, the counterpart of the Securities and Exchange Commission in the U.S.), aided by China's burgeoning FinTech industry, many retail investors turned to the online shadow-financing system for margin trading, which is an important issue for academia and practitioners, especially around the 2015 stock market turmoil.[2]

Anecdotal evidence suggests that it is reasonable to infer that Chinese investors borrow money through P2P lending and then invest on the stock market. In late 2014, in the bull market environment, a number of P2P platforms began to operate the equity allocation business online. The so-called equity allocation is to stimulate investors to borrow money through online P2P lending to trade in stocks. The usual financing ratio is about 5 times. That is, if an individual has 100,000 RMB, he or she can borrow another 500,000 RMB, to buy stocks. This business is very competitive compared to the margin trading businesses of securities firms: Although the interest rate is unified at 8.6%, the maximum financing ratio is only 60% of personal investment funds.[3] A P2P platform publishes such a seductive slogan, "I pay, you invest, and all the profits go to you". Another P2P platform stated that it has successfully matched 443 people, with a total loan amount of more than 18 million RMB.[4] In June 2015, just before the stock market collapse, borrowing from P2P lending peaked at about 200 billion RMB (Bian et al., 2021). "In China,

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[1] Source: "*Panic roils China's Peer-to-Peer lenders*"
https://www.bloombergquint.com/global-economics/panic-roils-china-s-p2p-lenders-as-savers-rush-to-withdraw-cash.
[2] We provide detailed discussion on the 2015 stock market turmoil in Section 2.
[3] Source: "*P2P borrowing money stocks strategy: 100,000 principal can borrow up to 1.5 million*" (in Chinese)
https://www.thepaper.cn/newsDetail_forward_1280883.
[4] Source: "*P2P platform madly pushes investors to borrow money to buy stocks, claiming that the lender has an annual rate of return of 24%*" (in Chinese)
https://www.yicai.com/news/4010212.html.

speculators adopt very aggressive trading strategies, gaming the rules... and pushing policy-makers' tolerance to the limit," said Stephen Huang, vice president of Shanghai See Truth Investment Management Co.[5]

Second, different from developing economies like the U.S. where serves as a supplement to traditional banking, due to the under-development of the economic infrastructure (e.g., traditional banking sector, the credit system, and the law enforcement system), Chinese P2P platforms are much more important for investors and borrowers, and they play a much more significant role in society (Jiang et al., 2021).[6] Specifically, based on the U.S. setting, Tang (2019) finds that credit expansion resulting from P2P lending likely occurs only among borrowers who already have access to bank credit. By comparison, Chinese P2P borrowers are much risker. They are often privately-owned small and medium-sized enterprises (SMEs) and individual consumers who are not able to obtain funds from formal sources (Shao and Bo, 2021).

Third, although the risk-return tradeoff principle and credit rationing theory are important for decision making (Stiglitz and Weiss, 1981), Chinese P2P lenders are mostly individual investors who seek short-term capital gains and use the P2P platform as a speculative investment tool (Shao and Bo, 2021). Due to time pressure, they appear to focus on interest rates and only partially account for credit ratings in their decisions (Liao et al., 2021).[7] During our sample

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5 Source: "*Shadow margin loans make a sly return as China stocks sizzle*" https://www.reuters.com/article/us-china-markets-leverage-idUSKCN1R30OP.

6 According to the statistics of Jiang et al. (2021), the total transaction volume in China P2P market in 2018 reached about \$178.89 billion. In comparison, the U.S. P2P platforms aggregate trading volume was \$8.21 billion for the same year. By February 2018, there were around 6,000 platforms in China, in contrast to approximately 200 in the U.S. over the same time period.

7 They indicate that 25% of bids are fulfilled within 48 s, while 75% are fulfilled within 3 min, with investors focusing on only one indicator, such as interest rates.

period, Chinese P2P lenders tend to blindly pursue high interest rates regardless of default risk, believing that the loans they invest in are guaranteed (Wang and Tong, 2020).[8]

We begin by carrying out a direct test on whether stock market indexes affect P2P lending behaviors. Consistent with the implications of anecdotal evidence above, we document that both the number of loans and the RMB volume of loans increase with the Shanghai Stock Exchange (SSE) composite index, indicating that better stock market performance can boost the demand for P2P borrowing, leading to more active transactions on the P2P lending market.

To establish causality, we build our empirical design on a well-documented fact that Chinese investors exhibit a disproportional level of attention when the SSE composite index is above the 3,500 threshold. Anecdotal evidence suggests that the SSE composite index reaching above the 3,500 certain threshold serves as an attention-grabbing event that can light up investors' enthusiasm. Indeed, employing Baidu search index as a proxy for the information demand of uninformed individual investors (Wen, Xu, Ouyang, and Kou, 2019; Hsieh, Chan, and Wang, 2020), we find that retail investors' attention experiences a disproportional increase after the SSE composite index pumps over 3,500.

As stock market fluctuations around the threshold are largely not driven by changes in economic fundamentals, we are able to employ this attention-grabbing event as a regression discontinuity design that explores the disproportion in attention from retail investors, we find that both default rate and delinquency rate, the percentage of months in which the borrower fails to

[8] They are concerned about the risk-return trade-off on the interest rate only after 2018 when the "de-guarantee policy" formally came into effect. We discuss about the details in Section 2.

deliver the scheduled monthly payment in time, have a disproportional jump for loans borrowed above the 3,500 threshold of the SSE composite index, suggesting that the average borrower of the P2P market becomes risker when the stock market performs better. The main effect is more pronounced when loan quality is lower and investors are more overconfident. Furthermore, we find that when the SSE composite index exceeds 3,500, there is a disproportional increase in interest rate and the fulfill time needed to achieve the target borrowing amount, and a disproportional decrease in borrowers' credit score and the loan amount. These results indicate that the overall creditworthiness of borrowers disproportionally becomes worse when the SSE composite index is above the 3,500 threshold. Overall, our evidence suggests that stock market booms can stimulate risky investors to borrow money from online P2P platforms, which increases the overall credit risk on the P2P lending market. However, P2P lenders seem to neglect such risks, aiming to earn higher returns by providing loans to those risky borrowers.

Our paper contributes to several strands of literature. This paper contributes to the emerging research on P2P lending, especially issues related with credit risk. Prior studies reveal that factors such as gender gap, arbitrage, and information asymmetry could determine the credit risk of P2P lending (Lin, Prabhala, and Viswanathan, 2013; Chen, Huang, and Ye, 2020; Tian, Wang, and Wu, 2021). The relation between the P2P lending market and the bank loan market becomes an emerging topic (e.g. Cole, Cumming, and Taylor, 2019; Tang, 2019; Erel and Liebersohn, 2020; De Roure, Pelizzon, and Thakor, 2021). To the best of our knowledge, we are the first to link the stock market performance with P2P lending performance. In particular, we propose that stock market index, especially the disproportion in attention from retail investors around the 3,500 threshold of the SSE composite index, can crucially determine applicants' creditworthiness. Our paper is also related with prior studies showing that investor attention indicated by Baidu search index (He, Qin, and Zhang, 2021) and real estate bubbles (Shao and Bo, 2021) can affect the average interest rate of P2P platform.

Our paper also has important policy implications. Our findings imply that speculative investors on the stock market could become risky borrowers on the P2P lending market when stock market booms, while both capital suppliers and demanders on the P2P lending market, the majority of which are retail investors, will suffer from tremendous losses when the stock market goes bust. Therefore, we reveal a specific channel through which the development of FinTech could amplify financial risks. In particular, as many other emerging economies share similarities with China regarding weak investor protections and immature financial system, our findings could throw light on how to cultivate the emerging Fintech industry and balance the issues of preventing credit risks and stabilizing the stock market.

The remainder of the paper is organized as follows. Section 2 introduces institutional background. Section 3 describes data and variable construction. Section 4 reports estimation results. Section 5 concludes.

2. Institutional Background

2.1 The 2015 stock market turmoil in China

Although the cause and consequences of the 2015 stock market turmoil is not the main focus of our paper, the boom and bust of the stock market around this time point significantly alters

P2P investors' behavior, which is closely related to our research theme, and eventually determines the fortune of various P2P platforms in China. Therefore, we discuss the general background of the 2015 stock market turmoil in this section.

China's stock market has experienced tremendous growth over the past two decades. In 2006, the total market capitalization in China's stock market did not surpass 1 trillion USD (Carpenter and Whitelaw, 2017). However, by 2020, it has grown more than ten times to over 10 trillion USD, making it the world's second largest.[9] Unlike the US market, China's stock market is dominated by retail investors, as they contribute 85% of the daily trading volume (Jones, Shi, Zhang, and Zhang, 2020).

Yet, such a high growth rate is often accompanied by extreme turbulence. One such example is the stock market run-up and crash in the spring and summer of 2015. From June 2014 to June 2015, prices in the Shanghai Stock Exchange increased more than doubled. As shown in Figure 1, in June 2014, the Shanghai Stock Exchange (SSE) composite index was only around 2,000 (the blue line). The index experienced a steady growth to about 3,100 in January 2015, followed by a strong run-up, peaked at 5,178 in mid-June. An unusually large part of this run-up was fueled by enthusiastic retail investors who borrowed to buy equities.

[Insert Figure 1 here]

The market took a dramatic nosedive since June 15th. By July 9th, the Shanghai stock market had fallen by 30 percent, as 1,400 companies, or more than half listed, filed for a trading halt in

[9] Source: "*China's Stock Market Tops $10 Trillion First Time Since 2015*". https://www.bloomberg.com/news/articles/2020-10-13/china-s-stock-market-tops-10-trillion-for-first-time-since-2015., 2020-10-13.

an attempt to prevent further losses.[10] A third of the market capitalization of A-shares on the Shanghai Stock Exchange was lost within one month (Bian, Da, He, Lou, Shue, and Zhou, 2021). The episode continued with major aftershocks on July 27th and August 24th. By the end of August 2015, the SSE composite index was about 2,851, almost 50% less than its peak value right before the bubble popped. Excessive leverage and the subsequent leverage-induced fire sales are considered to be the main contributing factor to this market turmoil. Fundamental conditions related to the real economy, however, are not considered as the main reason for the stock market crash.[11] In response, the Chinese government aggressively purchased stocks to support prices, and the market became stabilized in mid-September 2015.

2.2 The peer-to-peer lending platform: Renrendai

The P2P lending industry in China has experienced the most drastic developments and destructive busts (Li and Hasan, 2021). The first P2P platform in China, FinVolution Group, was established in 2007. Being regarded as financial innovation in retail banking by the government and regulators, the whole industry enjoyed phenomenal growth, and gradually became the largest in the world (Jiang et al., 2021). However, regulators did not set regulatory standards until mid-2016.[12] Lax regulations also allow the platforms to operate in risky shadow banking areas. They collect investors' fund with guaranteed return and lend the money to risky borrowers,

[10] "*China's Stock Market Selloff Explained in Six Charts*", https://www.bloomberg.com/news/articles/2015-07-10/china-s-stock-market-selloff-explained-in-six-charts

[11] Source: "*China Stock Market Divorced From Reality*", https://www.forbes.com/sites/kenrapoza/2016/01/27/china-stock-market-divorced-from-reality/?sh=2b729f934f99, 2016-01-27.

[12] Indicate that there are at least two reasons why regulators did not rush to bring these businesses under regulation. First, many government officials saw the value of financial inclusion in fintech businesses and so they were reluctant to disrupt such "financial innovation"; Second, China's financial regulatory framework is one segregated by industry and focuses on financial institutions, and fintech companies fell into the gap area, to which no specific regulator was responsible.

exposing themselves to borrowers' credit risk.[13]

Chinese P2P platforms, composed of financial intermediaries, pyramid schemes, and a few information intermediaries, have led to chaos in the Chinese P2P lending industry. As indicated by He, Qin, and Zhang (2021), there were 108 P2P platforms crashes in only 42 days including some big platforms from June 1st, 2018 to July 12th, 2018. The default debt amount accumulated to 120 billion, and over 0.7 million investors lost their money. Until the end of 2018, there had been 5,503 P2P platforms, and 70.9% or 3902 P2P platforms had bankrupted.

The P2P platform innovation comes with advantages and disadvantages (Caglayan, Talavera, and Zhang, 2021). By eliminating layers of costly intermediation, P2P platforms permit investors of any number and size to lend to a single borrower, enabling the supply of funds from multiple sources to cover the amount requested. These platforms involve swift, simple procedures that facilitate rapid lending decisions and provide attractive interest-rate deals for both borrowers and lenders. Its broad coverage of clients leads to economies of scale, which ensures the provision of more favorable and affordable interest rates (Wang, Yu, Yang, and Zhang, 2021). The downside is that lenders bear the direct risk of loss from a P2P loan default, without the remedies available to traditional lenders, not to mention the risk that the platform itself may collapse.

Founded in May 2010, Renrendai was one of the first peer-to-peer marketplaces in China, providing online credit and investment services to individual borrowers and investors. It mainly targeted white-collar employees and small business owners as its customers, profiting from

[13] Typically, P2P platforms themselves have no claims on these payments. Instead, they earn fees for related services including the assessment of credit risk, the matching of lenders with borrowers, and the collection and allocation of payments of interests and principals, etc. (Chen, Kavuri, and Milne, 2020).

management fees charged to borrowers. There was no requirement on the minimum level of wealth or historical records for borrowers on the platform. Instead, the company managed default risks by measuring borrowers' income, occupation, assets, and family connections. Lenders were compensated by a high interest rate, which far exceeded the one-year deposit rate from commercial banks. The rise of the platform attracted significant attention from the industry, and was considered as a rising star for financial innovation. As a result, it was included in the list of Top 100 Internet Companies in China and the Hurun New Financial 100 list.[14] Renrendai was also widely considered as a safe peer-to-peer platform with minimum credit risk. It was the only peer-to-peer company certified with AAA credit rating by the Credit Rating Center of Internet Society of China.[15]

As shown in Figure 1 (the red line), Renrendai experienced a steady growth since 2013. In January 2013, the total number of loans from Renrendai was only about 5,000. By June 2015, this number rise by more than 80 times, reaching to over 400,000. The growth of Renrendai was accompanied by the run-up of the China's stock market. This positive correlation between the two markets echoes our main hypothesis that stock market bubbles spur individuals' borrowing activities at least in part. The interaction between the stock market and the lending market was particularly relevant in China, since the CSRC imposed very stringent rules to qualify for

[14] The Top 100 Internet Companies in China is published by the Internet Society of China and Ministry of Industry and Information. It is a list consisting of China's leading enterprises in terms of "comprehensive internet strength". Hurun Report is a well-known private company that produces influential lists and research. Hurun New Financial 100 list is an annual list issued by Hurun Report that consists of China's leading enterprises in terms of FinTech and financial innovation.

[15] The Credit Rating Center of Internet Society of China a rating organization approved by the Ministry of Commerce, Ministry of Industry and Information Technology. The AAA rating is the highest credit rating in the rating system.

brokerage-financed margin trading.[16] Instead, many retail investors turned to the online shadow-financing system for margin trading (Bian et al., 2021).[17] Unlike the brokerage-financing system, the shadow-financing system was in a regulatory grey area that did not require minimum level of wealth or trading history, but a high interest rate to lenders instead. Following the market turbulence, the year 2015 also witnessed a wave of bankruptcy in peer-to-peer industry, by the end of 2015, more than one-third of peer-to-peer companies had become "problem platforms", and shadow financing was believed to be one of the major factors.[18] Given the evidence above, Renrendai could be arguably considered as one of the shadow-financing platforms.

On June 12th, 2015, the CSRC released a set of draft rules to regulate the shadow-financing system, aiming to tighten leverage constraints. The market started to take a drastic plunge from the following trading day. The activities from Renrendai also took a hit. As Figure 1 suggests, the accumulation in the total number of loans from Renrendai slowed down dramatically during the stock market turmoil, from over 40,000 loan applications per month to less than 10,000 loan applications per month. This was likely driven by both the CSRC announcement and the pop of the stock market bubble.

3. Data and Variable Construction

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[16] For example, a qualified investor needs to have a trading account with the broker for at least 18 months, with a total account value exceeding 0.5 million RMB (or about 80,000 USD).

[17] Examples of such online shadow-financing facilities include HOMS, MECRT, and Royal Flush.

[18] "*P2P Series Part 1: Peering Into China's Growing Peer-to-Peer Lending Market*", https://www.piie.com/blogs/china-economic-watch/p2p-series-part-1-peering-chinas-growing-peer-peer-lending-market

We hand-collected all loan applications from Renrendai's website during the period of Jan 2013 to Dec 2017, i.e., two years before and two years after the 2015 stock market turmoil.[19] For each loan application, Renrendai provides a variety of information including interest rate, duration, credit score, and personal details. We require that: (1) each borrower must be matched to a lender; (2) applications are successful; (3) loans are matured by 2020, the time when we finish collecting the data. We end up with 470,228 loans in our sample.

Applications on Renrendai go through an auction process, in which borrowers bid for interest rate (*Interest*), the RMB value of the loan (*Volume*), and maturity (*Duration*). After the process, borrowers collect the money raised from lenders, and need to meet a pre-scheduled monthly payment. Interest rates are quoted in terms of annualized percentage of returns. Panel A of Table 1 shows that the average interest rate in our sample is about 10.6%, far exceeding the fixed-term deposit rates from commercial banks.[20] On average, a successful loan from Renrendai has a RMB value of about ¥58,000 (or roughly 9,300 USD). *Duration* is defined as the total number of months between the start day of the loan and its maturity day. The median duration in our sample is about three years. Generally speaking, since the platform is very active during our sample period, loan applications from our sample get fulfilled quickly. The average fulfilment time (*Fulfilltime*) is about 30 seconds, and each lender (*Vol/Lender*) contributes ¥1,300.

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[19] Source: https://www.renrendai.com/. Although we do not focus on the 2015 stock market turmoil in our paper, we are interested in this time period because both the stock market and the P2P lending market experienced significant boom and bust patterns during this time period. Also, the government implemented an important "de-guarantee" policy in 2016, which formally came into effect in 2018 and therefore fundamentally changed lending behaviors on P2P platforms (Wang and Tong, 2020). We are able to avoid the influence of this regulatory change by restraining our sample to this period.

[20] Before the market crash, the one-year, three-year, and five-year deposit rates are 2.50%, 3.50%, and 3.75%, respectively. (https://www.bankofchina.com/fimarkets/lilv/fd31/201505/t20150510_5002198.html)

[Insert Table 1 here]

To capture the credit risk from Renrendai platform, we compute two proxies: *Default* and *Delinquency*. *Default* is a dummy variable that equals one if the load defaults, and zero otherwise. *Delinquency* is the percentage of months in which the borrower fails to deliver the scheduled monthly payment in time. The overall credit risk on Renrendai is moderate. In our sample, about 0.6% of the loans eventually default, and the average delinquency rate is about 1%.

Renrendai provides detailed profiles on borrowers. We consider the following variables to control for borrowers' characteristics: (1) *Age*, the age of the borrower; (2) *Education*, the education level of the borrower. This is a categorical variable, in which 0 represents high school or below, 1 and 2 denote two levels of vocational school, 3 denotes college, and 4 denotes postgraduate school; (3) *Female*, a dummy variable that equals one if the borrower is a female, and zero otherwise; (4) *Married*, a dummy variable that equals one if the borrower is married, and zero otherwise; (5) *Wage*, the monthly income level of the borrower. This is also a categorical variable, in which 0 denotes ¥1,000 to ¥2,000, 1 denotes ¥2,000 to ¥5,000, 2 denotes ¥5,000 to ¥10,000, 3 denotes ¥10,000 to ¥20,000, 4 denotes ¥20,000 to ¥50,000, and 5 denotes over ¥50,000; (6) *Flat*, a dummy variable that equals one if the borrower owns a flat, and zero otherwise; (7) *Car*, a dummy variable that equals one if the borrower owns a car, and zero otherwise. In addition, the platform provides two variables to measure the risk level of borrowers. *Onsiteverify* is a dummy that equals one if the borrower's personal details have been verified by Renrendai onsite. *Score* is a credit score provided by Renrendai to assess the borrower's credit level based on his personal details, whether or not the details have been verified onsite, and historical records on the platform.

Panel B of Table 1 outlines the borrowers' characteristics from our sample. The median borrower in our sample is a high income middle-aged married man without a higher education. The platform conducts active risk management on borrowers, as 86% of the borrowers are verified onsite. The median credit score is about 180, which corresponds to a relatively safe credit risk level.[21]

4. Estimation Results

4.1 The interaction between the stock market and the lending market

We first examine if there is indeed an interaction between the stock market and the lending market. More specifically, we run the following time-series regression:

$$Loan_{t+1} = \alpha + \beta\ Index_t + \boldsymbol{\gamma}\ \boldsymbol{X}_t + \varepsilon_{t+1}\ , \tag{1}$$

where $Loan_{t+1}$ is either the daily number of loans or the daily RMB volume of loans from Renrendai in day t+1. The main independent variable is $Index_t$, the SSE composite index level from day t. Control variables include: (1) *Shibor*, the daily Shanghai interbank offering rate; (2) *Mktrf*, the excess daily market return; (3) *SMB*, the daily China's size factor, constructed following Liu, Stambaugh, and Yuan (2019); (4) *VMG*, the daily China's value factor, also constructed following Liu, Stambaugh, and Yuan (2019); and (5) *Volatility*, the standard deviation of the daily SSE composite index returns from the past year. Results are reported in Table 2.

[21] Renrendai categorizes credit scores into seven levels: AA (*Score*>=210), A (180<=*Score*<210), B (150<=*Score*<180), C (130<=*Score*<150), D (110<=*Score*<130), E (100<=*Score*<110), and HR (0<=*Score*<100).

[Insert Table 2 here]

Table 2 shows that both the number of loans and the RMB volume of loans increase with the SSE composite index, indicating that stock market performance boosts the demand for P2P borrowing. For example, columns (2) and (4) suggest that, when the SSE composite index rises by 100, daily number of loans will increase by 53 and the daily RMB volume of loans will increase by ¥3.6 million.

4.2 Regression discontinuity design

In order to provide causal evidence on our argument, we conduct a regression discontinuity design that explores the disproportion in attention from retail investors. Existing studies have shown that retail investors have limited attention in financial markets (e.g., Huberman and Regev, 2001; Hong, Torous, and Valkanov, 2007; Hou, 2007; Cohen and Frazzini, 2008; Hirshleifer, Lim, and Teoh, 2009; Cohen and Lou, 2012; Lou, 2014; Huang, 2015; Hartzmark, 2015; Huang, Huang, and Lin, 2017). Thus, attention-grabbing events can attract enthusiastic public attention, which in turn disproportionally induce retail investors to participate into the stock market, resulting in a quick run-up in prices even though no genuinely new information has been presented.

One of such attention-grabbing events that can light up investors' enthusiasm is the SSE composite index reaching above a certain threshold. Anecdotal evidence suggests that investors take the SSE composite index reaching 3,500 as a starting point for a promising bull market. On March 17th, 2015, soon after the 2015 China's National People's Congress and Political Consultation Congress, the SSE composite index exceeded 3,500 for the first time, reaching to a record-breaking level in the past seven years. Mainstream media like the China Central Television (CCTV), People's Daily and the Shanghai Securities News reported this breaking news, describing it as a sign of a new round of market boom.[22] Investors raised extremely optimistic expectation about China's stock market. The Baidu search index on the keyword "*market boom*" almost tripled, from 525 on March 15th to 1,427 on March 17th. An above 3,500 index can attract a disproportionally high level or retail investors to invest into the stock market. Also, many market commentators regard 3,500 as a level for the index that Chinese authorities will aggressively defend.[23] Therefore, the discontinuity of retail participation around the 3,500 index level can serve as a regression discontinuity cutoff to test the relation between stock market bubble and credit risk in the lending market.

To verify that investors' attention indeed has a disproportional jump after the 3,500 index threshold, in Figure 2, we compare the relation between the SSE composite index and the subsequent search index provided by Baidu, the most important search engine in China. Baidu search index is the analogy of Google search index in mainland China, which is calculated from the searching data obtained from users in Baidu Search engine, it provides quantitative measures for internet search intensity through Baidu based on key words (He, Qin, and Zhang, 2021). We obtain Baidu search index directly from Baidu by searching for the keyword "*SSE composite index*". Due to the nature of high retail participation in China's stock market, Baidu index can be

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[22] See http://tv.cctv.com/2015/03/16/VIDE1426491966076421.shtml , http://finance.people.com.cn/stock/n/2015/0318/c67815-26711068.html and http://news.cnstock.com/news,yw-201503-3370903.htm

[23] https://www.seattletimes.com/business/global-markets-stabilize-us-indexes-open-higher-on-earnings/; https://www.reuters.com/article/us-china-markets-reaction-idUSKCN0UT1OP

a good proxy of retail investor's attention (Wen, Xu, Ouyang, and Kou, 2019; Hsieh, Chan, and Wang, 2020).

[Insert Figure 2 here]

In Figure 2, we first group daily SSE composite index levels by a bandwidth of 100. Each dot represents the mean Baidu search index within each corresponding index bandwidth. For example, the dot at 3,500 represents that, when the SSE composite index is within the range of 3,500-3,600, the average subsequent Baidu search intensity for the stock market is about 200,000. Figure 2 shows that Baidu search index has a disproportional relation with the SSE composite index. When the index is below 3,500, the search intensity is below 200,000, indicating a relatively low attention from the public. However, after the index pumps over 3,500, attentions to the stock market intensify. The search index doubles to a peak over 400,000, and remains at a higher level.

We further confirm this pattern through regressions. Specifically, we follow Ben-Rephael, Da, and Israelsen (2017) and run the following time-series regressions:

$$Baidu\ search\ index_{t+1} = \alpha + \beta_1\ Index_t + \beta_2\ Index_t \times I(Index_t > 3{,}500) + \boldsymbol{\gamma}\ \boldsymbol{X}_t + \varepsilon_{t+1}\ , (2)$$

where *Baidu search index*$_{t+1}$ is the Baidu search index from day t+1, $Index_t$ is the SSE composite index level on day t, $I(Index_t{>}3{,}500)$ is a dummy variable that equals one if the index on day t is above 3,500, and zero otherwise. We consider a vector of control variables that may also be related to investors' attentions: (1) *Cret*, the cumulative return from the SSE composite index in the past 52 weeks; (2) *Vol*, the standard deviation of the daily returns from the SSE composite index in the past 52 weeks; (3) *Low52*, a dummy variable that equals one if the SSE composite index is the 52-week low, and zero otherwise; (4) *High52*, a dummy variable that equals one if the SSE composite index is the 52-week high, and zero otherwise; (5) *Turnover*, the value-weighted turnover rate of A-share market on day *t*; (6) *Vwhltoh* the value-weighted price range divided by daily highest price in the A-share market on day *t*. Results are reported in Table 3.

[Insert Table 3 here]

Results from Table 3 collaborate with our descriptive analysis in Figure 2: investors exhibit a disproportional level of attention when the SSE composite index is above the 3,500 threshold. More specifically, column (4) shows that, when the index is below the threshold, when the index goes up by 100, Baidu search index will go up for 10,200. However, when the index is above the threshold, when the index goes up by 100, Baidu search index will go up for 11,800. This difference is significant at all conventional levels (*t*-value = 3.46).

As we have described in Section 2, this stock market fluctuation during our sample period is not driven by changes in economic fundamentals. Therefore, the disproportional increase in investors' attention should not be related to other factors (i.e., income, unemployment, inflation, etc.) that may affect their credit conditions. Therefore, the 3,500 index threshold can be considered as a quasi-exogenous regression discontinuity design to help pin down the causal relation between stock market bubbles and credit risk. Following Cellini, Ferreira, and Rothstein (2010), the baseline regression specification is:

$$Credit\ Risk_i = \alpha_0 + \alpha_1\, D + P_g\, (Index_i, \gamma_u) + u_i\ , \tag{3}$$

where $Credit\ Risk_i$ is the credit risk associated with loan i and is proxied by either *Default* or

Delinquency. D is a dummy variable that equals one if the SSE composite index on the day before loan i is borrowed from the platform is above 3,500, and zero otherwise. $P_g(.)$ is a polynomial of order g, $Index_i$ is the index level on the borrowing day, and γ_u are the coefficients in the polynomial.[24] u_i is the residual term that is asymptotically orthogonal to $Index_i$ (and therefore with α_1). The discontinuity we estimate is the value of α_1. We use uniform kernel and MSE-optimal bandwidth in estimating the regression discontinuity models, and standard errors are clustered by year-month. We report the estimate on α_1 in Table 4.

[Insert Table 4 here]

Results from Table 4 indicate that both *Default* and *Delinquency* have a disproportional jump for loans borrowed above the 3,500 threshold of the SSE composite index. In column (1), the estimate on α_1 for the baseline model using *Default* is 0.014 (*t*-statistic = 5.80). This suggests that loans borrowed above the 3,500 index threshold are 1.4% more likely to suffer from a default event. This result is not only statistically significant but also economically large, considering that the average default rate in our sample is about 0.0063. Similarly, in column (2), the estimate on α_1 for the baseline model using *Delinquency* is 0.021 (*t*-statistic = 6.81). This suggests that loans borrowed above the 3,500 index threshold are 2.1% more likely to suffer from delayed scheduled monthly payment. This result is also economically meaningful, considering that the average delinquency rate in our sample is about 0.0096. We obtain similar results after including various control variables: age, education level, gender, marriage status,

[24] Following Gelman and Imbens (2015), we use polynomial of order one in the regressions and results are similar if we use polynomial of higher orders.

wage level, flat dummy and car dummy. Detailed definitions for these variables can be found in Section 3.

To visualize the results in Table 4, Figure 3 plots the regression discontinuity design on credit risk by the SSE composite index. Similar to Figure 2, we first group daily the SSE composite index levels by a bandwidth of 100. Each dot in Panel A (Panel B) represents the mean *Default* (*Delinquency*) for all loans borrowed on days with the index within the bandwidth. For example, in Panel A (Panel B), the average default rate (delinquency rate) for loans borrowed in the 3,500-3,600 bandwidth is about 0.009 (0.015). Both panels in Figure 3 collaborate with our regression analyses in Table 4, and help visualize the structural breaks in *Default* and *Delinquency* above the 3,500 index threshold. For example, Panel A of Figure 3 shows that, loans borrowed below the 3,500 index threshold have an average default rate of about 0.0029. However, for loans borrowed above the 3,500 index threshold, the average default rate increases to 0.0137, and can go as high as 2.3% for loans borrowed near the peak value of the index. Panel B shows similar patterns for delinquency.

Overall, both Table 4 and Figure 3 help support our main argument that stock market bubble spur a disproportional increase in credit risks in the lending market for retail investors.

4.3 Cross-sectional analyses

To further justify our main findings in the previous subsection, we conduct further analyses to examine two auxiliary predictions. More specifically, we explore cross-sectional heterogeneities in terms of loan quality and overconfidence.

If investors use Renrendai as a shadow financing source for their equity investments, we should expect that the relation between credit risk and stock bubble becomes stronger in the subsample with lower loan quality. We consider two proxies for loan quality. First, loan applications posted during working hours (9am to 5pm from Monday to Friday) may indicate that the borrowers need money for work-related issues, while loan applications posted during off hours may indicate shadow financing. We rerun our main results in these two subsamples and report the results in Panel A of Table 5. Panel A of Table 5 shows that our main results mainly concentrated on the subsample of loans applied during off hours. For example, column (2) suggests that the effect on *Default* is more than two times for loans applied during off hours, compared to loans applied during working hours. The difference, 0.014, is significant at all conventional levels. Similar results are obtained using *Delinquency* as well.

[Insert Table 5 here]

Second, we divide our sample in detailed vs. brief, based on the median number of words in the application descriptions. Panel B of Table 5 shows that our main results mainly concentrate on the subsample with brief loan description. The probability of a default event for loans with brief descriptions is about seven times larger than the default probability for loans with detailed descriptions.

We extend our analysis on overconfidence. Existing studies suggest that males and young people are more likely to exhibit overconfidence and conduct aggressive investment strategies (e.g., Odean, 1999; Barber and Odean, 2001; Hirshleifer, 2001; Barber and Odean, 2008; among others). Indeed, Chen, Huang, and Ye (2020) show that lending to female borrowers has higher creditworthiness. If these investors use Renrendai as a shadow financing platform, their equity investment loss will increase the likelihood of having credit events in the Renrendai market. Therefore, we divide our sample into subsamples based on female vs. male (Panel A of Table 6), and elder vs. young (Panel B of Table 6). Young and elder investors are divided based on sample median (35 years old). We find that our main results mainly come from the subsamples consisting of young borrowers and male borrowers. The differences in *Default* and *Delinquency* between female vs. male (elder vs. young) are both significant at 1%.

[Insert Table 6 here]

4.4 Further discussion

In this section, we extend our analysis in Section 4.2 to explore the disproportional effect of stock market bubble on other loan characteristics: (1) interest rate (*Interest*); (2) credit score (*Score*), (3) the natural logarithm of fulfillment time (*Log(Fulfilltime)*); (4) the natural logarithm of RMB volume per lender (*Log(Vol/Lender)*).

Consistent with our main argument that stock market bubble spurs lending market activities, we find that there exists a disproportional increase in interest rate, driven by increasing borrowing activities on the platform. When the SSE composite index exceeded 3,500, annual interest rate increased by 2.01%, or 19% relative to the sample mean. Meanwhile, the overheat in the borrowing sentiment also led to a significant decrease in borrowers' credit scores, as *Score* went down by 8.56. Even though the magnitude of this drop in *Score* may not seem huge, it pushed the median credit rating of borrowers from A to B. Accompanied by these changes, loan fulfillment time increased and average contribution from lenders decreased, both indicating a worse-off market environment for borrowers.

[Insert Table 7 here]

5. Conclusion

In this paper, we establish a direct link between the stock market and the P2P lending market by examining whether and how stock market indexes affect creditworthiness of P2P borrowers. Based on the fact that investors tend to exhibit a disproportional level of attention when the SSE composite index is above the 3,500 threshold on the Chinese stock market, we find that both default rate and delinquency rate, the percentage of months in which the borrower fails to deliver the scheduled monthly payment in time, have a disproportional jump for loans borrowed above the 3,500 threshold of the SSE composite index. The main effect is more pronounced when loan quality is lower and investors are more overconfident. Furthermore, when the SSE composite index exceeds 3,500, there is a disproportional increase in interest rate and the fulfill time needed to achieve the target borrowing amount, and a disproportional decrease in borrowers' credit score and the loan amount. Our overall findings indicate that stock market booms can stimulate risky investors to borrow money from online P2P platforms, which increases the overall credit risk on the P2P lending market.

Our paper is one of the first to establish a direct link between stock market indexes and credit risks of the P2P lending market, which has important contribution to the P2P lending literature. Our paper also has important policy implications by revealing a specific channel through which the development of FinTech could amplify financial risks.

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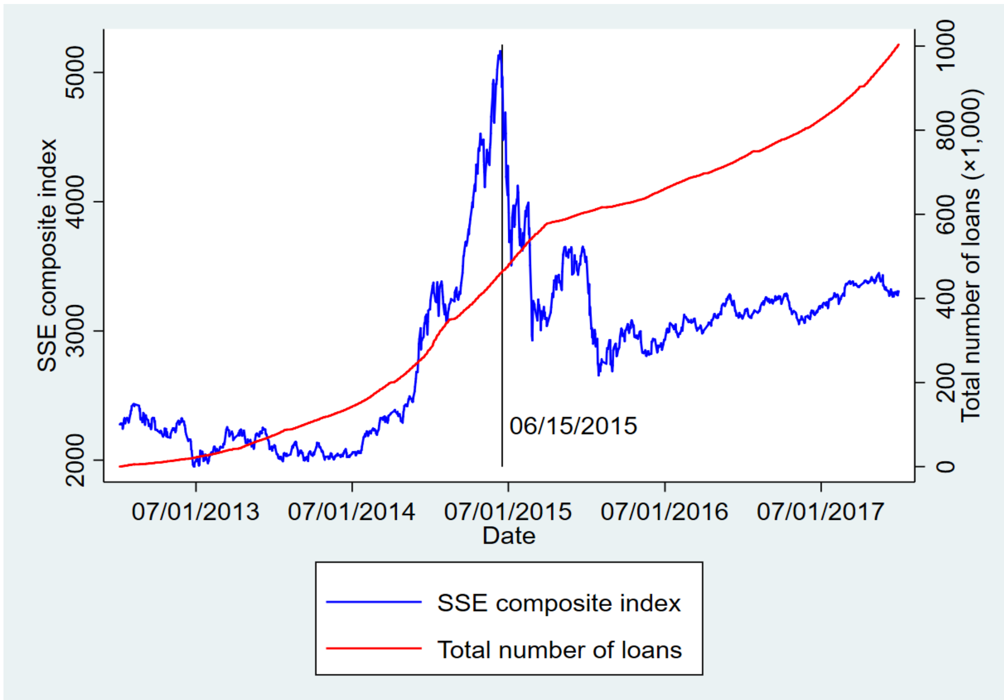


Figure 1: The trend in the SSE composite index and the growth of Renrendai

This figure presents the trend in the SSE composite index (the blue line) and the cumulated total number of loans from Renrendai (the read line, in thousands) from 2013 to 2017.

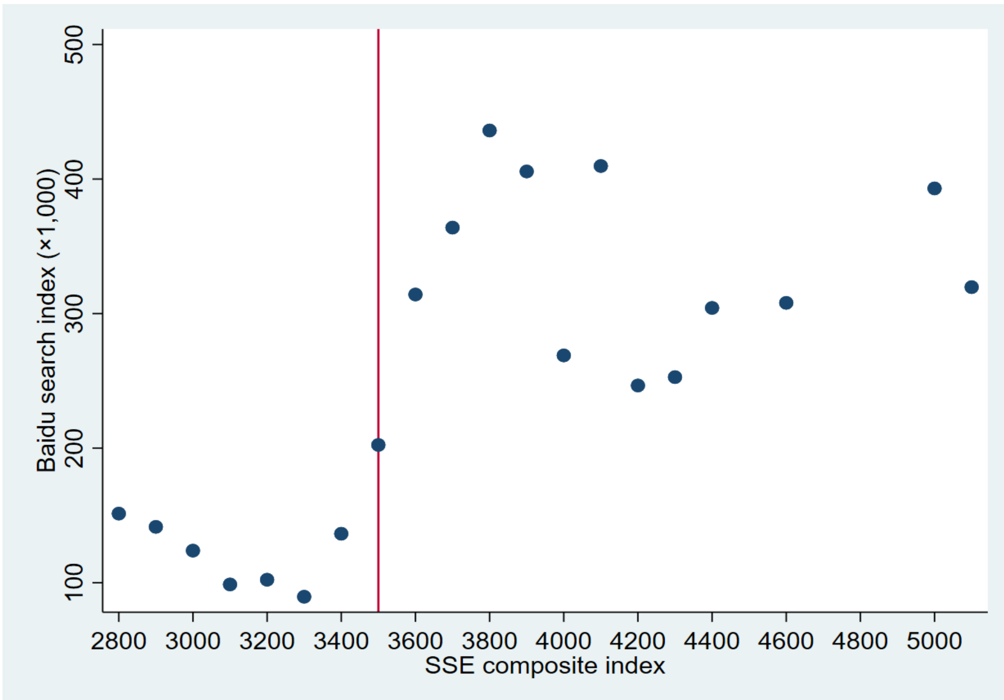
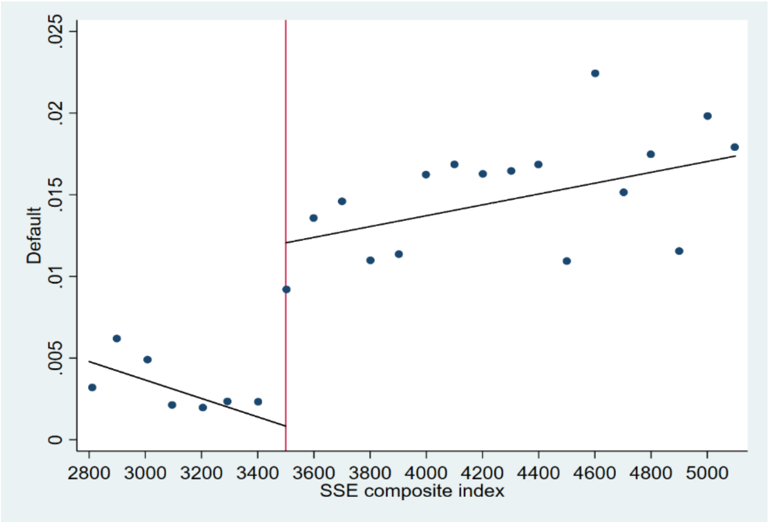
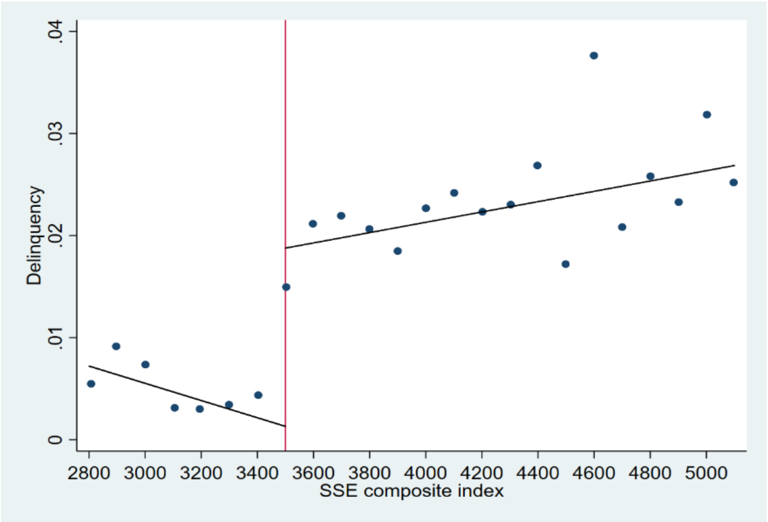


Figure 2: Baidu search index and the SSE composite index

This figure presents the relation between the Baidu search index for the keyword "the SSE composite index" and the SSE composite index. We group daily SSE composite index by a bandwidth of 100. Each dot represents the mean Baidu search index within each corresponding index bandwidth. The red line indicates the 3,500 SSE composite index.



Panel A: Default



Panel B: Delinquency

Figure 3: Credit risk from Renrendai and the SSE composite index

This figure presents the relation between credit risk from Renrendai and the SSE composite index. We group daily SSE composite index by a bandwidth of 100. Each dot represents the mean value of credit risk within each corresponding index bandwidth. The red line indicates the 3,500 SSE composite index. In Panel A, credit risk is proxied by *Default*, a dummy variable that equals one if the loan defaults, and zero otherwise. In Panel B, credit risk is proxied by *Delinquency*, the percentage of months in which the borrower fails to deliver the scheduled monthly payment in time.

Table 1: Summary statistics

This table presents summary statistics for our sample. *Default* is a dummy variable that equals one if the loan defaults, and zero otherwise. *Delinquency* is the percentage of months in which the borrower fails to deliver the scheduled monthly payment in time. *Interest* is the annualized interest rate. *Log(Volume)* is the natural logarithm of the RMB amount borrowed. *Duration* is the total number of months between the start day of the loan and its maturity day. *Log(Fulfilltime)* is the natural logarithm of the seconds needed to achieve the target borrowing amount. *Log(Vol/Lender)* is the natural logarithm of the total RMB amount borrowed divided by the number of lenders. *Age* is the age of the borrower. *Education* is the education level of the borrower. This is a categorical variable, in which 0 represents high school or below, 1 and 2 denote two levels of vocational school, 3 denotes college, and 4 denotes postgraduate school. *Female* is a dummy variable that equals one if the borrower is a female, and zero otherwise. *Married* is a dummy variable that equals one if the borrower is married, and zero otherwise. *Wage* is the monthly income level of the borrower. This is also a categorical variable, in which 0 denotes ¥1,000 to ¥2,000, 1 denotes ¥2,000 to ¥5,000, 2 denotes ¥5,000 to ¥10,000, 3 denotes ¥10,000 to ¥20,000, 4 denotes ¥20,000 to ¥50,000, and 5 denotes over ¥50,000. *Flat* is a dummy variable that equals one if the borrower owns a flat, and zero otherwise. *Car* is a dummy variable that equals one if the borrower owns a car, and zero otherwise. *Onsiteverify* is a dummy that equals one if the borrower's personal details have been verified by Renrendai onsite. *Score* is a credit score provided by Renrendai to assess the borrower's credit level based on his personal details, whether or not the details have been verified onsite, and historical records on the platform.

Panel A: Loan Characteristics						
Variables	N	Mean	Std	P25	P50	P75
Default	470,228	0.0063	0.0790	0.00	0.00	0.00
Delinquency	470,228	0.0096	0.0812	0.00	0.00	0.00
Interest	470,228	10.63	1.24	10.00	10.20	11.40
Log(Volume)	470,228	10.98	0.76	10.50	11.11	11.54
Duration	463,034	31.15	8.82	24.00	36.00	36.00
Log(Fulfilltime)	470,228	3.30	2.16	1.79	3.09	4.42
Log(Vol/Lender)	470,228	7.20	1.06	6.51	7.20	7.79
Panel B: Borrow Characteristics						
Variables	N	Mean	Std	P25	P50	P75
Age	470,226	36.03	12.37	29.00	35.00	42.00
Education	456,018	2.18	0.98	2.00	2.00	3.00
Female	470,228	0.33	0.47	0.00	0.00	1.00
Married	470,228	0.62	0.49	0.00	1.00	1.00
Wage	455,869	3.59	1.21	3.00	3.00	4.00
Flat	470,228	0.47	0.50	0.00	0.00	1.00
Car	470,228	0.27	0.44	0.00	0.00	1.00
Onsiteverify	470,223	0.86	0.35	1.00	1.00	1.00
Score	470,009	176.13	22.70	180.00	180.00	180.00

Table 2: The SSE composite index and lending from Renrendai

This table presents time-series regressions of daily lending activities from Renrendai on lagged SSE composite index. Daily lending activities are proxied by daily number of loans, or the daily RMB volume of loans (in millions). *Index* is the daily SSE composite index. *Shibor* is the daily Shanghai interbank offering rate. *Mktrf* ,is the excess daily market return. SMB is the daily China's size factor, constructed following Liu, Stambaugh, and Yuan (2019). VMG is the daily China's value factor, also constructed following Liu, Stambaugh, and Yuan (2019). Volatility, is the standard deviation of the daily SSE composite index returns from the past year. Apart from *Index*, all control variables are standardized to have a mean of zero and a standard deviation of one. Heteroscedasticity and auto-correlation-consistent standard errors are reported in parenthesis. ***, ** and * denotes statistical significance at 1%, 5%, and 10%, respectively.

Dep. Var	*Number of loans*		*Volume of loans*	
	(1)	(2)	(3)	(4)
Index	0.456***	0.534***	0.030***	0.036***
	(0.016)	(0.019)	(0.001)	(0.001)
Shibor		3.648		0.130
		(12.331)		(0.869)
Mktrf		6.724		0.368
		(16.913)		(0.999)
SMB		-10.103		-1.472
		(26.735)		(1.612)
VMG		7.207		0.210
		(23.458)		(1.398)
Volatility		-214.566***		-15.839***
		(11.877)		(0.880)
Constant	-489.874***	-714.978***	-27.676***	-44.059***
	(42.125)	(50.450)	(3.171)	(3.957)
N	1,181	1,181	1,181	1,181
R^2	0.311	0.466	0.286	0.468

Table 3: The SSE composite index and Baidu search index

This table presents time-series regressions of daily Baidu search index for the keyword "the SSE composite index" (in thousands) on lagged SSE composite index. *Index* is the daily SSE composite index. I(Index>3,500) is a dummy variable that equals one if the SSE composite index is above 3,500, and zero otherwise. *Cret* is the cumulative return from the SSE composite index in the past 52 weeks. *Vol* is the standard deviation of the daily returns from the SSE composite index in the past 52 weeks. *Low52* is a dummy variable that equals one if the SSE composite index is the 52-week low, and zero otherwise. *High52* is a dummy variable that equals one if the SSE composite index is the 52-week high, and zero otherwise. *Turnover* is the value-weighted turnover rate of A-share market on day *t*. *Vwhltoh* is the value-weighted price range divided by daily highest price in the A-share market on day *t*. Apart from *Index*, all control variables are standardized to have a mean of zero and a standard deviation of one. Heteroscedasticity and auto-correlation-consistent standard errors are reported in parenthesis. ***, ** and * denotes statistical significance at 1%, 5%, and 10%, respectively.

Dep. Var	*Baidu Search Index*			
	(1)	(2)	(3)	(4)
Index	0.169***	0.107***	0.111***	0.102***
	(0.006)	(0.004)	(0.004)	(0.003)
*Index*3500*			0.043***	0.016***
			(0.005)	(0.005)
Cret		11.776***		4.141
		(4.241)		(4.915)
Vol		39.985***		39.736***
		(2.297)		(2.313)
Low52		-1.369**		-1.158*
		(0.657)		(0.664)
High52		-4.723**		-3.609**
		(1.906)		(1.808)
Turnover		-6.913		-16.604***
		(5.751)		(6.413)
Vwhltoh		73.119***		73.483***
		(7.831)		(7.693)
Constant	-343.697***	-164.131***	-196.597***	-157.945***
	(16.073)	(10.904)	(10.284)	(10.116)
N	1,181	1,181	1,181	1,181
R^2	0.494	0.798	0.566	0.804

Table 4: Stock market bubble and credit risk

This table presents the relation between stock market bubble and credit risk from a regression discontinuity design. Credit risk is proxied by (1) *Default*, a dummy variable that equals one if the loan defaults, and zero otherwise; (2) *Delinquency*, the percentage of months in which the borrower fails to deliver the scheduled monthly payment in time. The discontinuity threshold for the SSE composite index is 3,500. We include borrowers' characteristics as control variables. The detailed definitions for these control variables can be found in Table 1. Standard errors (in parentheses) are clustered by year-month. ***, ** and * denotes statistical significance at 1%, 5%, and 10%, respectively.

Dep. Var	*Default*	*Delinquency*
	(1)	(2)
RD at 3500	0.014***	0.021***
	(0.002)	(0.003)
N	470,228	470,228
RD with controls	0.012***	0.020***
	(0.002)	(0.003)
N	455,857	455,857

Table 5: Cross-sectional Comparisons: Loan Qualities

This table presents the relation between stock market bubble and credit risk from a regression discontinuity design for subsamples divided based on borrowing time and loan description. In Panel A, working time is 9am to 5pm on working days. In Panel B, we first count the total number of words in the loan application, and then divide the sample into detailed vs brief subsamples based on the median number of words. Credit risk is proxied by (1) *Default*, a dummy variable that equals one if the loan defaults, and zero otherwise; (2) *Delinquency*, the percentage of months in which the borrower fails to deliver the scheduled monthly payment in time. The discontinuity threshold for the SSE composite index is 3,500. We include borrowers' characteristics as control variables. The detailed definitions for these control variables can be found in Table 1. Standard errors (in parentheses) are clustered by year-month. ***, ** and * denotes statistical significance at 1%, 5%, and 10%, respectively.

Panel A: Borrowing Time				
Dep. Var	*Default*		*Delinquency*	
	Working time	Non-working time	Working time	Non-working time
	(1)	(2)	(3)	(4)
RD at 3500	0.011***	0.025***	0.017***	0.038***
	(0.002)	(0.007)	(0.002)	(0.010)
N	373,855	96,373	373,855	96,373
RD with controls	0.010***	0.020***	0.017***	0.033***
	(0.002)	(0.007)	(0.003)	(0.010)
N	364,839	91,018	364,839	91,018
Panel B: Loan Description				
Dep. Var	*Default*		*Delinquency*	
	Detailed	Brief	Detailed	Brief
	(1)	(2)	(3)	(4)
RD at 3500	0.003***	0.028***	0.004***	0.044***
	(0.001)	(0.005)	(0.001)	(0.006)
N	226,889	243,339	226,889	243,339
RD with controls	0.002**	0.025***	0.004***	0.041***
	(0.001)	(0.004)	(0.001)	(0.006)
N	225,690	230,167	225,690	230,167

Table 6: Cross-sectional Comparisons: Overconfidence

This table presents the relation between stock market bubble and credit risk from a regression discontinuity design for subsamples divided based on borrowers' gender (Panel A) and age (Panel B). In Panel B, we divide the sample into elder vs young subsamples based on the median age from borrowers. Credit risk is proxied by (1) *Default*, a dummy variable that equals one if the loan defaults, and zero otherwise; (2) *Delinquency*, the percentage of months in which the borrower fails to deliver the scheduled monthly payment in time. The discontinuity threshold for the SSE composite index is 3,500. We include borrowers' characteristics as control variables. The detailed definitions for these control variables can be found in Table 1. Standard errors (in parentheses) are clustered by year-month. ***, ** and * denotes statistical significance at 1%, 5%, and 10%, respectively.

Panel A: Gender				
Dep. Var	*Default*		*Delinquency*	
	Female	Male	Female	Male
	(1)	(2)	(3)	(4)
RD at 3500	0.007***	0.016***	0.010***	0.026***
	(0.001)	(0.003)	(0.002)	(0.004)
N	153,770	316,458	153,770	316,458
RD with controls	0.006***	0.014***	0.010***	0.024***
	(0.001)	(0.003)	(0.002)	(0.004)
N	150,098	305,759	150,098	305,759

Panel B: Age				
Dep. Var	*Default*		*Delinquency*	
	Elder	Young	Elder	Young
	(1)	(2)	(3)	(4)
RD at 3500	0.008***	0.022***	0.011***	0.036***
	(0.002)	(0.003)	(0.003)	(0.004)
N	215,721	254,507	215,721	254,507
RD with controls	0.007***	0.018***	0.009***	0.032***
	(0.002)	(0.003)	(0.002)	(0.004)
N	215,652	240,206	215,652	240,206

Table 7: Other loan characteristics

This table presents the relation between stock market bubble and other loan characterstics from a regression discontinuity design. *Interest* is the annualized interest rate. *Score* is a credit score provided by Renrendai to assess the borrower's credit level based on his personal details, whether or not the details have been verified onsite, and historical records on the platform. *Log(Fulfilltime)* is the natural logarithm of the seconds needed to achieve the target borrowing amount. *Log(Vol/Lender)* is the natural logarithm of the total RMB amount borrowed divided by the number of lenders. The discontinuity threshold for the SSE composite index is 3,500. We include borrowers' characteristics as control variables. The detailed definitions for these control variables can be found in Table 1. Standard errors (in parentheses) are clustered by year-month. ***, ** and * denotes statistical significance at 1%, 5%, and 10%, respectively.

Dep. Var	*Interest*	*Score*	*Log(Fulfilltime)*	*Log(Vol/Lender)*
	(1)	(2)	(3)	(4)
RD at 3,500	2.011***	-8.556***	1.550***	-1.397***
	(0.259)	(1.417)	(0.376)	(0.365)
N	470,228	470,009	470,228	470,228
RD with controls	1.807***	-8.220***	1.491***	-1.204***
	(0.254)	(1.341)	(0.349)	(0.343)
N	455,857	455,643	455,857	455,857