What Does Peer-to-Peer Lending Evidence Say About the Risk-taking Channel of Monetary Policy?

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Abstract

This paper uses loan application-level data from a peer-to-peer lending platform to study the risk-taking channel of monetary policy. By employing a direct ex-ante measure of risk-taking and estimating the simultaneous equations of loan approval and loan amount, we are the first to provide quantitative evidence of the impact of monetary policy on the risk-taking of nonbank financial institution. We find that the search-for-yield is the main workhorse of the risk-taking effect, while we do not observe consistent findings of risk-shifting from the liquidity change. Monetary policy easing is associated with a higher probability of granting loans to risky borrowers and a greater riskiness of credit allocation, but these changes do not necessarily relate to a larger loan amount on average.

Keywords: Monetary Policy, Risk-taking, Nonbank Financial Institution, Peer-to-Peer Lending, Search-for-yield, Risk-shifting
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1 Introduction

The risk-taking channel of monetary policy has attracted more attention since the global financial crisis. A low interest rate and lax monetary environment have been accused of giving rise to the higher risk preference of financial institutions, which was at the root of the financial tsunami (Adrian and Shin 2008, 2009, Angeloni and Faia 2013, Bernanke and Reinhart 2004, Mishkin 2011, Schularick and Taylor 2012, Taylor 2009). This channel, if it holds true, implies that monetary policy goes far beyond the traditional impact on price stability and economic growth; it also has implications for systemic risk and financial stability (Borio and White 2004, Issing 2003, Smets et al. 2014, Stein 2012). Expansionary monetary policy can result in the increase of credit quantity (Gambacorta and Marques-Ibanez 2011, Kashyap and Stein 2000) as well as the decrease in credit quality (Borio and Zhu 2012, Jiménez et al. 2014). Therefore, the relationship between monetary policy and macroprudential management becomes more convoluted and challenges the policymakers. The answers to the question of whether and how monetary policy affects risk-taking are pivotal to the policy discussion and of great academic interest.

This paper studies the risk-taking channel of monetary policy based on the evidence from peer-to-peer (P2P, henceforth) lending. Specifically, we intend to answer the following three questions. First, whether the P2P platform's risk tolerance increases through higher probabilities and larger loan amounts to riskier borrowers when monetary policy eases. Second, what is the mechanism behind the risk-taking channel. In particular, this study investigates whether the search-for-yield and funding liquidity play a role in the risk-taking channel. Third, the tightening of regulation policy for the P2P industry in China provides a good experiment to study whether the financial regulation policies can curb the increased risk-taking during the expansionary monetary policy period.

Using loan application-level data, we establish new evidence for the risk-taking channel of monetary policy. The main findings are threefold. To begin, a financial institution tends to take more risks when monetary policy eases by lending to riskier borrowers. Meanwhile, the impact of the increased funding liquidity in the liability side on risk-taking is ambiguous. In addition, stricter regulation is effective in limiting the increased risk-taking from the eased monetary policy.

This study contributes to the literature from the following perspectives. The first is the measurement of ex-ante risk-taking. The key point of the risk-taking channel in comparison with the credit channel or balance sheet channel is in the risk perception and ex-ante risk-taking of financial institutions. Previous studies mostly rely on the survey data of bank lending standards (Dell'Ariccia et al. 2017, Paligorova and Santos 2012, Maddaloni and Peydró 2011) or loan-level data of previous firms' default information

(Ioannidou et al. 2014, Jiménez et al. 2014). We have the credit scores of each loan applicant, which are developed by the P2P platform based on big data, and the loan application results, which allow us to capture the institution's loan approval decision and use the credit scores of approved and rejected applicants to directly measure risk-taking and study the relationship between risk and return.

Second, we are the first to provide evidence of risk-taking from a non-bank financial instituion. According to Adrian and Shin (2009) and Adrian and Shin (2010a), as the economy becomes more increasingly market-based, the shadow banking system becomes more important in conveying information about the credit conditions running the economy. Moreover, the reason that Rajan (2006) focus on the incentives of managers with investors and the nature of risks undertaken by the system is that investment managers have displaced banks and reintermediate themselves between individuals and markets, while banks are moving to more illiquid transactions, where explicit contracts are hard to specify or where the consequences need to be hedged by trading in the market. The same argument applies to the emphasis on the nonbank financial intermediary in this study. In addition, for these nondepository institutions, their liabilities are funds from other investors and the search-for-yield incentive can be stronger with the absence of deposit insurance. The risk management in nonbank financial institutions, such as the P2P platforms, is essential to understanding the risk in the financial system. Moreover, the nonbank financial institution in this study is a FinTech internet lending company. FinTech allows the loan officers to obtain accurate and timely information much more efficiently and to reduce monitoring efforts (Rajan 2006), thus becoming more focused on searching for yields and responding to policy changes. It also generates advantages by providing a better measurement of ex-ante risk-taking. Big data and financial technology allow lenders to collect the borrowers' information at a greatly reduced cost and largely improved speed; thus, their perception of risk is more descriptive, and their reaction to monetary policy change is more prompt. Because of the limits in the literature, a more accurate measurement of risk-taking and evidence from a FinTech nonbank financial institution can carry the study a step forward.

In addition, we provide evidence from a large emerging economy. Most existing studies use US data, for instance Dell'Ariccia et al. (2017), Altunbasa et al. (2014), Buch et al. (2014b) and Delis et al. (2017). Others use datasets from European banks, including Jiménez et al. (2014), using Spain data; Geršl et al. (2015), using data from the Czech Republic; and Gaggl et al. (2010), using Austrian data. The only exception from a developing country is Ioannidou et al. (2014), who use Bolivian data. Our evidence from China also fills in the gap of the literature.

There are two main mechanisms in the literature which are used to explain the risk-taking channel of monetary policy. The first is the search-for-yield. Financial institutions usually enter into long-term contracts with a significant percentage of their borrowers and investors involving a commitment to produce a certain nominal rate of return, and they need to match this return to their liabilities based on their assets (Altunbasa et al. 2014, De Nicolò et al. 2010, Rajan 2006). When monetary policy eases, the nominal return of the previous investment portfolio also goes down. To reach the committed nominal return, the managers of the financial intermediary would turn to riskier investments. As documented in Gambacorta (2009) and BIS (2004), in 2003-2004, many investors shifted from low-risk government bonds into higher-yielding but riskier corporate and emerging market bonds. They were seeking to meet the nominal returns they had been able to achieve when interest rates were higher. Moreover, for behavioral reasons, investors tend to use the short-term return as a way to judge the managers' competence and this judgment is related to the managers' compensation and the assets they can obtain(Rajan 2006). Thus, the managers are encouraged to increase the risk exposure, especially in the periods of low interest rates because the incentive to search for yield goes up. Altunbasa et al. (2014) use the panel dataset of listed banks in Europe and the US and find that low levels of interest rates over an extended period of time contributed to an increase in the banks' risk. Buch et al. (2014a) also confirm a search-for-yield mechanism by using the US bank survey dataset and documenting that small domestic banks increase their exposure to risk following an expansionary monetary policy shock.

The second mechanism is risk-shifting and the pass-through. Dell'Ariccia et al. (2017) provide a simple model of interest rates, leverage, and bank risk-taking[1]. They capture the banks' risk-taking through the incentives to monitor by modeling both the risk-shifting and pass-through effects. This is how the risk-shifting effect works: when the reference rate reduces, bank funding is cheaper; the profits in the event of success increases, and the financial distress decreases, which leads to higher monitoring incentives and less risk-taking. However, there is also a pass-through effect, as the reduced monetary policy rate leads to a lower lending rate; then, the profits and incentive to monitor decrease, which indicates more risk-taking. The implications are that bank risk-taking is negatively associated with the policy interest rate, but this effect is less pronounced when the bank is poorly capitalized and has a higher leverage. According to this model, the risk-taking relates to both the reference rate and the banks' capital structure, and it depends on the relative strength of risk-shifting and pass-through. [2] However, this might be the place

[1]The model is in the Appendix A of Dell'Ariccia et al. (2017).

[2]Similarly, De Nicolò et al. (2010) argues that if the financial institution has a high level of liability compared to its own capital, it can enjoy larger spread and profits when monetary policy eases, thus it has less incentive to take risks. This is because lower policy rate transmits more efficiently to the liability side than the asset side of financial intermediaries, thus spreads increase and lead to larger profits. When the financial intermediary has more skin in the game, especially when liability increases in relative to

where the difference between banks and nonbanks matter. As we will see in section 3.2, for the Chinese P2P lending market, its financial return on the liability side is rather stable and maintained at a high level to compete with bank deposits, of which the adjustment in face of monetary policy is limited. If the cost of funding is relatively inelastic to the monetary policy, then the risk offsetting effect of reduced financial distress could be small.

Furthermore, the additional availability of liquidity after the monetary policy loosens (Buch et al. 2014a) may also induce risk-taking. On one hand, the value-at-risk constraints are weakened with more liquidity. On the other hand, adverse selection problems in the credit market are mitigated; thus, the financial intermediary's screening incentives are reduced, and the financial institution becomes more risk-taking. [3]

There is also macro evidence in support of the risk-taking channel[4], though most studies as well as this paper use bank-level or loan-level micro data. For instance, Bekaert et al. (2013) find that a lax monetary policy decreases risk aversion, Angeloni and Faia (2009) document that a monetary restriction reduces leverage using a DSGE model of prudential regulation and monetary policy with fragile banks, and Kodres et al. (2008) find that emerging market spread falls significantly when industrial country interest rates fall unexpectedly and when the interest rate volatility is low.

There are five major challenges for empirically identifying the risk-taking channel of monetary policy, and the loan application-level dataset in this paper works well in coping with these challenges. First, it is difficult to accurately measure ex-ante risk-taking. Most papers use the bank performance indicators such as bank leverage, VaR, Z-score, risk-weighted asset ratio, loan default rate, or market volatility measures and others,

equity, it is less likely to take more risks, vice versa.

[3]There are other factors that are claimed to be the workforce of the risk-taking channel, such as the impact on real valuation of the financial intermediary's liabilities and assets mentioned in Delis et al. (2017) and Gaggl et al. (2010). However, we believe this is the crucial element of the broad credit channel and not the heart of the risk-taking channel.

[4]It is important to distinguish the risk-taking channel from other monetary policy transmission channels. Many existing studies use the impact of monetary policy on the health of financial intermediaries in terms of leverage and asset quality to claim the risk-taking channel. However, it is different from the impact on the perception of risk and the willingness to bear risk, and it is the result of bank lending and balance sheet channel instead of the risk-taking channel (López et al. 2012). For instance, Adrian et al. (2018) show that when monetary policy tightens, the term spread reduce, net interest margin lower, and credit supply is reduced, vice versa. Thus, they claim that the relationship between expansionary monetary policy and more credit supply is evidence of risk-taking channel. Valencia (2014) also document that the lower funding cost from lower risk-free rate incentives the banks to increase lending and thus leverage. As we can see, Adrian et al. (2018) and Valencia (2014) focus on the quantity effect of monetary policy, however, the risk-taking channel of monetary policy should focus on the risk appetite of the financial intermediary and the credit quality instead of credit quantity. Although Adrian and Shin (2010b) argue that balance sheet quantities emerge as a key indicator of risk appetite and hence for the risk-taking channel of monetary policy, a more direct measure of risk appetite would contribute to disentangle the risk-taking channel from the bank lending channel. In this sense, modeling the monitoring incentive in Dell'Ariccia et al. (2017) is closer to the essence of risk-taking channel than modeling the credit supply in Adrian et al. (2018).

to indicate risk-taking[5]. In fact, these indicators are the results of the financial institutions' risk management decisions instead of the risk tolerance itself. These ex-post measurements are simultaneously determined by lenders' risk perception and the borrowers' ability to pay; thus the pure effect of the risk-taking channel cannot be isolated, as both can be affected by monetary policy. In our dataset, we observe each loan application, including whether or not the loan is granted, and a rich set of the applicants' characteristics, including credit score, basic demographic information, mobile contacts, credit card history and online shopping behavior. We use the borrowers' credit scores at the time of loan application to measure each loan's ex-ante risk. This score is determined before the loan takes place and it is calculated based on big data to reflect the borrower's credit quality. In addition, we also have each borrower's overdue history in other loans, which can also be employed as an ex-ante indicator of riskiness.

Second, monetary policy may be endogenous to financial stability. If monetary policy is eased because of a stable financial market or tightened because of a volatile financial market, then the finding of more risk-taking with an easing monetary policy is likely to be underestimated. Alternatively, if the agents in the financial market see an easing monetary policy as a signal of a stable financial condition, then they may engage in riskier behaviors and the findings tend to be overestimated. Two approaches are adopted in this paper to deal with the possible endogeneity of monetary policy. First, we analyze the contents of the Monetary Policy Executive Report to gauge the attention given to financial stability in monetary policy, following Dell'Ariccia et al. (2017). We find that the frequency of mentioning financial stability is relatively low (See Appendix). Second, in the spirit of the argument in Jiménez et al. (2014), the monetary policy is country-wide and should be universal to different provinces. Thus, we control the province fixed effect in the estimation given that the monetary policy should be exogenous at the province-level.

Third, it is difficult to isolate the impact on credit supply and credit demand. If a reduced monetary policy rate is associated with a higher loan demand from riskier borrowers, then the essence of the risk-taking channel of monetary policy, i.e., the increased risk-preference of the credit supplier, is mixed with riskier profiles on the demand side. Our data is fitted to alleviate this concern in the following ways. First, we have the overall loan application entries, which include not only the loans that are granted but also those which are rejected. Even if the borrower profile changes with the monetary policy, the granting process is fully controlled by the credit supplier and it is their key step of risk management. Therefore, an investigation of the probability for similar applicants to be granted the loan, in terms of ex-ante credit scores, would be able to isolate the impact of

[5]A detailed discussion of the measurement can be found in section 2.

demand. Second, we use the total amount of all loan applications in each day (including the rejected ones), to construct a proxy for aggregate demand. In addition, the number of borrowers in the overall P2P market is another proxy for credit demand, though at a lower frequency (monthly). We control these demand proxies in the regression, and the risk-taking findings still hold.

Fourth, the impact of monetary policy on loan amount can be biased without a consideration of loan granting. In addition to testing whether the loans are allocated to riskier borrowers when the monetary policy eases, we are also interested in how the loan amount changes. If the loan amounts decrease, even the borrowers become riskier, and the increase in riskiness for the financial institution and financial system can be limited. Moreover, using the observations of whose loan applications are granted leads to biased results, as shown in Jiménez et al. (2014). Benefiting from the data structure, we are able to conduct a similar two-step analysis to first estimate the probability of loan granting and then the granted loan size.

Fifth, it is necessary to distinguish the impact from monetary policy on existing loans and new loans. Buch et al. (2014b) distinguish the forward-looking and backward-looking bank risk because lower interest rates may reduce risk as the firms' interest burden is lowered, and the value of the collateral increases; thus, the repayment probability increases. This increase can lead to a decreased risk of existing loans but not new loans. Moreover, this also strengthens the necessity to use ex-ante risk-taking measurement instead of ex-post measurement. Our dataset focuses on the new loan applications; thus, it is not affected by the existing loans and purely reflects the change in risk-perception of the financial institution.

Finally, we admit several drawbacks of this study. First, this study leaves blank the impact of monetary policy on pricing, collateral requirement and actual default probabilities over the life of the loan as we only have the information on the application and approval stage but not over the life of the loan. However, based on the research that has investigated these perspectives, such as Ioannidou et al. (2014), there is assurance that a financial institution does not compensate for the extra risk taken by adjusting loan conditions, such as loan price and collateral values. Buch et al. (2014a) also find that the increase of the risk composition of loan portfolios is not compensated by higher risk premia[6]. In addition, there are studies using the loan pricing as indicators of risk-taking which conclude that the spreads to riskier borrowers relative to the spreads to safer borrowers become lower during the periods of low short-term rates.

Second, though it is innovative enough to provide evidence from a nonbank financial

[6]Loan spread is measured as the difference between risky loan rate and the riskless loan rate proxied by 1-year treasury bond rate.

institution such as a P2P lending platform, we only have the dataset of one specific platform and cannot control the platform fixed effect. Though we provide statistics to show it is a typical P2P platform in China, we can only observe the lending relationships of each borrower who has applied multiple times in the same platform at different times, but not each borrower who applies to multiple financial institutions at the same time. Thus, we cannot completely isolate the impact of monetary policy on the demand side and the supply side as the specification in Jiménez et al. (2014), which uses bank fixed effects in addition to borrower fixed effects to control the heterogeneity among credit suppliers.

This study provides meaningful policy implications. First, consistent with Berger and Udell (2004), a financial intermediary takes more risks during monetary policy expansion, but the risks are only revealed later because it takes time to expose the loan performance problem. Thus, the implication is that the regulators should closely watch the unnoticed buildup of financial risks during the periods of low interest rates. Our analysis period is August 2017 to April 2018, during which the monetary policy generally eased. Increased risk-taking during the monetary policy easing is accumulated to break out a wave of default of P2P platforms in the summer of 2018[7]. Second, monetary policy should take account of its effect on incentives. The competition to attract funding in the P2P market results in a pseudocommitment to high financial returns for investors, and this intensifies the search-for-yield mechanism when monetary policy rate is low. Third, the statistics from banks may no longer be sufficient for the quality of financial activities and prudential regulations should apply to address perverse behaviors in the nonbank financial institutions. Monetary policy should be coordinated with prudential regulation policies to balance the economic growth and financial stability.

The paper is structured as follows. Section 2 describes the loan application-level data and monetary policy variables used in the paper. Section 3 develops the hypotheses in empirical analysis based on the theoretical background and raw evidence from the data. Section 4 shows three empirical designs and presents the results. Section 5 discusses further concerns related to this study. Section 6 conducts several robustness checks. Section 7 concludes.

[7] There are over 200 P2P platforms defaulted in the single month of July in 2018.

2 Data and Variables

2.1 P2P Loan Applications and Contracts

The loan application-level data comes from a P2P internet lending platform in China. First of all, it is necessary to point out the specific practice of peer-to-peer lending in China. There are different business models of peer-to-peer lending. The first type of platforms are more like information intermediary, which allow individual borrowers to publicly list their loan demands and then individual lenders to view the listings and choose which to lend. The P2P platforms in the US and Europe are more of this type. The other type of platforms are more like credit intermediary, which package the loan targets and then individual lenders choose products with certain maturity and investment return without knowing specific loan listings or specifying the borrower pools they are investing in. And the platforms are in charge of the success or failure of each loan listing. The first type of P2P platforms also exist in China, such as Renrendai in its early stage. But the second type of platforms becomes more and more popular as the first type requires much efforts from individual lenders and thus limit the scale and profitability of the platform. Moreover, due to the immature credit scoring system, the credit intermediary type of P2P platforms are typical in China, including the one we from which we obtain the data[8]. Thus, more and more P2P platforms in China play the role of nonbank financial intermediaries rather than merely information intermediaries, and they are sensitive to the macro environment and monetary policy adjustments. We provide a figure of the business model of this P2P platform in the appendix.

Equipped with FinTech and big data, the P2P platform closely monitor the borrower profiles[9] and optimize the loan granting using information from their credit history and digital footprints. We observe loan characteristics including whether or not the loan is granted, the loan amount, maturity and interest rate. In addition to gender and age, we observe rich applicant characteristics including the information from mobile carriers such as the borrowers' amount of calls in number and time length; their contact with family and other call habits; the information from the credit card reported by the borrowers such as their transactions in the past 12 months; number of cards and banks; history of cash out, interest payment, credit line usuage and overdue count as well as amount;

[8]Due to disclosure principles, we hide the name of this platform. Later we show its representativeness in the aggregated P2P industry, and the desensitized data for results replication is available with the publication of the paper.

[9]It is worth noticing that the platform sets a very low entry barrier for borrowers, as the minimum requirement is to have a mobile phone and a national identity card, thus there is little pre-screen issues here. In contrast, it usually requires income certificates or real estate to proofs to start a loan application in banks.

and implicit income and credit card information from Alipay[10]. Most importantly, we observe the credit score for each applicant. Unlike the FICO score which is based on the hard information from credit card history, the P2P platform employs an algorithm to assess the riskiness and probability of delinquency of each registered user based on all the observed characteristics mentioned above. The official credit information system is heavily criticized in China, and it is common for financial institutions with FinTech and big data to develop independent credit score algorithms to manage risk[11]. For the pricing policy, the interest rate of each loan is determined by the credit score and loan maturity.[12]

As described in the introduction, there are several advantages to using this dataset to investigate the risk-taking channel of monetary policy. First, the credit score provides an excellent measurement of ex-ante risk-taking because it is a direct judgment by the platform before the loan contract comes into effect of the borrowers' trustfulness and probability of default. Most papers use the bank performance indicators such as leverage, VaR, Z-score, risk-weighted asset ratio, loan default rate, or market volatility measures, such as VIX and others, to indicate risk-taking (Adrian and Shin 2010c, Adrian et al. 2018, Bruno and Shin 2015, Cebenoyan and Strahan 2004, Esty 1998, Khan et al. 2017, Laeven and Levine 2009, López et al. 2011). However, these indicators are the results of financial institutions' risk management decisions instead of the risk tolerance itself. These ex-post measurements are simultaneously determined by the lenders' risk perception and the borrowers' ability to pay; thus, the pure effect of the risk-taking channel cannot be isolated as both can be affected by monetary policy. Recently, papers have employed quasi-ex-ante risk indicators. For instance, Jiménez et al. (2014) and Geršl et al. (2015) evaluate the loan risk based on the borrowers' credit history of whether they have had nonperforming loans, which is an improvement but still quite coarse; Buch et al. (2014b) use the share of noninterest income to total income; Delis et al. (2017) use the loan-specific coupon spread as a markup over LIBOR; López et al. (2012) use the ratio of the loan amount to risky borrowers to safe borrowers; and Maddaloni and Peydró (2011) use the survey data to measure the lending standard. Borrowers' credit scores would be a significant improvement to capture the financial institution's perception of risk.

Second, the dataset allows the estimation of the probit and selection model in section

[10]A popular third-party mobile and online payment platform in China.

[11]The most known credit score system in China may be the Sesame credit scores from Alipay. The P2P platform in this paper develops its own credit score system and it is different from the Sesame credit scores. Especially, the loan applicants do not observe their own credit scores in our data, and the credit scores here do not update as frequently as the Sesame credit scores.

[12]This is similar to the LendingClub, the interest rates in which are determined by FICO score, debt-to-income ratio, credit history, loan amount and loan maturity. In the platform we study, the credit score has already taken into account the information including debt-to-income ratio and credit history, and have accounted for additional information from the big data.

4 based on the observation of both granted and rejected loan applications. One of the most important steps in risk management is loan granting. The decision of which loan applications to approve and which to reject largely captures the risk perception of the financial institution. An investigation into the change of riskiness of the granted loan borrowers with a different monetary policy environment is a good way to see how the monetary policy affects risk-taking, and this is the method used in most studies and in the first baseline results of this paper. However, the probability of obtaining the loan and the granted loan amount for borrowers with different riskiness as the monetary policy eases or tightens provides richer information, and it requires data for both rejected and granted loan applications. The dataset in this paper makes it possible to estimate a selection model of loan granting and loan amount, similar to the one adopted in Jiménez et al. (2014).

Third, the dataset focuses on new loans and exclude existing loans and thus can separate the new risk from the realized risk. A reduced monetary policy rate may affect the default probability of existing loans because it brings down the financing pressure of firms. Thus, the realized risk decreases while the new risk increases, making the overall risk undetermined. By only including the new loan applications, the dataset in this paper excludes the impact on existing loans and the effect of the lower probability of default of outstanding loans during low interest rate periods.

The P2P loan data to which we have access is a 10% random sample of the loan applications on each day from the beginning of August 2017 to the end of March 2018. We clean the data by dropping 19 applications from individuals who are on the credit black list from the supreme court, and dropping the days on which the loan granting ratio is lower than the 1st or higher than the 99th percentile. To make the results comparable across specifications, the sample contains only borrowers that apply more than once. We have a total of 73,264 loan applications, of which 13,266 are granted, and these applications come from 17,344 borrowers, 6,498 of which have been approved a loan. Table 1 and Table 2 present the summary statistics of the dataset we use in this paper.

Figure 1 demonstrates the representativeness of the loan dataset from the specific P2P platform in this paper by plotting the time-series of the granted loan amount in our sample and that of an aggregated index designed to capture the overall development of the P2P industry in China. It shows that the two series move together, indicating that the dataset in this study has a consistent pattern similar to the aggregated P2P industry. For a better illustration, we use weekly data in the figure by aggregating the granted loan amount for each week and by taking the weekly average of the original daily P2P industry development index. The pairwise correlation of the two series is 0.41 and is significant at

1%.

Figure 2 shows the histogram of the granted loan amount and maturity in the data. Over 90% of the granted loans are smaller than 40,000 yuan (approximately 6,150 dollars using an exchange rate of 6.5 RMB/USD), and more than 80% have the tenor within one year. Statistics also show that the mean and median of the loan amounts are 17,500 yuan (approximately 2,700 dollars) and 13,000 yuan (approximately 2,000 dollars). It should be noted that we are unable to identify the usage of the loans, nor can the P2P platform as it does not restrict the usage except for warnings to the borrowers that the loan cannot be used for a real estate downpayment. Judging from the average size and maturity of the loan, a plausible hypothesis would be that most of the loans are applied for consumption use or a small business operation. Using consumer loans to investigate the risk-taking channel is supported by Maddaloni and Peydró (2011), who document that the risk-taking channel also holds for household loans.

Another loan characteristic in which we are interested is the borrowing interest rate and investing return of the P2P platform. The search-for-yield hypothesis assumes that the return for investors (burdened by the P2P platform) is more stable relatively, than the loan interest rates, and adjusts to a lower frequency when the monetary policy rate changes. Although we cannot access the investor return data for the specific P2P platform in this paper, we have the daily composite return of the wealth management products of the overall P2P industry from WDZJ[13]. Figure 3 shows the time-series of the industry-level investment return rates and the daily average loan interest rates from the specific P2P platform. First, the spread between the interest rates for borrowers and investors are as large as over ten percentage points. Second, the return for P2P investors stay relatively stable across the sample periods. The average return is 8.60% and the standard error is 0.3. Third, even when we take the average from one specific P2P platform, the loan interest rates are very volatile, with the average rate at 19.61% and standard error at 1.68. These observations indirectly validate the search-for-yield hypothesis in the literature.

2.2 Monetary Policy Environment and P2P Industry

China has a monetary policy framework that is quite different from that of the advanced economy. According to the official documents, China's monetary policy is not inflation-targeting and not Taylor-rule based, although the empirical evidence is ambiguous (Burdekin and Siklos 2008, Zhang 2009, Liu and Zhang 2010, Xiong 2012). Moreover, it is in transition from quantity-based to price-based and the current state is a hybrid. To save space, we present a detailed description of the background of China's monetary policy in

[13] An information platform for the Chinese P2P market, it provides daily statistics of the industry.

the appendix[14].

We use both rates and quantity indicators to measure China's monetary policy. First, we select three rates to proxy the monetary policy: the 7-day pledged repo rates between all financial institutions (R007) and between depository financial institutions (DR007) in the interbank market, and the unsecured 7-day interbank repo rates in the Shanghai wholesale money market (Shibor(1w)). Among them, DR007 is mentioned in the Quarterly Monetary Policy Executive Reports as "an active role to cultivate the market base rate" and is closely watched by the market as the policy rate. In addition to the interest rates, we also use a quantity-based indicator of monetary policy: the weekly net liquidity withdrawal by the central bank open market operation[15]. Liquidity withdrawal is consistent with the change in other interest rates in the direction of interpretation, with a larger value indicating a tighter monetary policy and vice versa. Thus, we include both the monetary policy instruments and intermediate targets, and both the interest rates and quantity indicators to proxy China's monetary policy[16].

Figure 4 plots the time-series of the detrended daily monetary policy rates of DR007, R007 and Shibor(1w), and the weekly net liquidity withdrawal from open marker operation. The daily rates show rich volatility, and the quantity-based indicator comoves with price-based indicators. Table 3 reports the cross-correlation coefficients between them. The three rates are significantly and positively correlated and the correlations between the quantity indicator and detrended DR007 and Shibor(1w) are also significantly positive; its correlation with the DR007 is less significant but still positive.

The potency of the risk-taking channel could be sensitive to the measures of monetary policy innovations(Delis et al. 2017). In the existing literature of the risk-taking channel of monetary policy, there are studies using the change in monetary policy rate, such as Jiménez et al. (2014); however, Delis and Kouretas (2011) argue that the investigation should be done using the level of interest rates instead of the change of interest rates. Others use the gap between the real policy rate and the natural policy rate or the Taylor-type rule residuals (Altunbasa et al. 2014, Delis et al. 2017). Gaggl et al. (2010) emphasize that the the analysis should be conducted for particular monetary policy phases such as the period when the Taylor rule gap is at least 25 or 50 basis points instead of a quarter-to-quarter change. Gambacorta (2009) and Maddaloni and Peydró (2011) also emphasized

[14]A comprehensive review of China's monetary policy framework can be found in McMahon et al. (2018) and Huang et al. (2019).

[15]Here the open market operation includes the traditional repurchase and reverse repurchase, and the newly introduced instruments such as Medium-term Lending Facility(MLF), Short-term Liquidity Operations(SLO) and Pledged Supplemental Lending(PSL).

[16]There are other monetary policy instance indices constructed based on market performance or text, but unavailable at such high frequency(daily or weekly) to match our loan application-level data. So we rely on the rates and quantity indicators to measure monetary policy in this paper, and this is consistent with the convention in the studies of the risk-taking channel.

a focus on the period that the interest rates had remained low for an extended period.

Consequently, we use all the level, change and detrended measures of the monetary policy to cross-check, and we conduct an analysis of consecutive low monetary policy periods in section 5.2. Table 4 displays the correlations between them. All the pairwise correlations are significant and positive. In the baseline results and main tables in this paper, we use the detrended DR007 to measure monetary policy. In the robustness check, we show that using the level and change of monetary policy indicators may produce different significance and quantities in the results but does not alter the quality of the main finding.

As the interest rate liberalization is not officially completed till late 2015 and the actual reform is still ongoing, nonbank financial institutions have been developing rapidly in China due to the repression in the bank sector. The share of non-bank financing has increased from almost zero before 2006 to approximately 20% in 2017. By defining shadow banking as the financing activities conducted by non-depository taking financial institutions, P2P is a key player in China's shadow banking and has shown the strongest momentum. It is also the largest and most dynamic in the world[17]. Figure 5 shows the development of China's P2P from January 2014 to April 2018. The monthly transaction volume climbed from approximately 5 billion US dollars in 2015 to a stable 30 billion US dollars since the last quarter of 2016. The loan balance increased by more than twenty times from 5 billion US dollars to 200 billion dollars from 2014 to 2018, at an average monthly growth rate of 6.9%. The P2P lending in China involves a large number of participants. The number of P2P platforms experienced a rapid increase as well as a decrease but remained above 2,000 by the end of April 2018. The number of investors and borrowers is approximately 4 million. Thus, an analysis of China's P2P can provide important implications for the global crowdfunding markets.

3 Hypothesis Development

Based on the theoretical discussion in the literature, the main workhorse of the risk-taking channel is the search-for-yield, while the risk-shifting and pass-through effects work in the opposite direction and produce ambiguous predictions when accounting for liability

[17]According to the Cambridge Center for Alternative Finance, in 2017, China makes more than 85% of the global alternative finance market and over 90% of the global P2P lending. The market share of P2P lending in the alternative finance is 40% in Americas, 57% in Europe, 60% in Asian Pacific(excluding China), and 90% in China. The alternative finance model includes P2P consumer lending, P2P business lending, P2P property lending, invoice trading, real estate crowdfunding, equity-based crowdfunding, reward-based crowdfunding, balance sheet business lending, debt-based securities, donation-based crowdfunding, minibonds, profit sharing, balance sheet consumer lending and others. The market share of P2P lending includes P2P consumer, business and property lending.

or liquidity (Rajan 2006, Dell'Ariccia et al. 2017, De Nicolò et al. 2010). We also need to take into account the specific characteristics of Chinese P2P platforms. This section presents some raw evidence to see how these mechanisms work in our dataset, and then we show the hypothesis and have a first-glance at the results based on the raw evidence.

3.1 Loose Monetary Policy Induces More Risk-taking

In support of the search-for-yield hypothesis, Figure 3 has shown that the investor returns (liability side) in the P2P industry is very stable, and the loan rate (asset side) is more volatile; thus, the managers have the incentive to turn to riskier assets to meet the return when monetary policy eases. This indicates that the riskiness of the loans with the same interest rate is higher when the monetary policy rate is lower.

To have a first look at the risk-taking channel, we compare the risk-return curves in different monetary policy periods. Figure 6 plots the quadratic fitted relationship between credit scores (in reverse order, interpreted as riskiness) and loan rates. The blue line and shading represent the estimated relationship and 95% confidence interval of the relatively tightening period, defined as when the detrended monetary policy rates (DR007 here) are above the 75th percentile, and the red line and shading represent the relatively easing period, when the monetary policy rates are below the 25th percentile[18]. First, this figure verifies the canonical risk-return trade-off. Riskier borrowers, i.e., borrowers with lower credit scores, are charged higher interest rates for their loans, and this trade-off exists in both kinds of monetary policy environments. Second, it implies more risk-taking when the monetary policy is easing. When monetary policy shifts from tightening to easing, the risk-return trade-off shifts from the blue line to the red line, implying that borrowers with the same credit score and riskiness are charged by lower interest rates or the loans go to riskier borrowers to maintain the same loan rate. Moreover, the more left-biased kernel distribution of borrowers' credit scores, as shown in Figure 7, indicates that the loans are granted to riskier borrowers during monetary policy easing periods, and this distribution difference is significant according to the two-sample Kolmogorov-Smirnov test, the details of which are described in the footnote of Figure 7. The left panel of Figure 8 again demonstrates that the credit scores of granted loans are lower during the easing period.

Moreover, we conduct t-test of the difference of credit scores between high and low monetary policy rate episodes. Table 5 shows the results for all loan applications, rejected loan applications and approved loan applications separately. Echoing Figure 7, the credit scores of approved loan applications are significantly lower by 1.32 points when monetary

[18]Findings are similar when we use the median value of the monetary policy rates to classify the tightening and loosening periods.

policy rate is low, suggesting that loans are granted riskier borrowers. Meanwhile, there are no significant differences for the total and rejected loan applications between high and low monetary policy episodes. This shows that there are no substantial change in borrower riskiness from the credit demand side, especially, the lower credit scores of the approved loans are not driven by the worsening of the credit quality of the applicants when monetary policy eases.

Additionally, we calculate the P2P financial institution's riskiness of credit allocation following IMF (2018). We first rank the credit scores of every approved loan at each time and divide them into ten quantiles by putting the lowest credit scores (thus the riskiest) in the tenth quantile and the highest credit scores in the first quantile. Consequently, we have a variable indicating the riskiness of each transaction from one to ten. Similarly, we next rank the loan amount of every approved loan and divide them into five quantiles by putting the largest amount in the fifth quantile and the smallest amount in the first quantile. Then, we calculate the average risk quantiles of the largest 20% loans and the smallest 20% loans and use the difference of the two average risk quantiles as the riskiness of credit allocation. A larger value indicates that more loans are allocated to riskier borrowers. The right panel of Figure 8 shows the box graph of the riskiness of credit allocation over different monetary policy environments. Consistent with the borrower-level measurement of credit scores, this platform-level measurement shows that the riskiness of allocation is higher during easing periods.

Based on the above raw evidence, we have the first empirical hypothesis: loose monetary policy induces more risk-taking by the financial institution.

3.2 Ambiguous Impact of the Interaction Between Funding Liquidity and Monetary Policy

For the risk-shifting effect, theoretical framework demonstrates that the risk-taking channel would be less significant when the financial institution is less capitalized or more leveraged, but it depends on the relative force of the pass-through effect. If the lowered monetary policy rate passes to the loan lending rate efficiently, even more efficiently than that to the liability side of the financial institution, which seems consistent with our data shown in Figure 3 and is in contrast to the theoretical hypothesis in De Nicolò et al. (2010), then the profitability of the financial institution does not necessarily increase, and its risk-taking incentive would not be constrained.

We conduct the same risk-return relationship analysis as in Figure 6, but here we distinguish the high and low liquidity conditions in addition to the monetary policy environment. Ideally, we should distinguish the leverage or the capitalization instead of the liquidity. However, our dataset comes from a single P2P platform, so there is no cross-sectional variation in capitalization, and we cannot directly observe the total liability nor leverage. With this limitation, we attempt to make use of the liquidation information, which is the amount of newly added funding flowing into the platform on each day. Assuming that the platform does not alter its equity, the change in liquidity assembles the change in leverage and the risk-shifting and pass-through story could also apply to liquidity. Figure 9 shows that the risk-taking effect is more significant when the financial institution has high liquidity and is insignificant during low liquidity periods. This result is in contrast with the risk-shifting mechanism and suggests that the pass-through effect may be stronger in this P2P platform. When monetary policy eases and the platform has a large pool of loanable funding, its profitability is weakened because the loan rate reduces, while the promised return to the funding inflow does not change. When the pool of loanable funding is small, the profit pressure is lower. Therefore, the platform has a large incentive of risk-taking when the monetary policy easing is accompanied by high liquidity.

On the other hand, the risk-shifting mechanism depends on the limited liability presumption, which holds firmly for banks but seemingly less for nonbank financial institutions. In general, the limited liability issue should be more serious for banks than nonbanks because the deposit insurance is only for depository-taking financial institutions. The P2P lending platforms in China, however, are notorious for severe moral hazard problems. Though they do not enjoy deposit insurance, their incentive to take full responsibility for the investors is very low. Many P2P platforms went into problem and their heads just flew away without any thought for the investors, to whom the platforms had promised a zero-risk repayment on the investment. This has been a social phenomenon, especially in the early development of P2P and in the lack of proper regulation by the government. Thus, the risk-shifting mechanism could be even stronger for the P2P platforms in China, which implies that the risk-taking is stronger when monetary policy tightens and is less when monetary policy eases.[19]

Thus, the role of liquidity in the risk-taking channel of monetary policy can be ambiguous. It is also noteworthy that these figures only show raw evidence, as the liquidity may be correlated with monetary policy. Therefore, we do not observe a clear hypothesis here. The investigation of the interaction between liquidity and monetary policy is an empirical question, and we leave it to Section 4.

[19] This severe moral hazard problem is echoed in the figure in the appendix. Without consideration of monetary policy environment, we investigate the change in risk-taking behavior purely with liquidity conditions. The more funding it attracts from investors, the more risk-taking the P2P platform is.

4 Empirical Results

We employ three empirical specifications to investigate the risk-taking channel. First, we test whether we can have similar findings in the literature using the granted loan subsample in our dataset, as most extant studies only observe granted loans. Specifically, we regress the riskiness measures of each granted loan on the monetary policy proxy. Second, we employ a probit model to investigate how the probability of loans being granted for borrowers with similar credit scores changes with monetary policy. In this specification, both the rejected and granted loan applications are used. Finally, we use a two-stage model with the granting of loan applications in the first stage and then the credit amount if the loan is granted in the second stage. This specification analyzes both the extensive and intensive margins of lending in different monetary policy environments.

4.1 Monetary Policy and the Riskiness of Granted Loans

First, we follow Dell'Ariccia et al. (2017) and Ioannidou et al. (2014) to estimate the following specification:

$$Credit\ Score_{ilt} = \alpha + \beta MP_{t-1} + \gamma_1 Loan_l + \gamma_2 Borrower_{it} + \gamma_3 Macro_t + \delta_p + \epsilon_{ilt} \quad (1.1)$$

$$\begin{aligned} Credit\ Score_{ilt} = \alpha + \beta_1 MP_{t-1} + \beta_2 Liquidity_{t-1} + \beta_3 MP_{t-1} \times Liquidity_{t-1} + \\ \gamma_1 Loan_l + \gamma_2 Borrower_{it} + \gamma_3 Macro_t + \delta_p + \epsilon_{ilt} \end{aligned} \quad (1.2)$$

where i indicates borrower, l indicates loan applications (here only the granted ones), t indicates time, and p indicates the province location of the borrower. $Credit\ Score_{ilt}$ is the credit score of borrower i at the time of the loan application l. MP_{t-1} is one of the monetary policy proxies as discussed in Section 2, and we use the detrended DR007 in the baseline results, while other proxies are used in robustness checks. $Liquidity_{t-1}$ represents the newly added loanable funding on the liability side at time $t-1$. $Loan_l$ includes loan characteristics such as maturity, interest rate and amount. $Borrower_{it}$ includes a group of variables relating to the borrower's mobile phone record, credit card history and online shopping behaviors. A list of the borrower characteristics is shown in Table 2. $Macro_t$ is a group of control variables of the macroeconomic condition, financial market condition, and the development in the aggregate P2P industry. In particular, it includes province-month level housing price change, country-month level change of banking total assets and banking leverage, daily stock return for the aggregate market and small- and medium-sized enterprises (SMEs), yield-curve, daily loan rate composite, popularity, development and investor composite return index of the P2P industry, as well as the monthly change in PMI and CPI.

We are interested in β in equation 1.1, and β_1, β_2 and β_3 in equation 1.2. We expect to see a positive β based on the first hypothesis, which shows that the credit scores of granted loans decrease with a decreased monetary policy rate, indicating that the P2P platform tends to lend to riskier borrowers when the monetary policy is eased. Based on the second hypothesis and the raw evidence in section 3.2, we expect to see a negative β_2 if the interaction term is not added, and ambiguous β_1, β_2 and β_3 when the interaction term is fully specified. For the estimation, we use the simple ordinary least square (OLS) estimator. To alleviate the concern of the endogenous monetary policy, we control the province fixed effect. As the time frequency of the loan applications is daily, we also show the results with a month fixed effect. We cluster the standard errors at the borrower-date level.

Table 6 presents the results for specification 1.1 and 1.2. Because the number of borrower characteristic control variables is large and they are not our main concern in this study, we drop the results for the borrower-level variables here for simplicity; however, full tables are available in the online appendix. Columns (1) -(6) show the estimates with province but without month fixed effect, and columns (7)-(12) show the estimates with both province and month fixed effect. We add control variables gradually. Columns (1)-(3) and Columns (7)-(9) do not analyze the role of liquidity, and the rest of the columns account for its effect. The significant and positive coefficients of the monetary policy is consistent with the first hypothesis and verifies the risk-taking channel of monetary policy.

Without consideration of the interaction between liquidity and monetary policy, the results in Table 6 show that a 100 basis points decrease in the monetary policy rate is associated with a 4.1% decrease in the credit scores of granted borrowers. Columns (4)-(5) and (10)-(11) show that the platform liquidity alone does not affect the riskiness of the granted loans, especially that the monetary policy reduces the role of liquidity. Column (6) shows that when there is no change in the monetary policy rate, a 1% increase in platform liquidity is associated with a 0.64% increase in the credit scores of granted loans. When the platform liquidity is average (4.31, note that here, the liquidity is rescaled by 10^{-3} its original value), the coefficient before detrended DR007 would be 0.038, and a one standard deviation above the average liquidity (5.39) brings the coefficient of detrended DR007 to 0.061. This means that the risk-taking channel is more significant when the platform has more loanable funding. This result is consistent with the raw evidence in Section 3.2.

When we replace the dependent variable of credit score with the borrowers' overdue history, the expected signs of the independent variables should be opposite. Table 7 shows the results using the number of overdue, overdue amount and the recent increase in overdue number as dependent variables in estimating equations 1.1 and 1.2. The significant and negative coefficients of monetary policy demonstrate that a lower monetary policy rate is associated with a higher overdue history and, thus, a higher riskiness of granted loans. However, the coefficients of the interaction term are no longer significant, implying that liquidity does not play an important role in altering the risk-taking effect of monetary policy.

Using the granted loan sample, we have found similar findings with existing literature and have basically established the risk-taking channel of monetary policy.

4.2 Monetary Policy and the Loan Granting Probability

Next, we make use of the granted as well as rejected loan application entries, and investigate the impact of monetary policy on the possibility of loans to be granted for borrowers with similar credit scores or riskiness. The risk-taking channel would imply that a lower monetary policy rate is associated with a higher probability to be granted for riskier borrowers.

The specification is as follows, and we use a probit model to estimate it. In the two-step analysis in section 4.3, the first stage equation is similar, but here we do not control the borrower and time fixed effect in this probit model. In equation 2, the $D(Granted_{ilt})$ is a dummy indicating that the loan application by borrower i at time t is granted. The other variables are interpreted in the same way as in equation 1.1 and 1.2.

$$\begin{aligned} D(Granted_{ilt}) = \alpha_{ilt} + \beta_1 MP_t + \beta_2 Credit\ Score_{ilt} + \beta_3 MP_{t-1} \times Credit\ Score_{ilt} + \\ \beta_4 Liquidity_{t-1} + \beta_5 Liquidity_{t-1} \times Credit\ Score_{ilt} + \beta_6 MP_{t-1} \times Liquidity_{t-1} \times Credit\ Score_{ilt} + \\ \gamma_1 Loan_l + \gamma_2 Borrower_{it} + \gamma_3 Macro_t + \epsilon_{ilt} \end{aligned} \tag{2}$$

We are interested in all the six coefficients β_1 to β_6, but we are most interested in β_3, which is the estimate of the interaction term between monetary policy and the credit score of the loan applicants. We expect to have a significantly negative β_1 and significantly positive β_2 and β_3 to verify the risk-taking channel. The interpretations are threefold. First, a lower monetary policy rate is associated with a higher probability of loan granting. Second, applicants with higher credit scores and lower riskiness are more likely to be granted a loan. Third, the probability of loan granting is higher for applicants with the same credit scores when the monetary policy rate is lower; i.e., monetary policy easing weakens the positive relationship between credit score and loan granting.

Table 8 shows the estimates of the probit model.Similarly, we add control variables gradually to see whether the results are stable. The standard errors are clustered at the borrower-date level. The first three rows report the coefficients of monetary policy, credit score and their interaction term. The estimates are consistent and significant across all columns. The marginal effect after estimation shows that a one standard deviation decrease in DR007 (0.09, or 9 bps) increases the probability of loan granting by 0.007[20], a one standard deviation increase in the logarithm credit score (0.04) increases the probability of loan granting by 0.059; and a one standard deviation decrease in liquidity (1.08) increases the probability of loan granting by 0.002. These results show that the most important determinant of loan granting is the credit score, and the impact of an easing monetary policy on the higher probability of loan granting is stronger than that of a lower liquidity. Based on the interaction term between the monetary policy and the credit score, the results show that for a loan applicant whose credit score is low (one standard deviation below mean, 6.41), a one standard deviation decrease in monetary policy rate (0.09, 9 bp) increases the probability of loan granting by 0.030-0.145; however, for loan applicants whose credit score is high(one standard deviation below mean, 6.49), the same decrease in monetary policy rate is associated with an increase in probability of loan granting by only as much as 0.054 or can even produce a decrease in probability by 0.053. These results show that monetary policy easing induces the P2P platform to grant the loan applications from riskier borrowers, and the risk-taking behavior is even stronger for riskier borrowers. For liquidity, the results show that a standard deviation increase in liquidity(1.08) can increase the loan granting probability for high risk borrowers by 0.012-0.120 and for low risk borrowers by -0.027-0.056. This result shows that the increase in liquidity is associated with more risk-taking and loan granting to riskier borrowers in particular. However, once more, the impact of liquidity is less than that of monetary policy. Moreover, the sixth and seventh rows in Table 8 show that liquidity does not show an impact by interacting with monetary policy.

4.3 Two-stage Selection Models for Loan Granting and Loan Amount

In addition to the extensive margin, we are interested in the intensive margin of new lending. In particular, we ask how does loan amount change with monetary policy and does the loan amount for riskier borrowers increase with monetary policy easing. Following Jiménez et al. (2014), we adopt the following two-step specification.

[20]A 100 basis points decrease in monetary policy rate increases the probability that a loan is granted to a borrower by 0.075 on average.

$$
\begin{aligned}
D(Granted_{ilt}) = \alpha_t + \alpha_i + \beta Credit\ Score_{ilt} + \delta MP_{t-1} \times Credit\ Score_{ilt} + \\
\gamma Liquidity_{t-1} \times Credit\ Score_{ilt} + \theta MP_{t-1} \times Credit\ Score_{ilt} \times Liquidity_{t-1} \\
+\Gamma Controls_{ilt} + \epsilon_{ilt}
\end{aligned}
\tag{3.1}
$$

$$
\begin{aligned}
Loan\ Amount_{ilt} = \alpha_t\prime + \alpha_i\prime + \beta\prime Credit\ Score_{ilt} + \delta\prime MP_{t-1} \times Credit\ Score_{ilt} + \\
\gamma\prime Liquidity_{t-1} \times Credit\ Score_{ilt} + \theta\prime MP_{t-1} \times Credit\ Score_{ilt} \times Liquidity_{t-1} \\
+\Gamma\prime Controls_{ilt} + \epsilon_{ilt}\prime
\end{aligned}
\tag{3.2}
$$

where all variables are defined in the same way as for the equations in section 4.1 and 4.2. For the first step, we employ a linear probability model here instead of a probit model, as was used in section 4.2, to control time and borrower fixed effects and make robust inferences, and we estimate it using the ordinary least square method. For the second step, we employ a two-step estimation procedure for panel data sample selection models as outlined by Kyriazidou (1997) using kernel least squares. We leave the estimation details, including the specific parameters of initial bandwidth and order of differentiability, to the original paper (Kyriazidou 1997) and the estimation documents in Jiménez et al. (2014). Because the borrower and time fixed effect are controlled, the variables MP_{t-1} and $Liquidity_{t-1}$, as well as other macro variables that do not vary with the borrower but only with time[21], do not appear in the estimation alone.

We are interested in the eight coefficients, that are, $\beta^{(\prime)}$,$\delta^{(\prime)}$,$\gamma^{(\prime)}$,$\theta^{(\prime)}$, before credit score and its double and triple interactions with the monetary policy rate and platform liquidity. Applicants with a higher risk, i.e., lower credit score, are expected to be approved with a lower probability and smaller amount; thus, we expect $\beta^{(\prime)}$ to be positive. According to the first hypothesis developed in Section 3 and the results in the above two subsections, we expect δ to be positive, as looser monetary policy is likely to induce more risk-taking and weaken the negative relationship between applicant risk and approval possibility and loan amount. However, our hypothesis does not have a certain expectation of $\delta\prime$ in the second stage.

Table 9 shows the estimates. Note here that the coefficient scale is different from Table 8 because we specify a linear probability instead of a probit model in the first step, and we control the borrower and time fixed effect, which is not controlled in section 4.2. To begin with, the first row in the first and second step show that a higher credit score is associated with a higher probability of loan granting and a larger loan amount

[21] Housing price is an exception, because it also varies at province level.

if the loan is granted. Next, the second row demonstrates that monetary policy plays a significant role in altering the loan granting probability. Monetary policy rate reduction is associated with a higher likelihood to obtain a loan for risky applicants. However, the insignificant coefficients in the second row in the second step show that monetary policy does not significantly affect the loan amount for risky applicants given that the loan is granted. Combining these results, we confirm that the risk-taking channel works in the credit quality as the loan applications from riskier borrowers are more likely to be granted, but not necessarily in the credit quantity as the loan amount is not significantly affected by the interaction between monetary policy and borrower riskiness. Again, there is no robust evidence to show that platform liquidity is associated with the risk-taking behavior in terms of loan granting probability as well as loan amount.

5 Discussion

In this section, we discuss the following four issues. First, the Chinese government strengthened the regulation on P2P industry at the end of 2017, and we would like to test the impact of regulation on the risk-taking channel. Second, the results so far are based on a one-time adjustment of monetary policy, and we are interested in whether the risk-taking effect is stronger in the periods when the monetary policy rate stays low for a long period. Third, we would like to further alleviate the concern on loan demand by controlling the proxy of aggregate demand. Fourth, the results above show the impact on the probability of loan granting to risky borrowers and the loan amount when the loan is granted; here, we construct an indicator of the riskiness of loan amount allocation to discuss whether the risk-taking channel of monetary policy exacerbates credit allocation quality.

5.1 The Role of Regulation

On December 1, 2017, the People's Bank of China and the China Banking Regulatory Commission jointly issued a strict regulation policy on internet lending with the purpose of mitigating the risks in the P2P industry. In particular, this regulation policy aimed to clean up controversial cash loans and the online microlending market by prohibiting loans to people without income and placing a limit on the total charges on runaway credit. The limits on the loan interest rate have affected the P2P industry significantly. All-in interest rates, which include the upfront fees charged for loans, are capped by the legally allowed annualized interest rate for loans, 36%.This upper limit may induce the P2P platforms to lend to safer borrowers, as the riskier borrowers usually require higher interest rates.

Thus, we are interested in whether and how the risk-taking behavior changes with the regulation tightening.

Tables 10 and 11 report the OLS and probit model analysis for subsamples before and after the regulation. Table 10 shows that the risk-taking channel of monetary policy only works before the regulation. After the regulation policy, the drop in monetary policy rates is no longer significantly associated with the drop in credit scores of the granted loan borrowers. Comparing the results of column (4) and column (8) in Table 11, when the macro economic conditions are controlled in addition to loan and borrower characteristics, we also find that the risk-taking channel disappears after the regulation. Even judging from columns (5)-(7), where the coefficients of monetary policy and its interaction with borrower credit scores remain significant, the scale decreases in the post-regulation period.

After the regulation, P2P platforms became more conservative, and when the monetary policy rate decreases, the search-for-yield motivation is repressed for two reasons. First, the loan rate cap makes it impossible to reach the riskiest borrowers. The willingness to undertake the high risk of those borrowers is dispelled because of the regulation. Second, compared to the previous periods without regulation, the managers now face more administrative pressures and they have to restrict the risk-taking to yield for soundness. These results imply that regulation, or other macro-prudential policies, is effective in constraining the risk-taking behavior from monetary policy easing. The policymakers can make use of the two kinds of policies together to balance growth stimulation and financial stability.

5.2 Consecutive Loose Monetary Policy Periods

As we have found that a financial institution is more likely to lend to riskier borrowers when the monetary policy eases, it is intuitive to predict that this risk-taking channel might be stronger when the monetary policy is "too low for too long" (Maddaloni and Peydró 2011). We identify the number of consecutive days of loose monetary policy by counting the days that the detrended monetary policy rate has been continuously negative and then repeat the OLS and probit analysis by replacing the monetary policy rate variable with the number of consecutive days of low monetary policy. The left panel of Figure 10 shows the predicted credit scores of approved loans when the monetary policy has been low for k days, $k = \{0, 1, ...8\}$[22], and the right panel shows the probability of loan applications to be approved for applicants with low, mean and high credit scores separately. The regression specifications are described in the note for Figure 10, and we

[22]We consider the case when monetary policy has been low as long as 8 days here. In the data, the longest consecutive low monetary policy period lasts for 14 days, but the observations of longer than 8 days are few, so we restrict the largest consecutive days of loose monetary policy to be eight.

report the full tables in the online appendix due to space constraints.

Figure 10 confirms the prediction that the longer the monetary policy remains loose, the more risk-taking occurs. Generally, the riskiness of approved loans is increasing, i.e., the credit scores of approved loan borrowers are decreasing, with the number of consecutive days of low monetary policy. Though there are some reversals in the 3rd to 5th day of consecutive loose monetary policy, the level of credit scores is not higher than when monetary policy is not easing. Moreover, the probability of a risky loan applicant(with low credit scores) being granted the loan is increasing with the length of periods in low monetary policy, while this relationship is not obvious for borrowers with average or low riskiness. These results suggest that the impact of low monetary policy rates on risk-taking is amplified by relatively long and consecutive loose monetary policy periods.

5.3 Impact of Monetary Policy on Loan Demand

The conventional analysis of monetary policy transmission suffers from the endogeneity and simultaneity of credit demand and credit supply, as they only observe the actual granted loans which are the outcome of changes in both demand and supply. Our data alleviate the concern on credit demand to a large extent because we observe the borrower profiles whose loans are granted as well as the other applications which are rejected. As the change in credit demand is captured through the expansion or contraction of loan applications, the change in loan granting from monetary policy is thus a pure test of the supply side, i.e., the internet lending platform in this paper. In addition, we have shown in Table 5 that there is no significant deterioration of loan applicant quality when monetary policy eases. The riskiness of applicants are similar from the demand side, and it is the supply side that drives the lower credit scores of the granted loans.

Nevertheless, we take a step further to account for the impact of monetary policy on loan demand. Specifically, we sum up the amount of all loan applications, regardless of being granted or not, for each day and take the natural logarithm of this value. We use this as a proxy for loan demand in this platform. Similarly, we sum up the amount of granted loans for each day and use its natural logarithm as a proxy of loan supply in this platform. Then, we use the date-level data to regress the monetary policy rate on demand proxy and supply proxy, controlling the macroeconomic conditions. Table 12 reports the results. In the control variables, the macroeconomic characters of change in PMI, CPI, bank sector total assets and bank leverage are monthly variables instead of daily, so they are absorbed in columns (4) and (8) when the month fixed effect is included. The coefficients of monetary policy when the dependent variable is the demand proxy are negative but insignificant, while the coefficients when the dependent variable is the supply proxy are significantly negative, suggesting that the concern of credit demand should not be critical in our data. These results also show that the traditional lending channel of monetary policy also holds for this specific platform, as a monetary policy expansion is significantly associated with an increase in loan supply. In addition, Table 12 indirectly demonstrates the interaction between banks and nonbanks, which is consistent with the findings in Tang (2019). Specifically, the results show that the condition in the housing and banking sector only significantly affects the demand side but not the supply side for the P2P. Because the internet loans are not allowed to finance housing, the increase in housing price would only increase the mortgage demand in the bank sector and negatively relate to the credit demand in the nonbanks. The increase in the total assets and leverage of the bank sector indicate that borrowers have more savings in the format of bank deposits or bank lending increases, and this prosperity in bank credit is positively related with the credit demand in the nonbank sector but not necessarily with the credit supply in the nonbank sector.

Moreover, we add the loan demand proxy to the baseline regressions. In addition to the daily total loan application amount, another proxy for loan demand is the number of borrowers in the aggregate P2P market(all P2P platforms, not only the one we use in the paper), but this variable is only available at monthly frequency. Tables 13 and 14 present the results for the OLS and probit estimations, respectively. The demand proxies are significant in both tables and suggest that a higher demand is associated with higher credit scores of the granted loans and lower probability of loan approval. The key results of the risk-taking channel of monetary policy still hold when the proxies for demand are controlled.

5.4 The Riskiness of Loan Allocation

As described in section 3.1, we calculate a proxy of the P2P platform's riskiness of credit allocation following IMF (2018). First, we rank the credit scores of every approved loan on each day and divide them into ten quantiles by putting the lowest credit scores (thus, the riskiest) in the tenth quantile and the highest credit scores in the first quantile. Thus, we have a variable indicating the riskiness of each transaction from one to ten. Next, we rank the loan amount of every approved loan and divide them into five quantiles by putting the largest amount in the fifth quantile and the smallest amount in the first quantile. Then, we calculate the average risk quantiles of the largest 20% loans and the smallest 20% loans, and use the difference of the two average risk quantiles as the riskiness of credit allocation. A larger value indicates that more loans are granted to riskier borrowers.

This variable is at the platform-date level; so, we drop all the loan-level information and simply regress the riskiness of loan allocation on monetary policy and other macro variables. The results are shown in Table 15, of which the even columns have also controlled the proxy of aggregate demand. Columns (1)-(4) show that a decrease in monetary policy rate is associated with an increase in the riskiness of credit allocation, i.e., more loans are allocated to riskier borrowers. Specifically, a one standard deviation decrease in the monetary policy rate is associated with a 0.12-0.13 standard deviation increase in the riskiness of credit allocation. Moreover, we define the easing periods as days when the monetary policy rate is below its 25th percentile and the normal periods as days when the rates lie within the [25th, 75th] percentile and create two dummies for the easing periods and normal periods. Thus, the results in columns (5)-(8) show that the riskiness of credit allocation is higher during monetary policy easing and normal periods than tightening periods. The riskiness of credit allocation is higher by 0.38-0.42 standard deviations during easing periods than tightening periods and by 0.35-0.42 standard deviations during normal periods than tightening periods; the impact in the easing periods is stronger than in the normal periods.

6 Robustness Check

This section checks the robustness of the results. By using a lower frequency of monetary policy variables, other measurements of monetary policy and conducting a placebo test, we show that our findings for the risk-taking channel of monetary policy do not change in quality.

6.1 Monetary Policy Measurement: Lower Frequency

First, we change the frequency of monetary policy to monthly from daily in the previous analysis. Because there are a large number of loan applications each day in our dataset, we are able to conduct the investigation using daily monetary policy variables. There might be concerns that the financial institutions do not react to monetary policy change at such a high frequency. Our response is threefold. First, the P2P platform in our dataset is also FinTech firm; it uses algorithms and big data to monitor the applicant profile and react to macro environment change. Thus, compared to traditional financial institutions, it faces much less administrative obstacles and acts quickly to any policy changes. Second, if we identify risk-taking in a high frequency, the effects should exist and be even larger in a low frequency environment. Third, we take the average of monetary policy rates for each month, and transform the platform liquidity to monthly variables by aggregating the daily added liquidity. Similarly, we collapse other macro variables to a monthly frequency, but the loan and borrower characteristics are still in the loan application-level.

Tables 16 and 17 report the OLS and probit estimation results. Consistent with our conjecture, the risk-taking channel still exists based on the significant coefficients before monthly monetary policy variables. Moreover, the scale of the coefficients is larger than the ones in the baseline results. This result demonstrates that the P2P platform responds to monetary policy changes by loosening the loan granting criteria and higher probability of granting loans to riskier borrowers, and this impact is significant and stronger if the monetary policy changes at a monthly frequency.

6.2 Other Measurements of Monetary Policy

All the results shown in the baseline analysis use the detrended DR007 to measure monetary policy. Here, we first use the level of DR007 and then use other rates that are proxies of monetary policy to replace the detrended DR007, and we find that the results do not change in quality.

Table 18 shows the results of using level of DR007 based on all period samples, pre-regulation and post-regulation subsamples. Again, we observe that the lower the monetary policy rate is (level of DR007 here), the lower the credit scores. Moreover, the risk-taking channel is stronger in the pre-regulation periods and becomes insignificant after regulation. Table 19 shows the results using the other two price-based monetary policy indicators, i.e., detrended R007 and shibor(1w), and the quantity based variable, the liquidity withdraw in open market operation. The risk-taking channel conclusion is again significantly observed when shibor(1w) and OMO liquidity are used to measure monetary policy. Though the results based on detrended R007 are insignificant, the signs are as expected.

6.3 Placebo Test: Longer-term Rates as Monetary Policy

As in most other countries, monetary policy targets are rates with short tenor(7-day) in China. We replace the policy rates with longer tenor interest rates, which are not the policy target and should not be used to measure an overnight monetary policy adjustment, as a placebo test to check whether the risk-taking channel works through the change in the supposititious monetary policy rates.

Thus, we select the 1-year interbank money market rates in the same series of DR007, R007 and Shibor(1w): DR1y, R1y, Shibor(1y), as well as the ten-year government bond yields. Tables 20 and 21 show the baseline results using these supposititious monetary policy rates. The significance and interpretation of other loan characteristics and macroeconomic variables are similar to the results obtained using true monetary policy rates;

however, the key results of the impact of monetary policy, as reflected in the coefficients of monetary policy and its interaction terms with credit scores, disappear. These results are strong arguments that the measurement of monetary policy is correct in the previous results, and the risk-taking channel does work through the easing or tightening of a true monetary policy.

7 Conclusion

Considerable analytical effort has been expended, especially after the recent global financial crisis, to understand the linkage between monetary policy and financial stability through an examination of the banks' risk-taking channels. The literature, however, leaves the question of the financial stability implications of monetary policy in the nonbank financial industry largely untouched. This is unsatisfactory, as nonfinancial institutions play increasingly important roles. This paper attempts to fill this gap in the literature by examining the risk-taking consequences of a nonbank financial institution using loan-application-level data from a P2P lending platform in China. Even in a bank-dominated financial system such as China's, banks do not tell the entire story. In recent years, nonbank financial institutions, including shadow bank transactions and FinTech platforms, have began to play greater roles. An investigation into the risk-taking behavior of nonbank financial institutions is of great importance in deepening the understanding of the risk-taking channel of monetary policy.

This paper represents the first academic effort to present quantitative evidence of the risk-taking implications of monetary policy in a nonbank financial institution. Based on the credit scores of each loan applicant, we estimate the effect of monetary policy easing on the average credit scores of granted loans, the loan granting probability and loan amount. In addition, we investigate the change in the risk-return relationship with the change in monetary policy. The results confirm the search-for-yield mechanism of monetary policy's risk-taking channel, while we do not find consistent evidence of the risk-shifting mechanism. We conclude that eased monetary policy is associated with a higher probability to grant loans to risky borrowers and a greater riskiness of credit allocation, but it does not necessarily relate to a larger loan amount on average and takes effect through the liquidity. In addition, we also find that the introduction of the new P2P regulation at the end of 2017 significantly reduces the risk-taking effect.

While the empirical analyses of this study use the data of a Chinese P2P platform, the findings are of general significance and provide some important policy implications. First, monetary policy does have important implications for financial stability. Thus, while the monetary policy's primary objectives should remain to achieve price stability and support economic growth, monetary policymakers should also focus on the financial stability consequences. Second, an assessment of the impacts of monetary policy on financial stability should go beyond the formal banking sector, as nonbanking financial institutions become increasingly important. Furthermore, the risk implications could be more significant for the generally underregulated FinTech companies. Third, macroprudential regulations could help mitigate the rising risks following monetary policy easing. Consequently, while it might be difficult for the monetary policymakers to explicitly incorporate financial stability into their decision process, they could work more closely with the policymakers responsible for macroprudential regulations. This consideration further points to the advantages of the regulatory models combining both monetary policy and macro-prudential regulations at the central bank.

Unfortunately, due to the limit of data availability, this study also suffers from some shortcomings, which also point to important directions for future research. First, this paper documents the risk-taking behavior of a nonbank financial institution but is not able to compare these findings with traditional banks. It would be extremely valuable to examine the differences of risk-taking motivations between banks and nonbank financial institutions using comparable data. This method could help draw more reliable implications for system-wide financial stability. Second, this paper is not able to explore the change in interest rate pricing mechanisms resulting from monetary policy changes due to the specific loan pricing model of the financial intermediary under study. Third, as the data ends in April 2018, we are unable to study the large-scale bankruptcy of P2P platforms in China since June 2018, which happened under the background of tightening liquidity and slowed-down economy growth. This could serve as the evidence of how the accumulated risk can explode when the loose policy is gone, which backs the findings in this paper.

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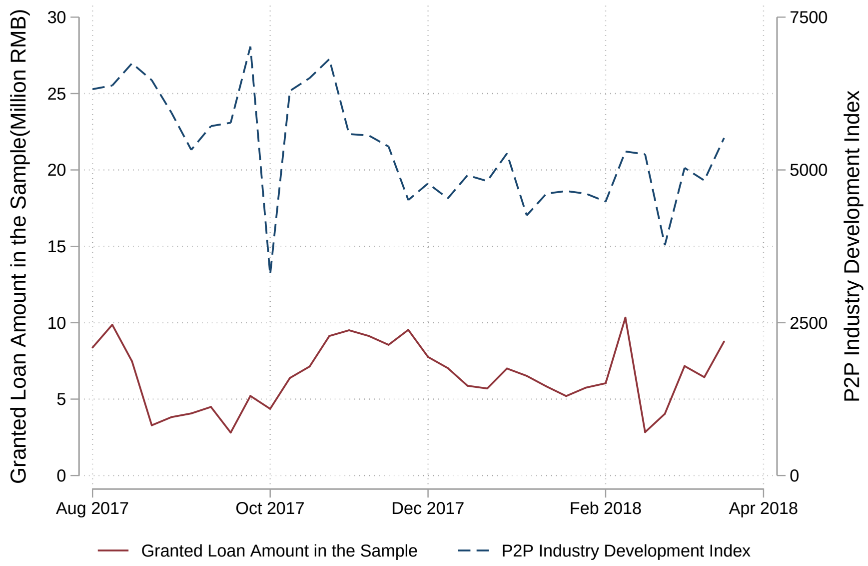
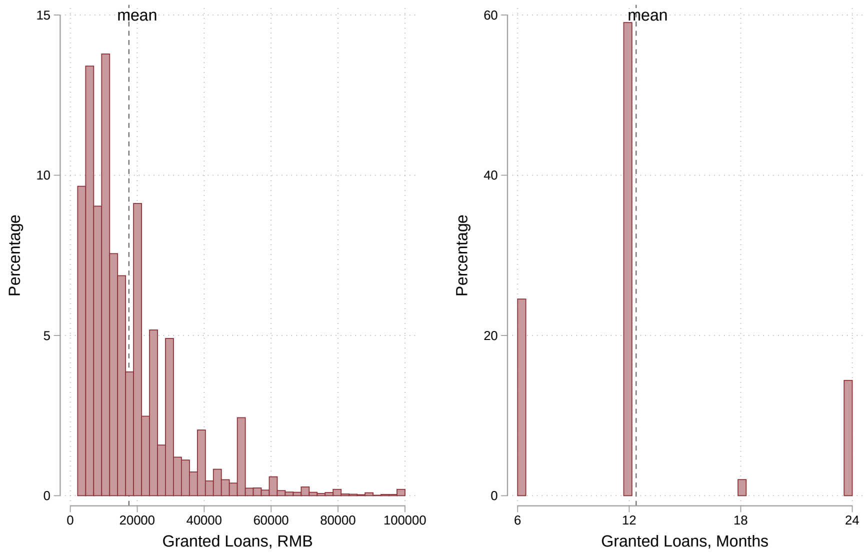
Figures and Tables

Figure 1: Aggregated Loan Amount in the Sample and Development Index in the P2P Industry



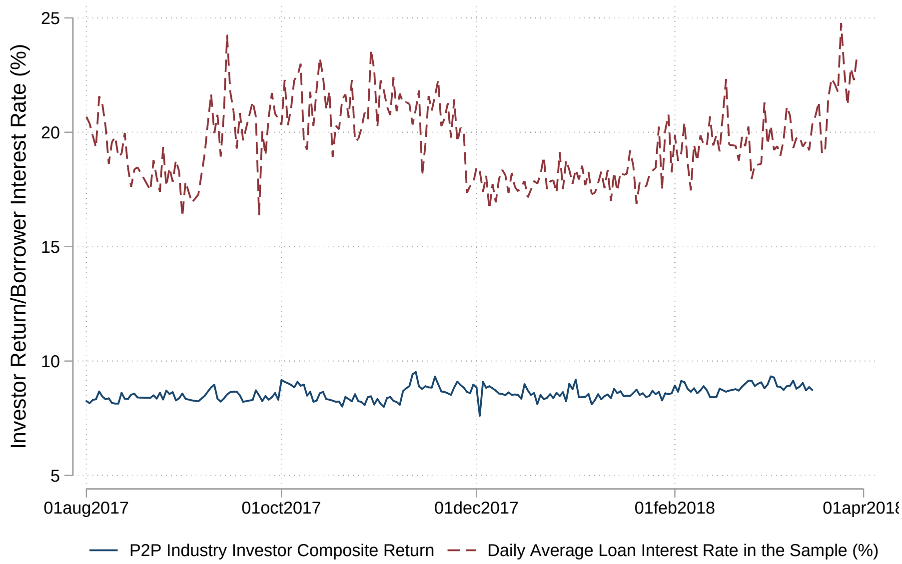
Note: (1) For better illustration, we transform the loan-level amount into weekly data by aggregating the granted loan amount for each week, and taking the weekly average of the original daily P2P industry development index. (2) The pairwise correlation of the two series is 0.41 and significant at 1%. (3) The P2P industry development index is from WDZJ, an information platform for the Chinese P2P industry. This index is a weighted average of the transaction, popularity, technology, leverage, liquidity, diversity, transparency and compliance of the P2P industry, covering every P2P platform in China. A higher value indicates more prosperity of the industry.

Figure 2: Distribution of Loan Amount and Maturity in the Sample



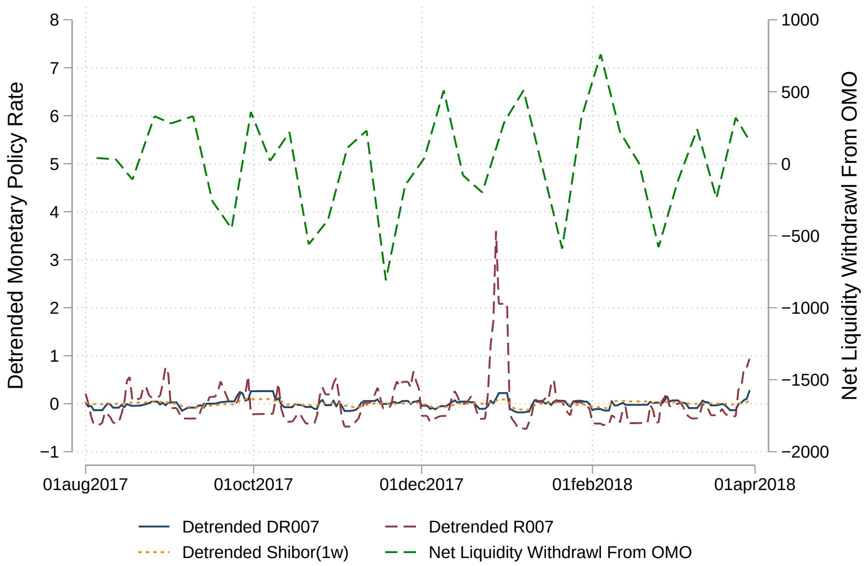
Note: Histograms for granted loan amount and maturity. The dashed vertical line indicates the mean value of each variable.

Figure 3: Loan Interest Rate and Investment Return in P2P



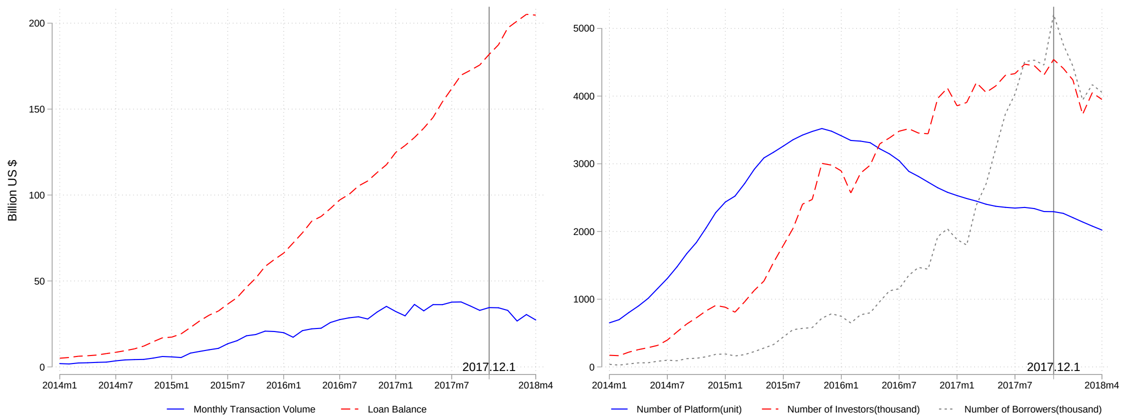
Note: The original data of the P2P industry investor composite return is at daily frequency and comes from WDZJ. The the original loan interest rate is at loan-level and comes from the specific P2P platform in this paper, and we take the average of the granted loans for each day to generate the red line time series.

Figure 4: Monetary Policy



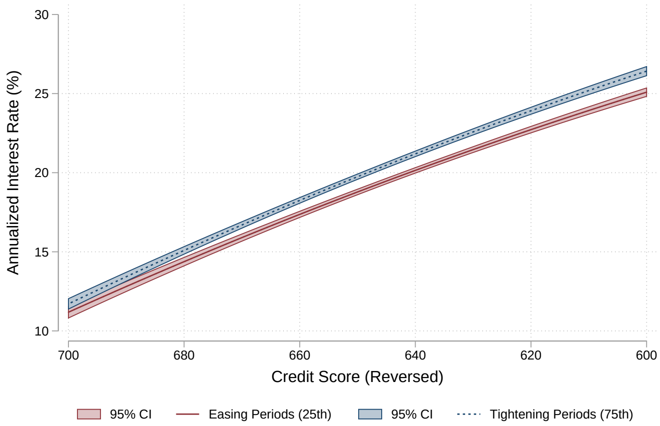
Note: The Net Liquidity Withdraw from OMO is weekly data, and the detrended DR007, R007 and Shibor(1w) are daily data.

Figure 5: Peer-to-Peer Lending in China



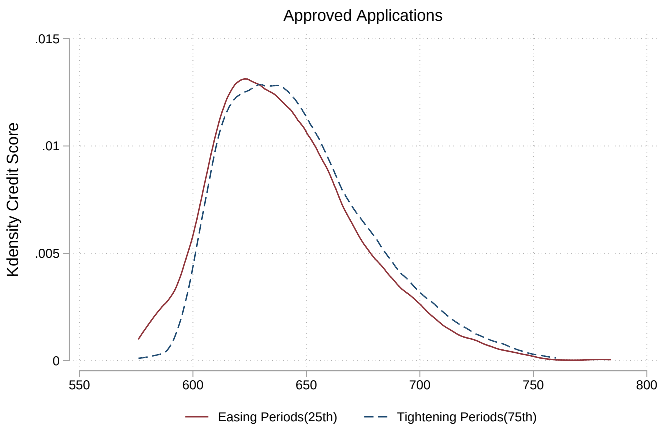
Note: There is a P2P regulation policy announced on Dec 1, 2017. The discussion on the regulation policy is in section 5.

Figure 6: Risk-return Relationship by Monetary Policy Environment



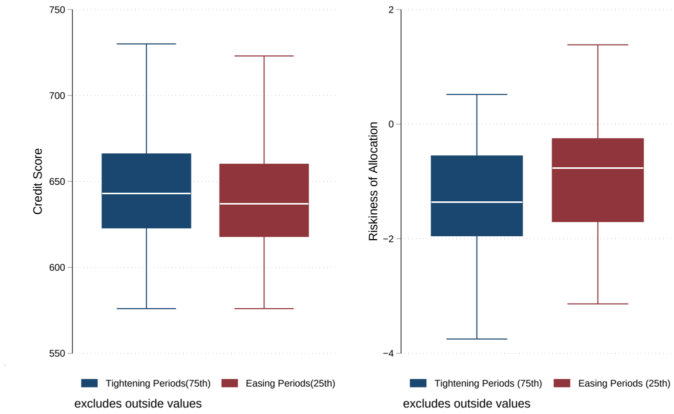
Note: this figure is based on the estimates of quadratic regression $Rates_l = \text{Credit Score}_l + \text{Credit Score}_l^2 + \epsilon$, where l indicates each granted loan. The equation is separately estimated for the loans in the monetary policy easing period and that in the tightening period.

Figure 7: Kernel Distribution of the Borrower Credit Scores by Monetary Policy Environment



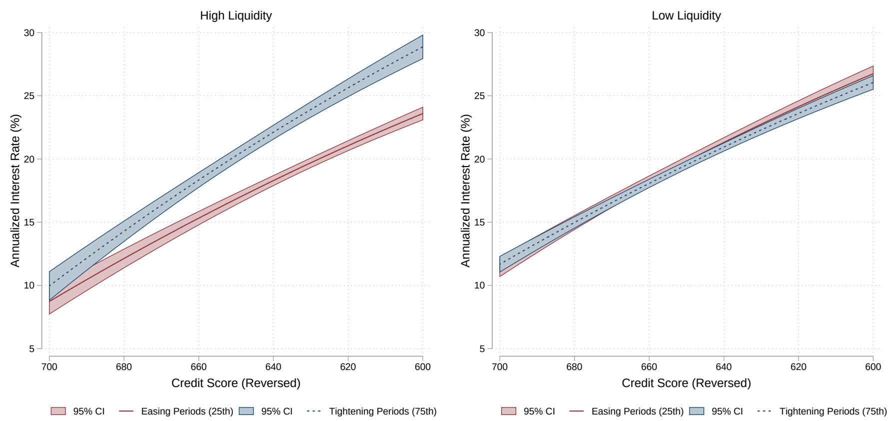
Note: We conduct a two-sample Kolmogorov-Smirnov test for equality of distribution. The approximate p-value of the hypothesis that the group of tightening monetary policy contains smaller credit scores than the the group of easing monetary policy is 0.998, and the p-value of the opposite hypothesis is 0.000. The largest difference between the distribution functions in the latter direction is 0.0728. The approximate p-value for the combined test is 0.000.

Figure 8: Credit Score and Riskiness of Allocation By Monetary Policy Environment



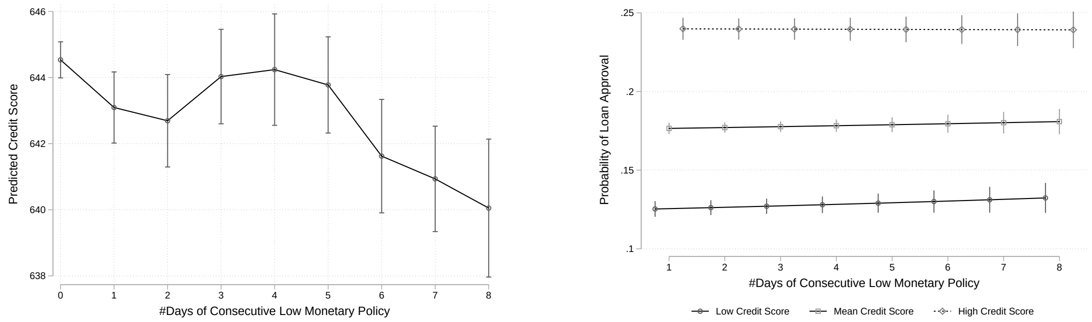
Note: the white line inside each box indicates the median value, and the upper hinge and lower hinge of the box represent the 75th(q_3) and 25th(q_1) percentile values. he upper and lower adjacent values are the most extreme values $q_3 + 1.5(q_3 - q_1)$ and $q_1 - 1.5(q_3 - q_1)$. Outliers are excluded in the figures.

Figure 9: Risk-return Relationship with Monetary Policy by Liquidity Conditions



Note: this figure is based on the estimates of quadratic regression $Rates_l = \text{Credit Score}_l + \text{Credit Score}_l^2 + \epsilon$, where l indicates each granted loan. The equation is separately estimated for the loans in the monetary policy easing period and that in the tightening period. For the figure in the left panel, the sample is limited to high liquidity periods, defined as the liquidity of the financial institution is above the 75th percentile. Similarly, the figure in the right panel is that for low liquidity periods.

Figure 10: Consecutive Days of Low Monetary Policy



(a) Credit Scores of Approved Loans

(b) Probability of Loan Approval

Note: The left panel is based on the alternative specification of equation 1.1: $\textit{Credit Score}_{ilt} = \alpha + \beta k\ \textit{Days in Consecutive Low Monetary Policy}_{t-1} + \gamma_1 Loan_{lt} + \gamma_2 Borrower_{it} + \gamma_3 Macro_t + \delta_p + \epsilon_{ilt}$, and the right panel is based on the alternative specification of equation 1.2: $D(Granted_{ilt}) = \alpha_{ilt} + \beta_1 k\ \textit{Days in Consecutive Low Monetary Policy}_t + \beta_2 \textit{Credit Score}_{ilt} + \beta_3 k\ \textit{Days in Consecutive Low Monetary Policy}_{t-1} \times \textit{Credit Score}_{ilt} + \beta_4 Liquidity_{t-1} + \beta_5 Liquidity_{t-1} \times \textit{Credit Score}_{ilt} + \beta_6 k\ \textit{Days in Consecutive Low Monetary Policy}_{t-1} \times Liquidity_{t-1} \times \textit{Credit Score}_{ilt} + \gamma_1 Loan_{lt} + \gamma_2 Borrower_{it} + \gamma_3 Macro_t + \epsilon_{ilt}$, where we replace the MP_{t-1} with $k\ \textit{Days in Consecutive Low Monetary Policy}_{t-1}$.

Table 1: Summary Statistics

	Mean	Standard Deviation	Min	Max	N
Loan Granted (Dummy)	0.18	0.38	0.00	1.00	73264
Loan Amount, All Applications (RMB)	21210.37	17565.54	2000.00	112000.00	73264
Loan Amount, Granted Loans Only	17509.62	14551.53	2200.00	100000.00	13226
Log(Loan Amount), Granted Loans Only	9.47	0.78	7.70	11.51	13226
Loan Maturity, All Applications (Month)	13.81	5.73	6.00	24.00	73264
Loan Maturity, Granted Loans Only	12.37	5.49	6.00	24.00	13226
Annualized Interest Rate (%)	21.18	6.92	13.35	42.58	73264
Annualized Interest Rate (%), Granted Loans Only	19.67	6.64	13.35	42.58	13226
Credit Score	633.43	27.94	576.00	786.00	73264
Credit Score, Granted Loans Only	643.17	31.69	576.00	785.00	13226
Log(Credit Score)	6.45	0.04	6.36	6.67	73264
Log(Credit Score), Granted Loans Only	6.47	0.05	6.36	6.67	13226
Riskiness of Credit Allocation of Granted Loans	-1.05	1.12	-4.40	4.12	73264
New Fundings Into the Platform	284.77	168.03	70.71	773.48	73264
Net New Fundings Into the Platform	103.75	104.03	-104.39	491.07	73264
Log(New Fundings Into the Platform)	5.49	0.57	4.26	6.65	73264
Log(Net New Fundings Into the Platform)	4.31	1.08	-0.56	6.20	67080
DR007	2.87	0.09	2.69	3.16	73264
Change in DR007	0.00	0.06	-0.33	0.19	73264
HP Filtered DR007	-0.01	0.09	-0.18	0.27	73264
R007	3.36	0.49	2.80	6.94	73264
Change in R007	0.00	0.30	-2.30	1.89	73264
HP Filtered R007	0.01	0.49	-0.53	3.60	73264
Shibor(1w)	2.86	0.04	2.74	2.97	73264
Change in Shibor(1w)	0.00	0.02	-0.12	0.13	73264
HP Filtered Shibor(1w)	-0.00	0.04	-0.13	0.10	73264
Open Market Operation Net Liquidity Withdrawl	34.19	352.57	-810.00	760.00	73264
HP Filtered Open Market Operation Net Liquidity Withdrawl	9.55	351.07	-828.36	722.68	73264
DR(6m)	4.99	0.32	4.38	5.70	73264
Change in DR(6m)	0.00	0.11	-0.66	0.53	73264
DR(1y)	5.02	0.26	4.52	5.33	73264
Change in DR(1y)	-0.00	0.07	-0.78	0.20	73264
Shibor(6m)	4.61	0.17	4.35	4.89	73264
Change in Shibor(6m)	0.00	0.01	-0.06	0.04	73264
Shibor(1y)	4.60	0.15	4.39	4.76	73264
Change in Shibor(1y)	0.00	0.01	-0.04	0.04	73264
P2P Industry Lending Rate, Composite Index	38.75	1.34	36.00	44.00	67523
P2P Industry Maturity, Days	229.63	38.54	135.00	311.00	67523
P2P Industry Popularity Index	63.32	19.36	19.43	131.37	67523
P2P Industry Development Index	5277.30	1477.53	2108.00	8548.00	67523
P2P Industry Return Rate (%)	8.61	0.30	7.61	9.52	67523
Daily Average Loan Interest Rate (%)	19.60	1.62	16.31	24.78	73264
Stock Market Return	-0.18	1.00	-4.05	1.83	73264
Change in Stock Market Return	-0.00	0.96	-3.79	5.03	73264
Housing Price, RMB/Square Meter (Province-Month Level)	10234.19	6515.65	3344.34	42235.84	65978
Percentage Change of Housing Price (Province-Month Level)	1.64	5.60	-33.25	35.01	65978

Table 2: Summary Statistics of Borrower Characteristics

	Mean	Standard Deviation	Min	Max	N
Male	0.72	0.45	0.00	1.00	73264
Age	32.83	6.39	19.00	63.00	73264
Number of Mobile Phone Carriers	1.22	0.96	0.00	31.00	73264
Number of calls In the Past 3 Months	1076.63	977.75	0.00	19553.00	73264
Longest Call Duration In The Past 12 Months	153.62	9490.74	0.00	592177.05	73264
Ratio of Frequent Calls In Contact Book In the Past 12 Months	0.66	0.26	0.00	1.00	73264
Number of Calls In the Black List In the Past 12 Months	0.02	1.62	0.00	205.00	73264
Number of Calls With Family In the Past 12 Months	382.16	646.29	0.00	9592.00	73264
Number of Calls With Agents As Caller	23.88	90.18	0.00	2973.00	73264
Number of Calls In the Past 3 Months As Caller	495.03	498.10	0.00	9473.00	73264
Longest Call Duration In The Past 12 Months As Caller	2277.36	1789.95	0.00	21710.00	73264
Median Call Duration In The Past 12 Months As Caller	43.61	20.98	0.00	816.00	73264
Number of Calls To Agents in the Past 12 Months As Caller	7.33	38.80	0.00	2450.00	73264
Number of Calls In the Black List In the Past 12 Months	0.02	1.25	0.00	155.00	73264
Ratio of Calls In Contact Book In the Past 12 Months As Caller	0.69	0.25	0.00	1.00	73264
Average Times of Being Called Per Day In the Past 12 Months	6.80	5.89	0.00	125.01	73264
Average Times of Being Caller Per Day In the Past 12 Months	5.91	5.53	0.00	84.04	73264
Average Mobile Bill In the Past 12 Months	94.01	129.88	0.00	6791.28	73264
Have Shortcuts for Family In the Past 12 Months	0.12	0.33	0.00	1.00	73264
Number of the Contacts In The Contact Book	672.15	888.01	0.00	31937.00	73264
Transaction Amount With Trading Companies In The Past 12 Months	77579.00	205767.79	0.00	6403776.00	73264
Transaction Number With Trading Companies In The Past 12 Months	12.45	26.02	0.00	671.00	73264
Number of Active Credit Cards	6.49	5.00	0.00	163.00	73264
Number of Banks of the Credit Cards	5.09	2.77	0.00	18.00	73264
Number of Cash Withdrawal in the Past 12 Months	10.76	35.81	0.00	1493.00	73264
Total Interest Charged In the Past 6 Months	4070.36	7637.09	0.00	154375.94	73264
Number of Interest Charged In the Past 12 Months	33.12	45.42	0.00	1317.00	73264
Number of Transactions Over 5000 RMB in the Past 12 Months	55.88	108.20	0.00	5766.00	73264
Highest Credit Line in the Past 12 Months	43522.03	39869.76	0.00	512488.74	73264
Repayment Rate in the Past 6 Months	0.68	0.33	0.00	1.00	73264
Minimum Repayment Rate in the Past 12 Months	0.42	0.39	0.00	1.00	73264
Usage Rate of Credit Line in the Past 6 Months	0.62	0.23	0.00	1.00	73264
Number Of Bank Relationship In The Past 3 Months	0.77	0.70	0.00	7.00	73264
Number Of Active Deposit Cards In The Past 3 Months	0.91	0.93	0.00	11.00	73264
Average Transfer Per Day In the Past 12 Months	312.42	983.04	0.00	25462.97	73264
Alipay Implied Credit Lines In The Past 12 Months	2279.37	9311.71	0.00	174100.00	73264
Alipay Implied Number of Banks of Credit Cards In The Past 12 Months	0.36	1.01	0.00	11.00	73264
Alipay Implied Highest Credit Line In The Past 12 Months	1314.59	4434.50	0.00	50000.00	73264
Alipay Implied Average Income Per Day In The Past 12 Months	210.28	715.48	0.00	27011.63	73264

Table 3: Cross-correlation Between Monetary Policy Variables

Variables	Detrended DR007	Detrended R007	Detrended Shibor(1w)	Net Liquidity Withdrawl From OMO (Lagged)
Detrended DR007	1.000			
Detrended R007	0.421**	1.000		
	(0.012)			
Detrended Shibor(1w)	0.747***	0.347**	1.000	
	(0.000)	(0.041)		
Net Liquidity Withdrawl From OMO (Lagged)	0.232	0.384**	0.300*	1.000
	(0.202)	(0.030)	(0.095)	

Note: p-values in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Cross-correlation Between Level, Change and Detrended Monetary Policy Rates

Variables	Level of DR007	Detrended DR007	Change in DR007
Level of DR007	1.000		
Detrended DR007	0.968***	1.000	
	(0.000)		
Change in DR007	0.312***	0.329***	1.000
	(0.000)	(0.000)	

Note: p-values in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: T-Test of Credit Scores By Monetary Policy Condition

	High Monetary Policy Rate	Low Monetary Policy Rate	Difference (High-Low)
All loan applications	633.30	633.56	-0.26
	(27.99)	(27.90)	(0.21)
Rejected loan applications	631.01	631.57	-0.56
	(26.47)	(26.67)	(0.22)
Approved loan applications	643.84	642.52	1.32***
	(32.04)	(31.33)	(0.55)

Note: standard errors in parentheses. High and low monetary policy rates are defined as the monetary policy rate(DR007) above and below its median value. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Monetary Policy Rates and Credit Scores of Granted Loans

This table shows the results from regressing the credit score of approved loan applications on monetary policy, the liquidity of the platform, i.e. newly added loanable funding, the interaction between monetary policy and platform liquidity, and a vector of control variables of the loan, borrower and macroeconomic conditions. Province and month fixed effects are controlled in respective columns. We use the sample of approved loan applications and employ OLS estimation for this table. The estimates for borrower characteristics are omitted here due to space limit. Standard errors are clustered at the borrower and date levels.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Ln(Credit Score)	Ln(Credit Score)	Ln(Credit Score)	Ln(Credit Score)	Ln(Credit Score)	Ln(Credit Score)	Ln(Credit Score)	Ln(Credit Score)	Ln(Credit Score)	Ln(Credit Score)	Ln(Credit Score)	Ln(Credit Score)
Lagged Detrended DR007	0.04***	0.04***	0.04***		0.04***	-0.05***	0.02***	0.01***	0.02***		0.02***	-0.03**
	(0.000)	(0.000)	(0.000)		(0.000)	(0.001)	(0.000)	(0.000)	(0.000)		(0.000)	(0.030)
Log Lagged Liquidity				-0.39	-0.29	0.64*				-0.19	-0.10	0.43
				(0.213)	(0.367)	(0.072)				(0.530)	(0.748)	(0.216)
Lagged Detrended DR007 × Log Lagged Liquidity						20.54***						11.47***
						(0.000)						(0.000)
Log Loan Amount		0.22	1.27***	1.35***	1.23***	1.21***		0.90**	0.86**	0.87**	0.86**	0.85**
		(0.607)	(0.002)	(0.002)	(0.005)	(0.006)		(0.019)	(0.031)	(0.039)	(0.043)	(0.043)
Loan Maturity		-1.67***	-1.82***	-1.82***	-1.81***	-1.81***		-1.82***	-1.87***	-1.87***	-1.86***	-1.86***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Loan Interest Rate		-0.01***	-0.01***	-0.01***	-0.01***	-0.01***		-0.01***	-0.01***	-0.01***	-0.01***	-0.01***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lagged Stock Market Return			0.04	-0.54	-0.20	-0.50			-0.54	-0.79	-0.62	-0.77
			(0.940)	(0.306)	(0.704)	(0.343)			(0.281)	(0.124)	(0.229)	(0.135)
Lagged Stock Market Return for SMEs			-0.30	0.66*	-0.35	-0.08			0.14	0.64*	0.11	0.24
			(0.413)	(0.065)	(0.351)	(0.834)			(0.699)	(0.072)	(0.764)	(0.515)
Lagged Yield Curve			0.02***	0.02***	0.02***	0.02***			0.01***	0.00	0.01***	0.01**
			(0.000)	(0.000)	(0.000)	(0.000)			(0.003)	(0.313)	(0.005)	(0.015)
P2P Industry Loan Rate Composite Index			0.70*	2.44***	1.43***	1.52***			0.58	1.33***	0.82*	0.90**
			(0.061)	(0.000)	(0.001)	(0.000)			(0.131)	(0.002)	(0.055)	(0.037)
P2P Industry Popularity Index			0.08***	0.10***	0.08***	0.07***			0.03*	0.04**	0.03*	0.03
			(0.000)	(0.000)	(0.000)	(0.001)			(0.056)	(0.022)	(0.074)	(0.169)
P2P Industry Investor Composite Return			0.65	0.86	-1.06	-0.67			-2.06	-2.20	-2.57	-2.43
			(0.695)	(0.624)	(0.547)	(0.704)			(0.222)	(0.226)	(0.156)	(0.178)
Lagged Change in Housing Price			-0.20**	-0.13	-0.17**	-0.15*			-0.14	-0.12	-0.13	-0.13
			(0.014)	(0.102)	(0.044)	(0.060)			(0.117)	(0.168)	(0.156)	(0.153)
Lagged Change in Banking Total Assets			0.05***	0.05***	0.05***	0.05***						
			(0.000)	(0.000)	(0.000)	(0.000)						
Lagged Change in Banking Leverage			-0.25***	-0.28***	-0.27***	-0.28***						
			(0.000)	(0.000)	(0.000)	(0.000)						
Lagged Change in PMI			-0.01***	-0.01***	-0.01***	-0.01***						
			(0.000)	(0.000)	(0.000)	(0.000)						
Lagged Change in CPI			-0.02***	-0.02***	-0.02***	-0.02***						
			(0.000)	(0.000)	(0.000)	(0.000)						
Constant	6.47***	6.55***	6.44***	6.37***	6.43***	6.41***	6.47***	6.56***	6.56***	6.53***	6.56***	6.55***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	11956	11956	10953	10008	9922	9922	11956	11956	10953	10008	9922	9922
Adjusted R-Squared	0.02	0.59	0.66	0.65	0.66	0.66	0.12	0.68	0.69	0.69	0.68	0.68
Loan Characteristics	NO	YES	YES	YES	YES	YES	NO	YES	YES	YES	YES	YES
Borrower Characteristics	NO	YES	YES	YES	YES	YES	NO	YES	YES	YES	YES	YES
Macro Characteristics	NO	NO	YES	YES	YES	YES	NO	NO	YES	YES	YES	YES
Borrower Province FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Month FE	NO	NO	NO	NO	NO	NO	YES	YES	YES	YES	YES	YES

p-values in parentheses

In this table the independent variable of Log Lagged Liquidity, Log Loan Amount, Loan Maturity, Lagged Stock Market Return, Lagged Stock Market Return for SMES,

P2P Industry Loan Rate Composite Index, P2P Industry Popularity Index, P2P Industry Investor Composite Return, Lagged Change in Housing Price and Lagged CHange in Banking Total Assets are rescaled by 10^{-3} times original value, for clear presentation of the estimates.

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

Table 7: Monetary Policy Rates and Riskiness of Granted Loans

This table shows the results from regressing the riskiness of approved loan applications, which is proxied by the number of overdue in the past 6 months in columns(1)-(3), the amount of overdue in the past 6 months in columns (4)-(6), the ratio of overdue number in the past 3 month to that in the past 9 month in columns(7)-(9), on monetary policy, the liquidity of the platform, i.e. newly added loanable funding, the interaction between monetary policy and platform liquidity, and a vector of control variables of the loan, borrower and macroeconomic conditions. Province and month fixed effects are controlled. We use the sample of approved loan applications and employ OLS estimation for this table. The estimates for borrower characteristics are omitted here due to space limit. Standard errors are clustered at the borrower and date levels.

	Number of Overdue(6M)			Amount of Overdue(6M)			Number of Overdue Ratio(3M to 9M)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lagged Detrended DR007	-367.26***	-353.93***	-874.39*	-52.89*	-47.53	-182.52*	-685.49***	-712.15***	-1692.12
	(0.002)	(0.006)	(0.059)	(0.068)	(0.133)	(0.053)	(0.006)	(0.008)	(0.129)
Log Lagged Liquidity		16.95*	22.37**		3.22**	4.63***		-14.10	-3.90
		(0.091)	(0.046)		(0.047)	(0.009)		(0.583)	(0.881)
Lagged Detrended DR007 × Log Lagged Liquidity			117.39			30.45			221.04
			(0.247)			(0.102)			(0.358)
Log Loan Amount	42.45***	41.34**	41.32**	11.92***	12.24***	12.24***	8.07	6.82	6.78
	(0.007)	(0.017)	(0.017)	(0.002)	(0.005)	(0.005)	(0.747)	(0.800)	(0.801)
Loan Maturity	3.71**	4.29**	4.29**	-0.10	-0.02	-0.02	-1.32	-1.29	-1.29
	(0.040)	(0.027)	(0.027)	(0.804)	(0.963)	(0.964)	(0.720)	(0.745)	(0.745)
Loan Interest Rate	3.30**	3.11**	3.11**	0.45	0.45	0.45	0.74	0.48	0.48
	(0.019)	(0.032)	(0.033)	(0.110)	(0.121)	(0.122)	(0.798)	(0.873)	(0.875)
Lagged Stock Market Return	-4.82	-2.00	-3.54	1.50	2.51	2.10	33.97	26.40	23.49
	(0.792)	(0.915)	(0.851)	(0.625)	(0.432)	(0.511)	(0.253)	(0.389)	(0.450)
Lagged Stock Market Return for SMEs	35.38**	31.42**	32.78**	6.31**	5.84**	6.19**	19.54	22.98	25.53
	(0.014)	(0.032)	(0.026)	(0.018)	(0.035)	(0.027)	(0.338)	(0.270)	(0.230)
Lagged Yield Curve	-45.08	-32.16	-42.39	-22.03	-19.85	-22.50	-218.59	-258.28	-277.54
	(0.623)	(0.746)	(0.673)	(0.217)	(0.309)	(0.255)	(0.216)	(0.175)	(0.151)
P2P Industry Loan Rate Composite Index	7.68	14.79	15.57	3.56	3.83	4.03	21.50	48.01	49.46
	(0.468)	(0.263)	(0.242)	(0.121)	(0.181)	(0.157)	(0.367)	(0.115)	(0.104)
P2P Industry Popularity Index	-0.50	-0.64	-0.72	-0.10	-0.14	-0.16	-1.01	-0.45	-0.59
	(0.342)	(0.255)	(0.204)	(0.351)	(0.203)	(0.145)	(0.364)	(0.708)	(0.621)
P2P Industry Investor Composite Return	-37.28	-53.57	-52.14	-21.72*	-23.11*	-22.74*	-107.05	-164.49	-161.81
	(0.457)	(0.334)	(0.347)	(0.070)	(0.084)	(0.090)	(0.368)	(0.224)	(0.233)
Lagged Change in Housing Price	0.99	1.68	1.68	-0.75	-0.75	-0.75	4.47	3.19	3.18
	(0.760)	(0.611)	(0.613)	(0.393)	(0.402)	(0.401)	(0.274)	(0.446)	(0.448)
Constant	-272.46	-419.54	-485.81	-41.90	-48.96	-66.15	1082.60	580.47	455.69
	(0.552)	(0.399)	(0.343)	(0.673)	(0.644)	(0.548)	(0.217)	(0.540)	(0.638)
Observations	10953	9922	9922	10953	9922	9922	10953	9922	9922
Adjusted R-Squared	0.03	0.03	0.03	0.06	0.07	0.07	0.01	0.01	0.01
Loan Characteristics	YES	YES	YES	YES	YES	YES	YES	YES	YES
Borrower Characteristics	YES	YES	YES	YES	YES	YES	YES	YES	YES
Macro Characteristics	YES	YES	YES	YES	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

p-values in parentheses

In this table the dependent variable of Number of Overdue (6M) and Number of Overdue Ratio(3M to 9M) are rescaled by 1000 times original value, for clear presentation of the estimates.

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

Table 8: Monetary Policy and Loan Granting Probability:Credit Score of Loan Applicants

This table shows the results from the Probit estimation of loan granting on monetary policy, the credit score of the loan applicant, the liquidity of the platform, i.e. newly added loanable funding, the full interaction terms between these three variables, and a vector of control variables of the loan, borrower and macroeconomic conditions. No fixed effects are controlled in this probit estimation, but will be controlled in the next two-step analysis. The estimates for borrower characteristics are omitted here due to space limit. Standard errors are clustered at the borrower and date levels.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Granted	Granted	Granted	Granted	Granted	Granted	Granted
Granted							
Lagged Detrended DR007	-0.14**	-36.30***		-93.67**	-83.15*	-87.73**	-74.95*
	(0.026)	(0.000)		(0.027)	(0.051)	(0.041)	(0.085)
Ln(Credit Score)		5.33***	8.56***	8.76***	8.38***	7.80***	8.15***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lagged Detrended DR007 × Ln(Credit Score)		5.58***		14.37**	12.72*	13.44**	11.64*
		(0.000)		(0.028)	(0.054)	(0.043)	(0.084)
Lagged Liquidity			4.65***	4.79***	4.84***	4.36***	2.96***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Lagged Liquidity × Ln(Credit Score)			-0.71***	-0.73***	-0.74***	-0.67***	-0.46***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Lagged Detrended DR007 × Lagged Liquidity				13.48	10.92	12.90	14.32
				(0.150)	(0.248)	(0.175)	(0.137)
Lagged Detrended DR007 × Ln(Credit Score) × Lagged Liquidity				-2.07	-1.67	-1.97	-2.24
				(0.154)	(0.255)	(0.180)	(0.134)
Log Loan Amount					-0.19***	-0.25***	-0.27***
					(0.000)	(0.000)	(0.000)
Loan Maturity					-0.03***	-0.03***	-0.02***
					(0.000)	(0.000)	(0.000)
Loan Interest Rate					-0.01***	-0.01***	-0.01***
					(0.000)	(0.000)	(0.001)
Lagged Change in Housing Price							0.01***
							(0.001)
Lagged Change in Banking Total Assets							-0.00***
							(0.000)
Lagged Change in Banking Leverage							3.45***
							(0.000)
Lagged Stock Market Return							-0.04***
							(0.000)
Lagged Stock Market Return for SMEs							0.01*
							(0.092)
Lagged Yield Curve							0.06
							(0.217)
P2P Industry Loan Rate Composite Index							-0.02*
							(0.077)
P2P Industry Popularity Index							0.00
							(0.167)
P2P Industry Investor Composite Return							0.01
							(0.725)
Lagged Change in PMI							0.21***
							(0.000)
Lagged Change in CPI							0.46***
							(0.000)
Constant	-0.92***	-35.32***	-56.49***	-57.76***	-53.02***	-48.85***	-49.29***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	72861	72861	66639	66236	66236	66236	54113
Loan Characteristics	NO	NO	NO	NO	YES	YES	YES
Borrower Characteristics	NO	NO	NO	NO	NO	YES	YES
Macro Characteristics	NO	NO	NO	NO	NO	NO	YES
Borrower FE	NO	NO	NO	NO	NO	NO	NO
Time FE	NO	NO	NO	NO	NO	NO	NO

p-values in parentheses

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

Table 9: Two-Step Model: Loan Granting and Amount

This table shows the results from the two-stage estimation. The first stage employs a linear probability model, by regressing loan granting on monetary policy, the credit score of the loan applicant, the liquidity of the platform, i.e. newly added loanable funding, the full interaction terms between these three variables, and a vector of control variables of the loan, borrower and macroeconomic conditions. Borrower and date fixed effects are controlled. The dependent variable in the second-stage is the amount of granted loans. For the second step, we employ a two-step estimation procedure for panel data sample selection models as outlined by Kyriazidou (1997) using kernel least squares. We leave the estimation details, including the specific parameters of initial bandwidth and order of differentiability, to the original paper (Kyriazidou 1997) and the estimation documents in Jiménez et al. (2014). Because the borrower and time fixed effect are controlled, the variables monetary policy and platform liquidity, as well as other macro variables that do not vary with the borrower but only with time do not appear in the estimation alone. The estimates for loan characteristics, borrower characteristics and macroeconomic conditions are omitted here due to space limit. Standard errors are clustered at the borrower and date levels.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
First Step: Granted								
Ln(Credit Score)	0.602***	0.594***	0.591***	0.584***	0.372***	0.359***	0.381***	0.367***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ln(Credit Score) × Lagged Detrended DR007		0.167***		0.176***		0.115*		0.128**
		(0.000)		(0.005)		(0.051)		(0.039)
Ln(Credit Score) × Lagged Liquidity			0.002*	0.002*			0.002	0.002
			(0.069)	(0.092)			(0.103)	(0.129)
Ln(Credit Score) × Lagged Liquidity × Lagged Detrended DR007				-0.004*				-0.003
				(0.096)				(0.325)
Observations	73264	72861	66639	66236	65978	65616	60091	59729
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Controls	No	No	No	No	Yes	Yes	Yes	Yes
Borrower Controls	No	No	No	No	Yes	Yes	Yes	Yes
Macroeconomic Controls	No	No	No	No	Yes	Yes	Yes	Yes
Second Step: Loan Amount								
Ln(Credit Score)	1.513***	1.518***	1.528***	1.532***	0.910**	0.899**	0.886**	0.870**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.013)	(0.014)	(0.016)	(0.018)
Ln(Credit Score) × Lagged Detrended DR007		-0.095		-0.179		-0.210		-0.333
		(0.744)		(0.568)		(0.557)		(0.374)
Ln(Credit Score) × Lagged Liquidity			-0.003	-0.003			-0.004	-0.004
			(0.521)	(0.558)			(0.386)	(0.415)
Ln(Credit Score) × Lagged Liquidity × Lagged Detrended DR007				0.020				0.020
				(0.295)				(0.282)
Observations	13226	13130	12085	11989	12042	11956	11011	10925
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Controls	No	No	No	No	Yes	Yes	Yes	Yes
Borrower Controls	No	No	No	No	Yes	Yes	Yes	Yes
Macroeconomic Controls	No	No	No	No	Yes	Yes	Yes	Yes

p-values in parentheses

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

Table 10: Granted Loan Only: Before and After Regulation

This table shows the results from regressing the credit score of approved loan applications on monetary policy, the liquidity of the platform, i.e. newly added loanable funding, the interaction between monetary policy and platform liquidity, and a vector of control variables of the loan, borrower and macroeconomic conditions. Province and month fixed effects are controlled in respective columns. We use the sample of approved loan applications and employ OLS estimation for this table. Columns(1)-(3) use the subsample before the regulation policy in December 2017, and columns(4)-(6) use the post-regulation subsample. The estimates for borrower characteristics are omitted here due to space limit. Standard errors are clustered at the borrower and date levels.

	Before Regulation			After Regulation		
	(1)	(2)	(3)	(4)	(5)	(6)
	Ln(Credit Score)	Ln(Credit Score)	Ln(Credit Score)	Ln(Credit Score)	Ln(Credit Score)	Ln(Credit Score)
Lagged Detrended DR007	0.04***	0.04***	-0.05*	-0.00	-0.00	0.01
	(0.000)	(0.000)	(0.062)	(0.697)	(0.761)	(0.686)
Log Lagged Liquidity		-0.04	1.43**		-0.46	-0.52
		(0.929)	(0.021)		(0.321)	(0.279)
Lagged Detrended DR007 × Log Lagged Liquidity			17.16***			-2.86
			(0.000)			(0.622)
Log Loan Amount	0.63	0.50	0.52	1.08*	1.17*	1.17*
	(0.250)	(0.391)	(0.372)	(0.057)	(0.055)	(0.054)
Loan Maturity	-1.96***	-1.95***	-1.95***	-1.82***	-1.82***	-1.82***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Loan Interest Rate	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lagged Stock Market Return	0.00	0.10	-0.47	-0.49	-0.57	-0.53
	(1.000)	(0.951)	(0.764)	(0.376)	(0.335)	(0.386)
Lagged Stock Market Return for SMEs	-1.88*	-2.16*	-1.91*	1.06***	1.15***	1.12***
	(0.091)	(0.057)	(0.093)	(0.009)	(0.006)	(0.008)
Lagged Yield Curve	0.02***	0.01***	0.01**	0.01**	0.01*	0.01*
	(0.000)	(0.002)	(0.011)	(0.050)	(0.062)	(0.056)
P2P Industry Loan Rate Composite Index	1.62*	1.60	1.66	0.43	0.44	0.40
	(0.083)	(0.114)	(0.101)	(0.349)	(0.423)	(0.462)
P2P Industry Popularity Index	0.06**	0.05*	0.04	0.02	0.03	0.03
	(0.036)	(0.091)	(0.162)	(0.303)	(0.178)	(0.167)
P2P Industry Investor Composite Return	-7.01*	-6.61	-5.63	-0.31	-0.40	-0.34
	(0.072)	(0.120)	(0.182)	(0.878)	(0.850)	(0.873)
Lagged Change in Housing Price	-0.48	-0.42	-0.41	-0.12	-0.10	-0.10
	(0.253)	(0.343)	(0.359)	(0.189)	(0.307)	(0.310)
Constant	6.56***	6.56***	6.54***	6.56***	6.56***	6.56***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	5653	5190	5190	5298	4730	4730
Adjusted R-Squared	0.71	0.70	0.70	0.64	0.64	0.64
Loan Characteristics	YES	YES	YES	YES	YES	YES
Borrower Characteristics	YES	YES	YES	YES	YES	YES
Macro Characteristics	YES	YES	YES	YES	YES	YES
Borrower Province FE	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES

p-values in parentheses

In this table the independent variable of Log Lagged Liquidity, Log Loan Amount, Loan Maturity, Lagged Stock Market Return, Lagged Stock Market Return for SMES, P2P Industry Loan Rate Composite Index, P2P Industry Popularity Index, P2P Industry Investor Composite Return, Lagged Change in Housing Price and Lagged Change in Banking Total Assets are rescaled by 10^{-3} times original value, for clear presentation of the estimates.

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

Table 11: Probit Analysis: Before and After Regulation

This table shows the results from the Probit estimation of loan granting on monetary policy, the credit score of the loan applicant, the liquidity of the platform, i.e. newly added loanable funding, the full interaction terms between these three variables, and a vector of control variables of the loan, borrower and macroeconomic conditions. No fixed effects are controlled in this probit estimation, but will be controlled in the next two-step analysis. Columns(1)-(3) use the subsample before the regulation policy in December 2017, and columns(4)-(6) use the post-regulation subsample. The estimates for borrower characteristics are omitted here due to space limit. Standard errors are clustered at the borrower and date levels.

	Before Regulation				After Regulation			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Granted	Granted	Granted	Granted	Granted	Granted	Granted	Granted
Granted								
Lagged Detrended DR007	-126.02*	-126.89*	-113.33	-129.70*	-121.13*	-109.86*	-110.47*	-56.97
	(0.065)	(0.069)	(0.104)	(0.075)	(0.055)	(0.082)	(0.088)	(0.416)
Ln(Credit Score)	8.01***	6.24***	5.19***	7.30***	7.88***	9.53***	9.22***	9.13***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lagged Detrended DR007 × Ln(Credit Score)	19.33*	19.51*	17.41	20.11*	18.75*	16.97*	17.07*	8.82
	(0.068)	(0.071)	(0.107)	(0.074)	(0.055)	(0.082)	(0.088)	(0.415)
Lagged Liquidity	3.41**	3.38**	2.58	3.45**	2.48*	2.43*	1.98	2.14
	(0.029)	(0.033)	(0.106)	(0.038)	(0.051)	(0.056)	(0.128)	(0.125)
Lagged Detrended DR007 × Lagged Liquidity	18.76	18.90	17.45	23.46	29.64*	27.53*	27.40*	15.06
	(0.183)	(0.188)	(0.225)	(0.118)	(0.064)	(0.086)	(0.095)	(0.393)
Ln(Credit Score) × Lagged Liquidity	-0.52**	-0.52**	-0.39	-0.54**	-0.38*	-0.38*	-0.31	-0.33
	(0.032)	(0.035)	(0.110)	(0.037)	(0.051)	(0.056)	(0.127)	(0.126)
Lagged Detrended DR007 × Ln(Credit Score) × Lagged Liquidity	-2.88	-2.91	-2.69	-3.66	-4.59*	-4.26*	-4.24*	-2.34
	(0.186)	(0.191)	(0.228)	(0.115)	(0.063)	(0.086)	(0.095)	(0.390)
Log Loan Amount		-0.15***	-0.22***	-0.22***		-0.24***	-0.29***	-0.31***
		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
Loan Maturity		-0.03***	-0.03***	-0.02***		-0.02***	-0.02***	-0.02***
		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
Loan Interest Rate		-0.02***	-0.02***	-0.01***		0.01***	0.01***	0.00
		(0.000)	(0.000)	(0.000)		(0.000)	(0.001)	(0.857)
Lagged Change in Housing Price				0.01				0.00
				(0.197)				(0.102)
Lagged Change in Banking Total Assets				-0.00***				0.00
				(0.000)				(0.210)
Lagged Change in Banking Leverage				0.14				-1.06
				(0.902)				(0.305)
Lagged Stock Market Return				-0.05				-0.04***
				(0.222)				(0.005)
Lagged Stock Market Return for SMEs				0.06**				0.01
				(0.034)				(0.604)
Lagged Yield Curve				-0.45***				-0.07
				(0.000)				(0.351)
P2P Industry Loan Rate Composite Index				-0.02				0.01
				(0.405)				(0.310)
P2P Industry Popularity Index				0.00				0.00
				(0.569)				(0.127)
P2P Industry Investor Composite Return				-0.00				-0.07
				(0.987)				(0.176)
Lagged Change in PMI				0.16***				-0.12*
				(0.000)				(0.052)
Lagged Change in CPI				0.63***				0.00
				(0.000)				(.)
Constant	-52.75***	-39.03***	-31.87***	-44.59***	-51.91***	-60.19***	-57.92***	-57.87***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	29289	29289	29289	25118	36947	36947	36947	28995
Loan Characteristics	NO	YES	YES	YES	NO	YES	YES	YES
Borrower Characteristics	NO	NO	YES	YES	NO	NO	YES	YES
Macro Characteristics	NO	NO	NO	YES	NO	NO	NO	YES
Borrower FE	NO	NO	NO	NO	NO	NO	NO	NO
Time FE	NO	NO	NO	NO	NO	NO	NO	NO

p-values in parentheses

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

Table 12: Monetary Policy on Credit Demand and Credit Supply

This table shows the results from the OLS estimation of regressing the credit demand and supply proxy on monetary policy and a vector of macroeconomic control variables. The proxy for credit demand is the aggregate amount of all loan applications, including the rejected ones, and the proxy for credit supply is the aggregate amount of granted loans on each day. Province and date fixed effects are controlled when indicated. Standard errors are clustered at the date level when indicated.

	Dep: Demand Proxy				Dep: Supply Proxy			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lagged Detrended DR007	-0.28	-0.28	-0.31	-0.05	-0.54*	-0.54**	-0.54**	-0.63**
	(0.261)	(0.222)	(0.198)	(0.850)	(0.068)	(0.027)	(0.043)	(0.027)
Lagged Change in Housing Price	-6.86*	-6.86**	-8.80**	-5.31	-3.86	-3.86	-6.76	-3.32
	(0.055)	(0.041)	(0.014)	(0.136)	(0.351)	(0.346)	(0.154)	(0.516)
Lagged Change in PMI	-0.37***	-0.37***	-0.38***		-0.08**	-0.08**	-0.09**	
	(0.000)	(0.000)	(0.000)		(0.028)	(0.030)	(0.030)	
Lagged Change in CPI	-0.76***	-0.76***	-0.76***		-0.07	-0.07	-0.05	
	(0.000)	(0.000)	(0.000)		(0.484)	(0.453)	(0.599)	
Lagged Change in Banking Total Assets	0.61***	0.61***	0.66***		0.05	0.05	0.10	
	(0.000)	(0.000)	(0.000)		(0.571)	(0.610)	(0.387)	
Lagged Change in Banking Leverage	-3.53***	-3.53***	-3.81***		-0.61	-0.61	-0.69	
	(0.000)	(0.000)	(0.000)		(0.398)	(0.383)	(0.372)	
Lagged Stock Market Return	-94.09**	-94.09**	-112.25**	-98.27**	-144.21***	-144.21**	-160.99***	-145.00***
	(0.030)	(0.030)	(0.010)	(0.013)	(0.004)	(0.010)	(0.006)	(0.010)
Lagged Stock Market Return for SMEs	22.86	22.86	20.99	6.20	21.71	21.71	21.74	15.55
	(0.466)	(0.284)	(0.379)	(0.793)	(0.551)	(0.516)	(0.553)	(0.674)
Lagged Yield Curve	-0.02	-0.02	0.08	0.44**	0.23	0.23	0.33*	0.35*
	(0.889)	(0.887)	(0.624)	(0.021)	(0.190)	(0.138)	(0.067)	(0.091)
Constant	14.33***	14.33***	14.30***	15.91***	13.70***	13.70***	13.67***	13.94***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	217	217	213	213	217	217	213	213
Adjusted R-Squared	0.49	0.49	0.48	0.54	0.16	0.16	0.13	0.19
Province FE	NO	NO	YES	YES	NO	NO	YES	YES
Month FE	NO	NO	NO	YES	NO	NO	NO	YES
Cluster	NO	Date	Date	Date	NO	Date	Date	Date

p-values in parentheses

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

Note: In this table the independent variable of Lagged Stock Market Return, Lagged Stock Market Return for SMEs, P2P Industry Loan Rate Composite Index, P2P Industry Popularity Index, P2P Industry Investor Composite Return, Lagged Change in Housing Price and Lagged Change in Banking Total Assets are rescaled by 10^{-3} times original value, for clear presentation of the estimates.

Table 13: OLS Analysis: Control Demand Proxy

This table shows the results from regressing the credit score of approved loan applications on monetary policy, the liquidity of the platform, i.e. newly added loanable funding, the interaction between monetary policy and platform liquidity, and a vector of control variables of the loan, borrower and macroeconomic conditions. Compared to the baseline estimates, we add the proxy of credit demand in the control variables. In columns(1)-(2), we use the logarithm of aggregated amount of all loan applications on each day as a proxy for credit demand, and in columns(3)-(4), we use the logarithm of number of borrowers in the P2P market in each month as a proxy for credit demand. Province fixed effect is controlled, but month fixed effect is not due to the monthly frequency of the second credit demand proxy. The estimates for borrower characteristics are omitted here due to space limit. We use the sample of approved loan applications and employ OLS estimation for this table. Standard errors are clustered at the borrower and date levels.

	Total Loan Application Amount		Aggregate Number of Borrowers	
	(1)	(2)	(3)	(4)
	Ln(Credit Score)	Ln(Credit Score)	Ln(Credit Score)	Ln(Credit Score)
Lagged Detrended DR007	0.043***	-0.051***	0.042***	-0.044***
	(0.000)	(0.000)	(0.000)	(0.002)
Log Lagged Liquidity		0.731**		0.402
		(0.042)		(0.265)
Lagged Detrended DR007 × Log Lagged Liquidity		20.948***		19.070***
		(0.000)		(0.000)
Demand Proxy-Ln(Total Loan Application Amount)	0.002*	0.002*		
	(0.081)	(0.061)		
Demand Proxy-Ln(Number of Borrowers in P2P Market)			0.023***	0.019***
			(0.000)	(0.000)
Log Loan Amount	1.259***	1.202***	1.196***	1.153***
	(0.003)	(0.006)	(0.004)	(0.009)
Loan Maturity	-1.816***	-1.814***	-1.801***	-1.802***
	(0.000)	(0.000)	(0.000)	(0.000)
Loan Interest Rate	-0.005***	-0.005***	-0.005***	-0.005***
	(0.000)	(0.000)	(0.000)	(0.000)
Lagged Stock Market Return	0.093	-0.412	-0.069	-0.646
	(0.854)	(0.434)	(0.891)	(0.217)
Lagged Stock Market Return for SMEs	-0.273	-0.049	-0.162	0.047
	(0.451)	(0.897)	(0.655)	(0.901)
Lagged Yield Curve	0.022***	0.020***	0.020***	0.019***
	(0.000)	(0.000)	(0.000)	(0.000)
P2P Industry Loan Rate Composite Index	0.622*	1.451***	0.292	1.127***
	(0.098)	(0.001)	(0.441)	(0.008)
P2P Industry Popularity Index	0.069***	0.056***	0.072***	0.065***
	(0.000)	(0.006)	(0.000)	(0.001)
P2P Industry Investor Composite Return	1.294	0.045	2.672	1.210
	(0.445)	(0.980)	(0.114)	(0.500)
Lagged Change in Housing Price	-0.188**	-0.145*	-0.043	-0.036
	(0.019)	(0.076)	(0.616)	(0.679)
Lagged Change in Banking Total Assets	0.045***	0.046***	0.045***	0.047***
	(0.000)	(0.000)	(0.000)	(0.000)
Lagged Change in Banking Leverage	-0.246***	-0.276***	-0.254***	-0.280***
	(0.000)	(0.000)	(0.000)	(0.000)
Lagged Change in PMI	-0.014***	-0.014***	-0.014***	-0.015***
	(0.000)	(0.000)	(0.000)	(0.000)
Lagged Change in CPI	-0.022***	-0.023***	-0.024***	-0.025***
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	6.415***	6.382***	6.244***	6.255***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	10953	9922	10953	9922
Adjusted R-Squared	0.656	0.658	0.657	0.659
Loan Characteristics	YES	YES	YES	YES
Borrower Characteristics	YES	YES	YES	YES
Macro Characteristics	YES	YES	YES	YES
Borrower Province FE	YES	YES	YES	YES
Month FE	NO	NO	NO	NO

p-values in parentheses

In this table the independent variable of Log Lagged Liquidity, Log Loan Amount, Loan Maturity, Lagged Stock Market Return, Lagged Stock Market Return for SMES, P2P Industry Loan Rate Composite Index, P2P Industry Popularity Index, P2P Industry Investor Composite Return, Lagged Change in Housing Price and Lagged CHange in Banking Total Assets are rescaled by 10^{-3} times original value, for clear presentation of the estimates.

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

Table 14: Probit Analysis: Control Demand Proxy

This table shows the results from the Probit estimation of loan granting on monetary policy, the credit score of the loan applicant, the liquidity of the platform, i.e. newly added loanable funding, the full interaction terms between these three variables, and a vector of control variables of the loan, borrower and macroeconomic conditions. Compared to the baseline estimates, we add the proxy of credit demand in the control variables. In columns(1)-(2), we use the logarithm of aggregated amount of all loan applications on each day as a proxy for credit demand, and in columns(3)-(4), we use the logarithm of number of borrowers in the P2P market in each month as a proxy for credit demand. The estimates for borrower characteristics are omitted here due to space limit. Standard errors are clustered at the borrower and date levels.

	Total Loan Application Amount		Aggregate Number of Borrowers	
	(1)	(2)	(3)	(4)
	Granted	Granted	Granted	Granted
Granted				
Lagged Detrended DR007	-88.94**	-70.51	-87.76**	-75.66*
	(0.038)	(0.106)	(0.041)	(0.084)
Ln(Credit Score)	7.88***	8.20***	7.81***	8.16***
	(0.000)	(0.000)	(0.000)	(0.000)
Lagged Detrended DR007 × Ln(Credit Score)	13.64**	10.97	13.44**	11.74*
	(0.039)	(0.104)	(0.044)	(0.083)
Lagged Liquidity	4.25***	2.90***	4.35***	2.94***
	(0.000)	(0.001)	(0.000)	(0.001)
Ln(Credit Score) × Lagged Liquidity	-0.65***	-0.45***	-0.66***	-0.46***
	(0.000)	(0.001)	(0.000)	(0.001)
Lagged Detrended DR007 × Lagged Liquidity	13.06	12.99	12.87	14.36
	(0.169)	(0.178)	(0.178)	(0.138)
Lagged Detrended DR007 × Ln(Credit Score) × Lagged Liquidity	-2.00	-2.03	-1.97	-2.24
	(0.172)	(0.173)	(0.183)	(0.134)
Demand Proxy-Ln(Total Loan Application Amount)	-0.10***	-0.13***		
	(0.000)	(0.000)		
Demand Proxy-Ln(Number of Borrowers in P2P Market)			-0.13*	-0.21**
			(0.090)	(0.024)
Log Loan Amount	-0.25***	-0.26***	-0.25***	-0.26***
	(0.000)	(0.000)	(0.000)	(0.000)
Loan Maturity	-0.02***	-0.02***	-0.03***	-0.02***
	(0.000)	(0.000)	(0.000)	(0.000)
Loan Interest Rate	-0.01***	-0.00***	-0.01***	-0.01***
	(0.000)	(0.004)	(0.000)	(0.002)
Constant	-47.73***	-47.49***	-47.85***	-47.61***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	66236	54113	66236	54113
Loan Characteristics	YES	YES	YES	YES
Borrower Characteristics	YES	YES	YES	YES
Borrower FE	NO	NO	NO	NO
Time FE	NO	NO	NO	NO

p-values in parentheses

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

Table 15: Riskiness of Credit Allocation and Monetary Policy

This table shows the results from regressing the platform-level riskiness of credit allocation on monetary policy and a vector of control variables of the macroeconomic conditions. We use the detrended DR007 to proxy monetary policy in columns(1)-(4), and the dummy of easing and normal periods to capture the effect of monetary policy in columns(5)-(8). Easing periods are defined to days when the monetary policy rate is below its 25th percentile and normal periods are defined as days when the rates lie within the [25th, 75th] percentile. We employ OLS estimation and robust standard errors for this table.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Detrended DR007	-1.55*	-1.47*	-1.66*	-1.58				
	(0.074)	(0.087)	(0.097)	(0.109)				
Easing Periods					0.43**	0.43**	0.48**	0.47**
					(0.043)	(0.044)	(0.039)	(0.039)
Normal Periods					0.39**	0.39**	0.47**	0.46**
					(0.036)	(0.039)	(0.014)	(0.015)
Proxy of Aggregate Demand		0.09		0.08		0.13		0.12
		(0.609)		(0.688)		(0.460)		(0.540)
Lagged Stock Market Return			0.18	0.18			0.18	0.19
			(0.251)	(0.236)			(0.229)	(0.208)
Lagged Stock Market Return for SMEs			-0.02	-0.02			-0.04	-0.04
			(0.897)	(0.877)			(0.762)	(0.755)
Lagged Yield Curve			0.43	0.40			0.48	0.42
			(0.304)	(0.351)			(0.218)	(0.292)
P2P Industry Loan Rate Composite Index			0.03	0.03			0.01	0.01
			(0.723)	(0.753)			(0.904)	(0.930)
P2P Industry Popularity Index			-0.01	-0.01			-0.01	-0.01
			(0.173)	(0.172)			(0.124)	(0.128)
P2P Industry Investor Composite Return			0.06	0.05			0.15	0.14
			(0.875)	(0.888)			(0.692)	(0.701)
Constant	-1.06***	-2.51	-2.05	-3.13	-1.37***	-3.44	-2.31	-4.10
	(0.000)	(0.379)	(0.482)	(0.436)	(0.000)	(0.226)	(0.432)	(0.303)
Observations	233	233	219	219	233	233	219	219

p-values in parentheses

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

Table 16: Robustness Check: Granted Loan Analysis Using Monthly Monetary Policy Rates

This table shows the results from regressing the credit score of approved loan applications on monetary policy, the liquidity of the platform, i.e. newly added loanable funding, the interaction between monetary policy and platform liquidity, and a vector of control variables of the loan, borrower and macroeconomic conditions. Compared to the baseline estimates, we use the monthly monetary policy variables here. Province fixed effect is controlled, but month fixed effect is not due to the now monthly frequency of the monetary policy. The estimates for borrower characteristics are omitted here due to space limit. We use the sample of approved loan applications and employ OLS estimation for this table. Standard errors are clustered at the borrower and month levels.

	(1)	(2)	(3)	(4)	(5)	(6)
	Ln(Credit Score)	Ln(Credit Score)	Ln(Credit Score)	Ln(Credit Score)	Ln(Credit Score)	Ln(Credit Score)
Lagged Detrended DR007(Monthly)	0.22***	0.21***	0.13***		0.43***	-4.43***
	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)
Log Lagged Liquidity(Monthly)				-0.01***	-0.02***	-0.01***
				(0.000)	(0.000)	(0.000)
Lagged Detrended DR007(Monthly) $\times$ Log Lagged Liquidity(Monthly)						0.56***
						(0.000)
Log Loan Amount		0.50	0.79*	0.93**	0.86*	0.86*
		(0.270)	(0.092)	(0.048)	(0.062)	(0.062)
Loan Maturity		-1.64***	-1.76***	-1.80***	-1.78***	-1.78***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Loan Interest Rate		-0.01***	-0.01***	-0.01***	-0.01***	-0.01***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lagged Stock Market Return			-0.06	0.12	-0.54	-0.54
			(0.901)	(0.819)	(0.284)	(0.284)
Lagged Stock Market Return for SMEs			0.90**	0.69*	0.68*	0.68*
			(0.010)	(0.051)	(0.052)	(0.052)
Lagged Yield Curve			-0.01***	-0.01***	0.00	0.00
			(0.000)	(0.004)	(0.166)	(0.166)
P2P Industry Loan Rate Composite Index			1.88***	2.80***	1.15***	1.15***
			(0.000)	(0.000)	(0.003)	(0.003)
P2P Industry Popularity Index			0.07***	0.08***	0.05***	0.05***
			(0.000)	(0.000)	(0.010)	(0.010)
P2P Industry Investor Composite Return			-2.43	-6.99***	-1.52	-1.52
			(0.166)	(0.000)	(0.382)	(0.382)
Lagged Change in Housing Price			-0.11	-0.43***	-0.12	-0.12
			(0.219)	(0.000)	(0.186)	(0.186)
Lagged Change in Banking Total Assets			0.00	-0.01***	-0.02***	-0.00
			(0.433)	(0.000)	(0.000)	(0.429)
Lagged Change in Banking Leverage			-0.04***	0.02	0.10***	-0.01
			(0.001)	(0.250)	(0.000)	(0.619)
Lagged Change in PMI			-0.00***	-0.00	0.01***	0.00***
			(0.000)	(0.102)	(0.000)	(0.000)
Lagged Change in CPI			-0.02***	-0.02***	0.02***	0.00
			(0.000)	(0.000)	(0.000)	(.)
Constant	6.47***	6.56***	6.50***	6.59***	6.76***	6.61***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	10361	10361	9358	9358	9358	9358
Adjusted R-Squared	0.03	0.64	0.66	0.66	0.67	0.67
Loan Characteristics	NO	YES	YES	YES	YES	YES
Borrower Characteristics	NO	YES	YES	YES	YES	YES
Macro Characteristics	NO	NO	YES	YES	YES	YES
Borrower Province FE	YES	YES	YES	YES	YES	YES
Month FE	NO	NO	NO	NO	NO	NO

p-values in parentheses

In this table the independent variable of Log Lagged Liquidity, Log Loan Amount, Loan Maturity, Lagged Stock Market Return, Lagged Stock Market Return for SMES, P2P Industry Loan Rate Composite Index, P2P Industry Popularity Index, P2P Industry Investor Composite Return, Lagged Change in Housing Price and Lagged Change in Banking Total Assets are rescaled by 10^{-3} times original value, for clear presentation of the estimates.

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

Table 17: Robustness Check: Probit Analysis Using Monthly Monetary Policy Rates

This table shows the results from the Probit estimation of loan granting on monetary policy, the credit score of the loan applicant, the liquidity of the platform, i.e. newly added loanable funding, the full interaction terms between these three variables, and a vector of control variables of the loan, borrower and macroeconomic conditions. Compared to the baseline estimates, we use the monthly monetary policy variables here. The estimates for borrower characteristics are omitted here due to space limit. Standard errors are clustered at the borrower and month levels.

	(1) Granted	(2) Granted	(3) Granted	(4) Granted	(5) Granted	(6) Granted	(7) Granted
Granted							
Lagged Detrended DR007(Monthly)	-0.72***	-244.90***		-1695.44	-935.48	-1763.25	-150.63***
	(0.007)	(0.000)		(0.197)	(0.477)	(0.192)	(0.004)
Ln(Credit Score)		5.73***	15.33***	18.44***	17.43***	19.58***	20.94***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lagged Detrended DR007(Monthly) × Ln(Credit Score)		37.74***		250.76	130.26	258.37	251.46
		(0.000)		(0.218)	(0.522)	(0.216)	(0.317)
Log Lagged Liquidity(Monthly)			7.77***	10.24***	8.96***	10.80***	7.06**
			(0.000)	(0.003)	(0.010)	(0.002)	(0.022)
Log Lagged Liquidity(Monthly) × Ln(Credit Score)			-1.18***	-1.52***	-1.32**	-1.61***	-1.80***
			(0.000)	(0.004)	(0.014)	(0.003)	(0.002)
Lagged Detrended DR007(Monthly) × Log Lagged Liquidity(Monthly)				179.83	85.98	183.34	0.00
				(0.243)	(0.577)	(0.247)	(.)
Lagged Detrended DR007(Monthly) × Ln(Credit Score) × Log Lagged Liquidity(Monthly)				-26.52	-11.66	-26.72	-26.23
				(0.266)	(0.625)	(0.275)	(0.372)
Log Loan Amount					-198.62***	-254.50***	-258.77***
					(0.000)	(0.000)	(0.000)
Loan Maturity					-23.11***	-23.24***	-25.59***
					(0.000)	(0.000)	(0.000)
Loan Interest Rate					0.00	-0.00	-0.00**
					(0.984)	(0.369)	(0.028)
Lagged Change in Housing Price							2.94
							(0.100)
Lagged Change in Banking Total Assets							-5.40
							(0.308)
Lagged Change in Banking Leverage							35.23
							(0.321)
Lagged Stock Market Return							-25.50**
							(0.022)
Lagged Stock Market Return for SMEs							3.98
							(0.601)
Lagged Yield Curve							-0.05
							(0.357)
P2P Industry Loan Rate Composite Index							-7.23
							(0.414)
P2P Industry Popularity Index							0.96**
							(0.027)
P2P Industry Investor Composite Return							-30.13
							(0.467)
Lagged Change in PMI							1.91
							(0.328)
Lagged Change in CPI							5.23
							(0.355)
Constant	-0.92***	-37.91***	-101.30***	-123.16***	-114.60***	-127.95***	-85.25**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.011)
Observations	64353	64353	64353	64353	64353	64353	52335
Loan Characteristics	NO	NO	NO	NO	YES	YES	YES
Borrower Characteristics	NO	NO	NO	NO	NO	YES	YES
Macro Characteristics	NO	NO	NO	NO	NO	NO	YES
Borrower FE	NO	NO	NO	NO	NO	NO	NO
Time FE	NO	NO	NO	NO	NO	NO	NO

p-values in parentheses

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

Table 18: Robustness Check: OLS Model Using DR007 Level

This table shows the results from regressing the credit score of approved loan applications on monetary policy, the liquidity of the platform, i.e. newly added loanable funding, the interaction between monetary policy and platform liquidity, and a vector of control variables of the loan, borrower and macroeconomic conditions. Compared to the baseline estimates, we use the level value of DR007 instead of detrended DR007 here. Province and month fixed effects are controlled as indicated. The estimates for borrower characteristics are omitted here due to space limit. We use the sample of approved loan applications and employ OLS estimation for this table. Standard errors are clustered at the borrower and date levels.

	All Period			Before Regulation			After Regulation		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Ln(Credit Score)	Ln(Credit Score)	Ln(Credit Score)	Ln(Credit Score)	Ln(Credit Score)	Ln(Credit Score)	Ln(Credit Score)	Ln(Credit Score)	Ln(Credit Score)
Lagged DR007 Level	0.02^{***}	0.02^{***}	-0.04^{**}	0.04^{***}	0.04^{***}	-0.04	-0.00	-0.00	0.01
	(0.000)	(0.000)	(0.014)	(0.000)	(0.000)	(0.124)	(0.672)	(0.736)	(0.753)
Lagged DR007 Level × Log Lagged Liquidity			12.66^{***}			14.82^{***}			-2.51
			(0.000)			(0.002)			(0.687)
Log Lagged Liquidity		-0.11	-35.99^{***}		-0.02	-41.70^{***}		-0.46	6.68
		(0.706)	(0.000)		(0.957)	(0.001)		(0.319)	(0.706)
Log Loan Amount	0.85^{**}	0.85^{**}	0.85^{**}	0.61	0.48	0.50	1.08^{*}	1.17^{*}	1.17^{*}
	(0.032)	(0.044)	(0.044)	(0.261)	(0.405)	(0.386)	(0.057)	(0.055)	(0.054)
Loan Maturity	-1.87^{***}	-1.87^{***}	-1.87^{***}	-1.97^{***}	-1.96^{***}	-1.96^{***}	-1.82^{***}	-1.82^{***}	-1.82^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Loan Interest Rate	-0.01^{***}	-0.01^{***}	-0.01^{***}	-0.01^{***}	-0.01^{***}	-0.01^{***}	-0.01^{***}	-0.01^{***}	-0.01^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lagged Stock Market Return	-0.54	-0.63	-0.93^{*}	-0.59	-0.56	-1.16	-0.50	-0.58	-0.53
	(0.276)	(0.221)	(0.073)	(0.681)	(0.705)	(0.437)	(0.372)	(0.331)	(0.389)
Lagged Stock Market Return for SMEs	0.16	0.15	0.36	-1.40	-1.62	-1.29	1.06^{***}	1.15^{***}	1.13^{***}
	(0.647)	(0.690)	(0.339)	(0.172)	(0.122)	(0.224)	(0.008)	(0.006)	(0.008)
Lagged Yield Curve	0.01^{***}	0.01^{***}	0.01^{**}	0.02^{***}	0.01^{***}	0.01^{***}	0.01^{*}	0.01^{*}	0.01^{*}
	(0.003)	(0.005)	(0.022)	(0.001)	(0.003)	(0.010)	(0.052)	(0.065)	(0.060)
P2P Industry Loan Rate Composite Index	0.59	0.84^{*}	0.88^{**}	1.66^{*}	1.67	1.67^{*}	0.43	0.44	0.41
	(0.123)	(0.051)	(0.041)	(0.074)	(0.100)	(0.099)	(0.346)	(0.420)	(0.457)
P2P Industry Popularity Index	0.03^{**}	0.03^{*}	0.03	0.06^{**}	0.06^{*}	0.05	0.02	0.03	0.03
	(0.049)	(0.063)	(0.147)	(0.029)	(0.072)	(0.140)	(0.304)	(0.178)	(0.170)
P2P Industry Investor Composite Return	-2.04	-2.52	-2.29	-7.21^{*}	-6.87	-5.91	-0.31	-0.39	-0.35
	(0.227)	(0.164)	(0.206)	(0.065)	(0.107)	(0.162)	(0.882)	(0.854)	(0.870)
Lagged Change in Housing Price	-0.14	-0.13	-0.13	-0.48	-0.42	-0.41	-0.12	-0.10	-0.10
	(0.115)	(0.154)	(0.152)	(0.247)	(0.338)	(0.353)	(0.189)	(0.307)	(0.310)
Constant	6.51^{***}	6.50^{***}	6.66^{***}	6.45^{***}	6.45^{***}	6.65^{***}	6.57^{***}	6.57^{***}	6.54^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	11039	10008	10008	5739	5276	5276	5298	4730	4730
Adjusted R-Squared	0.69	0.69	0.69	0.71	0.70	0.71	0.64	0.64	0.64
Loan Characteristics	YES	YES	YES	YES	YES	YES	YES	YES	YES
Borrower Characteristics	YES	YES	YES	YES	YES	YES	YES	YES	YES
Macro Characteristics	YES	YES	YES	YES	YES	YES	YES	YES	YES
Borrower Province FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

p-values in parentheses

In this table the independent variable of Log Lagged Liquidity, Log Loan Amount, Loan Maturity, Lagged Stock Market Return, Lagged Stock Market Return for SMES,

P2P Industry Loan Rate Composite Index, P2P Industry Popularity Index, P2P Industry Investor Composite Return, Lagged Change in Housing Price and Lagged CHange in Banking Total Assets are rescaled by 10^{-3} times original value, for clear presentation of the estimates.

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

Table 19: Robustness Check: OLS Model Using Other Monetary Policy Variables

This table shows the results from regressing the credit score of approved loan applications on monetary policy, the liquidity of the platform, i.e. newly added loanable funding, the interaction between monetary policy and platform liquidity, and a vector of control variables of the loan, borrower and macroeconomic conditions. Compared to the baseline estimates, we use the other measurements of monetary policy here. Columns(1)-(3) show the results using detrended R007 as monetary policy, columns(4)-(6) show that using detrended Shibor(1w) as monetary policy, and columns(7)-(9) show that using the weekly withdrawal amount from open market operation as monetary policy. Province and month fixed effects are controlled as indicated. The estimates for borrower characteristics are omitted here due to space limit. We use the sample of approved loan applications and employ OLS estimation for this table. Standard errors are clustered at the borrower and date levels.

	R007			Shibor(1w)			OMO Withdraw		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Ln(Credit Score)	Ln(Credit Score)	Ln(Credit Score)	Ln(Credit Score)	Ln(Credit Score)	Ln(Credit Score)	Ln(Credit Score)	Ln(Credit Score)	Ln(Credit Score)
Lagged Detrended R007	-0.00	-0.00	-0.01						
	(0.511)	(0.321)	(0.137)						
Lagged Detrended Shibor(1w)				0.06^{***}	0.06^{***}	-0.07^{**}			
				(0.000)	(0.000)	(0.037)			
Lagged OMO Liquidity Withdraw							0.01^{***}	0.00^{***}	-0.01^{**}
							(0.000)	(0.001)	(0.050)
Log Lagged Liquidity		-0.18	0.02		0.17	0.44		-0.09	-1.88^{***}
		(0.551)	(0.960)		(0.580)	(0.166)		(0.760)	(0.004)
Lagged Detrended R007 × Log Lagged Liquidity			1.02						
			(0.206)						
Lagged Detrended Shibor(1w) × Log Lagged Liquidity						28.53^{***}			
						(0.000)			
Lagged OMO Liquidity Withdraw × Log Lagged Liquidity									3.31^{***}
									(0.002)
Log Loan Amount	0.87^{**}	0.88^{**}	0.88^{**}	0.88^{**}	0.88^{**}	0.87^{**}	0.85^{**}	0.86^{**}	0.85^{**}
	(0.029)	(0.036)	(0.037)	(0.028)	(0.037)	(0.039)	(0.032)	(0.040)	(0.043)
Loan Maturity	-1.87^{***}	-1.86^{***}	-1.86^{***}	-1.86^{***}	-1.86^{***}	-1.85^{***}	-1.87^{***}	-1.86^{***}	-1.86^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Loan Interest Rate	-0.01^{***}	-0.01^{***}	-0.01^{***}	-0.01^{***}	-0.01^{***}	-0.01^{***}	-0.01^{***}	-0.01^{***}	-0.01^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lagged Stock Market Return	-0.67	-0.76	-0.90^{*}	-0.59	-0.63	-0.54	-0.60	-0.72	-1.16^{**}
	(0.175)	(0.140)	(0.087)	(0.237)	(0.223)	(0.296)	(0.225)	(0.163)	(0.029)
Lagged Stock Market Return for SMEs	0.63^{*}	0.66^{*}	0.70^{*}	-0.50	-0.69^{*}	-0.38	0.93^{**}	0.91^{**}	0.88^{**}
	(0.072)	(0.067)	(0.053)	(0.192)	(0.084)	(0.353)	(0.010)	(0.014)	(0.018)
Lagged Yield Curve	0.00	0.00	0.00	0.01^{***}	0.01^{***}	0.01^{***}	0.00	0.00	0.00
	(0.475)	(0.802)	(0.981)	(0.000)	(0.000)	(0.000)	(0.572)	(0.735)	(0.659)
P2P Industry Loan Rate Composite Index	1.05^{***}	1.35^{***}	1.34^{***}	0.55	0.78^{*}	0.80^{*}	1.16^{***}	1.40^{***}	1.26^{***}
	(0.005)	(0.001)	(0.002)	(0.149)	(0.066)	(0.060)	(0.002)	(0.001)	(0.003)
P2P Industry Popularity Index	0.04^{**}	0.04^{**}	0.04^{**}	0.04^{**}	0.04^{**}	0.03^{*}	0.06^{***}	0.05^{***}	0.06^{***}
	(0.015)	(0.019)	(0.029)	(0.015)	(0.032)	(0.079)	(0.002)	(0.005)	(0.004)
P2P Industry Investor Composite Return	-1.65	-2.31	-2.17	-1.04	-1.55	-1.43	-1.34	-1.84	-1.24
	(0.329)	(0.204)	(0.233)	(0.535)	(0.392)	(0.429)	(0.425)	(0.309)	(0.495)
Lagged Change in Housing Price	-0.13	-0.12	-0.12	-0.14	-0.13	-0.13	-0.13	-0.12	-0.12
	(0.134)	(0.178)	(0.178)	(0.102)	(0.134)	(0.134)	(0.128)	(0.168)	(0.179)
Constant	6.54^{***}	6.53^{***}	6.53^{***}	6.56^{***}	6.55^{***}	6.55^{***}	6.53^{***}	6.52^{***}	6.53^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	10953	9922	9922	10953	9922	9922	11039	10008	10008
Adjusted R-Squared	0.68	0.68	0.68	0.69	0.68	0.69	0.69	0.69	0.69
Loan Characteristics	YES	YES	YES	YES	YES	YES	YES	YES	YES
Borrower Characteristics	YES	YES	YES	YES	YES	YES	YES	YES	YES
Macro Characteristics	YES	YES	YES	YES	YES	YES	YES	YES	YES
Borrower Province FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

p-values in parentheses

In this table the independent variable of OMO Liquidity Withdraw,Log Lagged Liquidity, Log Loan Amount, Loan Maturity, Lagged Stock Market Return, Lagged Stock Market Return for SMES,

P2P Industry Loan Rate Composite Index, P2P Industry Popularity Index, P2P Industry Investor Composite Return, Lagged Change in Housing Price and Lagged CHange in Banking Total Assets are rescaled by 10^{-3} times original value, for clear presentation of the estimates.

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

Table 20: Placebo Test Using Long Term Rates

This table shows the results from regressing the credit score of approved loan applications on the pseudo monetary policy, the liquidity of the platform, i.e. newly added loanable funding, the interaction between pseudo monetary policy and platform liquidity, and a vector of control variables of the loan, borrower and macroeconomic conditions. Compared to the baseline estimates, we use the pseudo monetary policy here, i.e. various 1-year long-term interest rates. Province and month fixed effects are controlled as indicated. The estimates for borrower characteristics are omitted here due to space limit. We use the sample of approved loan applications and employ OLS estimation for this table. Standard errors are clustered at the borrower and date levels.

	DR1Y		R1Y		Shibor(1Y)		GovBond(10Y)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Ln(Credit Score)	Ln(Credit Score)	Ln(Credit Score)	Ln(Credit Score)	Ln(Credit Score)	Ln(Credit Score)	Ln(Credit Score)	Ln(Credit Score)
Lagged Detrended DR1Y	0.00	0.04						
	(0.962)	(0.159)						
Lagged Detrended DR1Y × Log Lagged Liquidity		-8.68						
		(0.152)						
Lagged Detrended R1Y			0.00	0.02				
			(0.149)	(0.222)				
Lagged Detrended R1Y × Log Lagged Liquidity				-3.21				
				(0.316)				
Lagged Detrended Shibor(6M)					0.00	-0.02		
					(0.969)	(0.826)		
Lagged Detrended Shibor(6M) × Log Lagged Liquidity						5.43		
						(0.815)		
Lagged Detrended Gov Bond Yield(10Y)							0.01	0.06
							(0.356)	(0.508)
Lagged Detrended Gov Bond Yield(10Y) × Log Lagged Liquidity								-9.45
								(0.600)
Log Lagged Liquidity	-0.19	-0.29	-0.14	-0.10	-0.19	-0.17	-0.22	-0.24
	(0.535)	(0.359)	(0.641)	(0.741)	(0.538)	(0.592)	(0.477)	(0.434)
Log Loan Amount	0.88**	0.88**	0.87**	0.88**	0.88**	0.88**	0.87**	0.87**
	(0.037)	(0.036)	(0.039)	(0.038)	(0.037)	(0.037)	(0.039)	(0.039)
Loan Maturity	-1.86***	-1.86***	-1.86***	-1.86***	-1.86***	-1.86***	-1.86***	-1.86***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Loan Interest Rate	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lagged Stock Market Return	-0.78	-0.72	-0.79	-0.76	-0.79	-0.78	-0.85	-0.90*
	(0.132)	(0.170)	(0.126)	(0.140)	(0.125)	(0.131)	(0.102)	(0.090)
Lagged Stock Market Return for SMEs	0.64*	0.60	0.53	0.53	0.64*	0.64*	0.68*	0.70*
	(0.081)	(0.101)	(0.149)	(0.154)	(0.077)	(0.078)	(0.061)	(0.054)
Lagged Yield Curve	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.314)	(0.337)	(0.276)	(0.352)	(0.403)	(0.397)	(0.289)	(0.298)
P2P Industry Loan Rate Composite Index	1.33***	1.32***	1.31***	1.33***	1.33***	1.33***	1.31***	1.31***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
P2P Industry Popularity Index	0.04**	0.04**	0.04**	0.04**	0.04**	0.04**	0.04**	0.04**
	(0.024)	(0.034)	(0.020)	(0.017)	(0.024)	(0.023)	(0.020)	(0.023)
P2P Industry Investor Composite Return	-2.21	-2.47	-2.18	-2.22	-2.20	-2.21	-1.89	-1.89
	(0.224)	(0.174)	(0.229)	(0.220)	(0.225)	(0.224)	(0.300)	(0.301)
Lagged Change in Housing Price	-0.12	-0.12	-0.12	-0.12	-0.12	-0.12	-0.12	-0.12
	(0.172)	(0.167)	(0.171)	(0.171)	(0.172)	(0.172)	(0.169)	(0.169)
Constant	6.53***	6.53***	6.53***	6.53***	6.53***	6.53***	6.53***	6.53***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	9922	9922	9922	9922	9922	9922	9922	9922
Adjusted R-Squared	0.68	0.68	0.68	0.68	0.68	0.68	0.68	0.68
Loan Characteristics	YES	YES	YES	YES	YES	YES	YES	YES
Borrower Characteristics	YES	YES	YES	YES	YES	YES	YES	YES
Macro Characteristics	YES	YES	YES	YES	YES	YES	YES	YES
Borrower Province FE	YES	YES	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES	YES	YES

p-values in parentheses

In this table the independent variable of Log Lagged Liquidity, Log Loan Amount, Loan Maturity, Lagged Stock Market Return, Lagged Stock Market Return for SMES, P2P Industry Loan Rate Composite Index, P2P Industry Popularity Index, P2P Industry Investor Composite Return, Lagged Change in Housing Price and Lagged Change in Banking Total Assets are rescaled by 10^{-3} times original value, for clear presentation of the estimates.

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

Table 21: Placebo Test Probit Model Using Long Term Rates

This table shows the results from the Probit estimation of loan granting on pseudo monetary policy, the credit score of the loan applicant, the liquidity of the platform, i.e. newly added loanable funding, the full interaction terms between these three variables, and a vector of control variables of the loan, borrower and macroeconomic conditions. Compared to the baseline estimates, we use the pseudo monetary policy here, i.e. various 1-year long-term interest rates. The estimates for borrower characteristics are omitted here due to space limit. Standard errors are clustered at the borrower and date levels.

	DR1Y		R1Y		Shibor(1Y)		GovBond(10Y)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Granted	Granted	Granted	Granted	Granted	Granted	Granted	Granted
Granted								
Lagged Detrended DR1Y	63.92***	-92.42						
	(0.003)	(0.305)						
Lagged Detrended DR1Y × Ln(Credit Score)	-9.82***	13.71						
	(0.004)	(0.325)						
Lagged Detrended R1Y			-11.08	19.59				
			(0.108)	(0.616)				
Lagged Detrended R1Y × Ln(Credit Score)			1.71	-3.10				
			(0.110)	(0.608)				
Lagged Detrended Shibor(1Y)					39.75	-104.10		
					(0.695)	(0.875)		
Lagged Detrended Shibor(1Y) × Ln(Credit Score)					-6.19	15.85		
					(0.693)	(0.877)		
Lagged Detrended Gov Bond Yield(10Y)							20.80	-306.59
							(0.622)	(0.259)
Lagged Detrended Gov Bond Yield(10Y) × Ln(Credit Score)							-3.23	47.38
							(0.621)	(0.260)
Log Lagged Liquidity		3098.23***		3031.26***		2786.30***		2856.23***
		(0.000)		(0.000)		(0.001)		(0.001)
Lagged Detrended DR1Y × Log Lagged Liquidity		22382.22						
		(0.232)						
Ln(Credit Score) × Log Lagged Liquidity		-478.39***		-470.13***		-431.75***		-442.61***
		(0.000)		(0.000)		(0.001)		(0.001)
Lagged Detrended DR1Y × Ln(Credit Score) × Log Lagged Liquidity		-3314.94						
		(0.252)						
Lagged Detrended R1Y × Log Lagged Liquidity				-8708.64				
				(0.381)				
Lagged Detrended R1Y × Ln(Credit Score) × Log Lagged Liquidity				1362.24				
				(0.376)				
Lagged Detrended Shibor(1Y) × Log Lagged Liquidity						34707.04		
						(0.818)		
Lagged Detrended Shibor(1Y) × Ln(Credit Score) × Log Lagged Liquidity						-5327.50		
						(0.819)		
Lagged Detrended Gov Bond Yield(10Y) × Log Lagged Liquidity								66661.22
								(0.233)
Lagged Detrended Gov Bond Yield(10Y) × Ln(Credit Score) × Log Lagged Liquidity								-10302.56
								(0.234)
Ln(Credit Score)	5.92***	8.09***	5.92***	8.06***	5.92***	7.89***	5.92***	7.95***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log Loan Amount	-264.61***	-266.34***	-264.67***	-265.71***	-264.64***	-265.63***	-264.65***	-265.76***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Loan Maturity	-23.96***	-24.28***	-23.92***	-24.14***	-23.91***	-24.08***	-23.92***	-24.07***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Loan Interest Rate	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male	0.03**	0.03**	0.03**	0.03*	0.03**	0.03*	0.03**	0.03*
	(0.024)	(0.049)	(0.024)	(0.056)	(0.024)	(0.057)	(0.024)	(0.057)
Age	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lagged Change in Housing Price	5.70***	5.02***	5.63***	5.11***	5.67***	5.22***	5.66***	5.19***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Lagged Change in Banking Total Assets	-0.56***	-0.54***	-0.56***	-0.55***	-0.56***	-0.55***	-0.56***	-0.55***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lagged Change in Banking Leverage	3.49***	3.25***	3.48***	3.35***	3.49***	3.40***	3.47***	3.38***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lagged Stock Market Return	-28.77**	-37.06***	-36.42***	-42.24***	-36.39***	-41.21***	-35.96***	-40.68***
	(0.012)	(0.002)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)
Lagged Stock Market Return for SMEs	2.54	5.63	8.08	10.16	6.40	7.23	6.20	7.25
	(0.749)	(0.487)	(0.305)	(0.208)	(0.411)	(0.363)	(0.429)	(0.371)
Lagged Yield Curve	0.09**	0.08*	0.09**	0.10**	0.09*	0.08	0.09**	0.09**
	(0.041)	(0.082)	(0.033)	(0.035)	(0.079)	(0.128)	(0.031)	(0.045)
P2P Industry Loan Rate Composite Index	-20.80**	-18.86**	-21.72***	-23.41**	-22.47***	-23.71**	-22.06***	-23.21**
	(0.012)	(0.048)	(0.009)	(0.014)	(0.007)	(0.013)	(0.008)	(0.015)
P2P Industry Popularity Index	0.27	0.55	0.25	0.31	0.27	0.37	0.28	0.40
	(0.508)	(0.205)	(0.536)	(0.470)	(0.510)	(0.388)	(0.491)	(0.354)
P2P Industry Investor Composite Return	-15.87	2.08	-3.12	-2.15	-1.04	-0.52	-2.55	0.60
	(0.685)	(0.961)	(0.936)	(0.959)	(0.979)	(0.990)	(0.948)	(0.989)
Lagged Change in PMI	0.20***	0.19***	0.21***	0.20***	0.21***	0.20***	0.21***	0.20***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lagged Change in CPI	0.46***	0.42***	0.47***	0.44***	0.47***	0.44***	0.47***	0.44***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-34.46***	-48.79***	-34.54***	-48.28***	-34.51***	-47.22***	-34.49***	-47.59***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	60000	54113	60000	54113	60000	54113	60000	54113
Loan Characteristics	YES	YES	YES	YES	YES	YES	YES	YES
Borrower Characteristics	YES	YES	YES	YES	YES	YES	YES	YES
Macro Characteristics	YES	YES	YES	YES	YES	YES	YES	YES

p-values in parentheses

In this table the independent variable of Log Lagged Liquidity, Log Loan Amount, Loan Maturity, Lagged Stock Market Return, Lagged Stock Market Return for SMES, P2P Industry Loan Rate Composite Index, P2P Industry Popularity Index, P2P Industry Investor Composite Return, Lagged Change in Housing Price and Lagged Change in Banking Total Assets are rescaled by 10^{-3} times original value, for clear presentation of the estimates.

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

Online Appendix

A1 Monetary Policy Framework in China

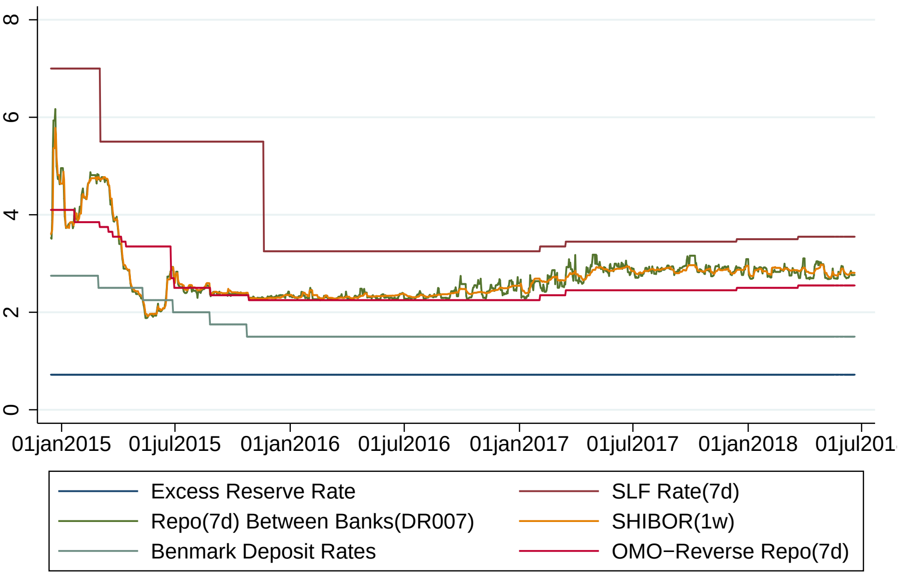
The same as the real economy, China's monetary policy framework is also in transition from quantity-based to price-based. The intermediate targets of the People's Bank of China (PBC) are threefold: money supply, bank credit and market interest rates (Huang et al. 2019). In the quantity-based monetary policy framework, PBC emphasize the first two quantity targets and watch closely at the aggregate indicators of M2 and bank loans. The interest rate was not liberalized and banks have to set the interest rates for loans and deposits within a ceiling and (or) floor of the benchmark rates decided by PBC.

Successive waves of interest rate liberalization, which started with money market rates and culminated with the formal elimination of the ceiling on bank deposit rates in 2015, have facilitated the transition toward a modern price-based monetary policy framework. Focus is increasing on short-term money market rates, that is, the 7-day Shanghai Interbank Offered Rates (Shibor 1w) and interbank pledged repo rate among depository-taking financial institutions (DR007). Although PBC has not officially confirmed DR007 as the policy interest rate yet[23], it is mentioned in the quarterly monetary policy reports as "an active role to cultivate the market base rate" and closely watched by the market. In addition to DR007 which is the repo rate between deposit institutions, R007, the repo rate not limited to certain trading institutions is also important for its high trading volume.

From the perspective of monetary policy instruments, PBC uses open market operations (OMOs) and the corresponding 7-day OMO repo/reverse repo rate to signal policy changes and influence the market. Combined with interest rates for standing lending facilities (SLF) and remunerated required/excess reserves, the monetary policy framework effectively provides a corridor, that is, an upper and lower bound. Figure A1 shows that the benchmark interest rates change at a low frequency and remains unchanged after October 2015. The market captures the monetary policy stance change from the OMO rates and the money market rates DR007 and R007. As China's monetary policy framework remains in transition and is currently a hybrid, quantity management still matters and the liquidity indicators based on open market operation reflects policy stance.

[23]As in many aspects the official language of China's economic policy lags the economic facts.

Figure A1: Interest Rate Corridor in China



A2 Peer-to-Peer Lending in China

Peer-to-Peer (P2P), a kind of business offering online lending to private borrowers, is the composition of consumer finance. Online lending meets the demand of financial service denied or ignored by the banks and credit cards, who are relative riskier or lower-net-worth. Accordingly, the P2P lending's high risk is paid back with a higher return by charging a higher interest rate on 24%-36%, much higher than the credit card's 12%-18% annualized interest rate.

Ideally, the P2P platforms perform as an information intermediate to connect the borrowers and lenders, by collecting the borrowers' credit applications and detailed private information for lenders' decision. Under such a case, the lenders get the return and take the risk of default. To help the lenders identify the risk of borrowers, the P2P platforms calculate the riskiness score of each loan application based on the borrower's profile, and charge fees for its service (e.g., matchmaking, credit checking).

However, the classic mode of P2P lending puts the entire default risk of unsecured personal loan on the exact lender, which sets a high barrier for lenders risk preference to the risky borrowers and weakens their interest to participate in. So, the platforms turn to a mode of the financial intermediate by collecting the lenders' money and making decisions on loan application by the platform itself, which spread the risk of one loan's default to lenders and offers a broader range of investment yield for the lenders by building up a portfolio on diversified borrowers. China's P2P platforms are precisely financial intermediates.

Over the development of past years, the P2P industry experienced rise and fall. The popularization of mobile and internet in China offer a strong driving force to online lending, which experienced rapid development since 2015. However, the history of China's P2P lending can trace back to a decade ago, when the first group P2P platforms came into the market like Lufax and PPdai. A vast number of platforms came and went, came for the attractive interest income and left for their failure in risk management or Ponzi game. The model of financial intermediates strengthens the information asymmetry of investors and platforms, i.e., lenders and borrowers, which may lead to a riskier preference of platforms in business operating and risk managing. Moreover, the absence of regulations before the end of 2017, the market was quite aggressive when picking the borrowers and controlling the loan risk, which tried to covers the default loss by charging a super high-interest rate over 36% and continuous inflow from new investors.

Things changed in December of 2017. The government published regulation on the online lending and cash loan, which set the cap of interest rate on 36% and limited cash loan business. As a result, the P2P firms adjusted to conservative strategy and check the loan application more strictly. The P2P industry came into a regulated status. Moreover, scores of Chinese online P2P lending platforms fell into financial or legal troubles in the mid of 2018 because of tightened regulation and liquidity.

A3 Financial Stability and Monetary Policy

To address the concern of endogenous relationship between monetary policy and financial stability, we follow Dell'Ariccia et al. (2017) to provide evidence that the attention given to financial stability in the monetary policy decisions are relatively low.

Specifically, we analyze the contents in the Quarterly Monetary Policy Executive Reports (MPER) by the People's Bank of China (PBC) and count the keywords that are highly related to financial stability. In line with the increasing literature using textual analysis to gauge monetary policy stance, the language in the MPER reflects PBC's judgement of economic situation and the rationality of monetary policy decisions.

As shown in Table A1, we include 16 keywords and distinguish the crisis time, post-crisis time and normal time in 2007Q1-2018Q4. For financial stability, we select "financial crisis", "systemic risk", "credit risk", "bank risk", and "default risk". We also select the broader words of negative general economic conditions which are beyond the financial stability, including "crisis", "downward" or "downward pressure", "leverage", "deleverage", "economy slowing", "unstable" and "vulnerable". Besides, we consider the words of traditional monetary policy targets: "price stability", "growth", and "employment".

We find that "financial crisis" and "systemic risk" are the most frequent keywords to demonstrate the attention to financial stability over the past decade. The mentioning of financial stability peaked during the crisis time (2007-2010), and then dropped soon after the crisis, and remained low in the relative tranquil periods. Moreover, compared to the other keywords capturing the broad negative economic conditions as well as the monetary policy targets of price stability and employment, the frequency of financial stability in the MPER is relatively low, especially during the normal time, in which lies the data used in this study. Thus, the word counting evidence shows that there is no severe endogeneity from financial stability to monetary policy.

Table A1: Keywords Counting in the Quarterly Monetary Policy Executive Reports

Counts of Keywords	Crisis Time 2007-2010	Post-Crisis 2011-2014	Normal Time 2015-2018
	Financial Stability		
Financial Crisis	171	54	37
Systemic Risk	29	22	14
Credit Risk	13	6	3
Bank Risk	1	3	6
Default Risk	2	5	7
	General Negatvie Economic Conditions		
Crisis	338	231	60
Downward Pressure	5	29	73
Downward	83	158	275
Leverage	46	48	215
Deleverage	5	14	73
Economy slowing	10	19	40
Unstable	26	19	23
Vulnerable	2	3	12
	Monetary Policy Target		
Price Stability	76	225	156
Growth	311	224	217
Employment	121	215	222

A4 Additional Figures and Tables

Figure A2: Business Model of The P2P Platform in This Paper

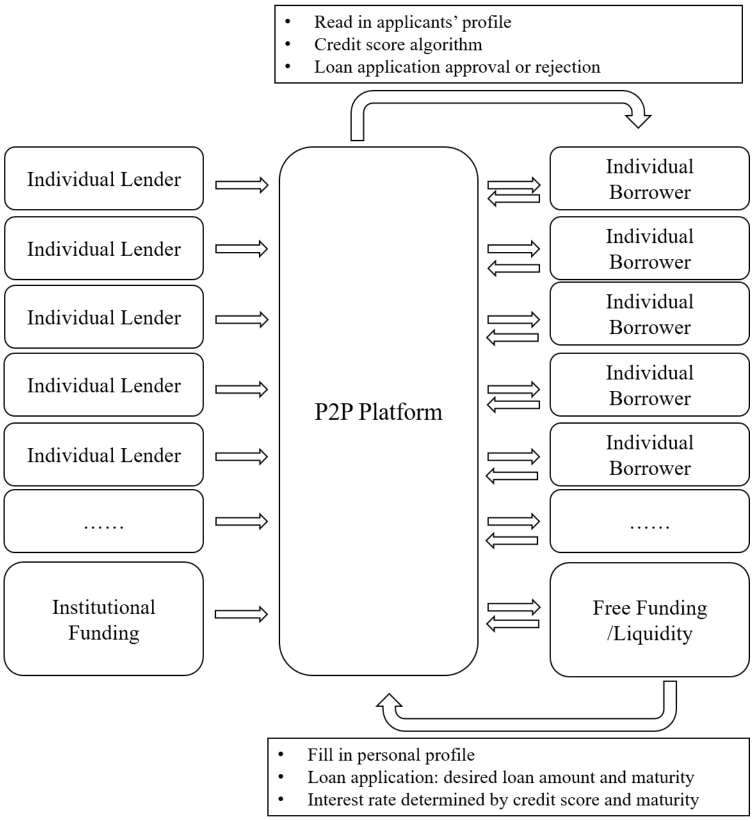


Figure A3: Risk-Return Relationship By Monetary Policy: Easing and Tightening Based on Median Value

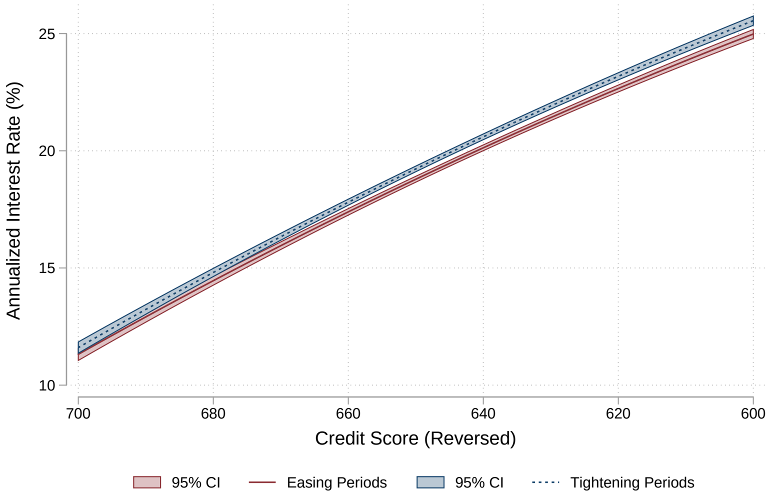


Figure A4: Riskiness of Credit Allocation By Monetary Policy: Easing and Tightening Based on Median Value

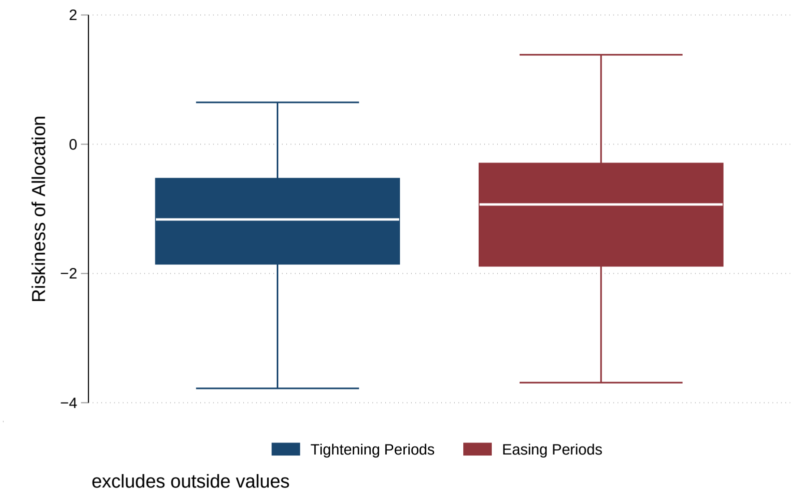
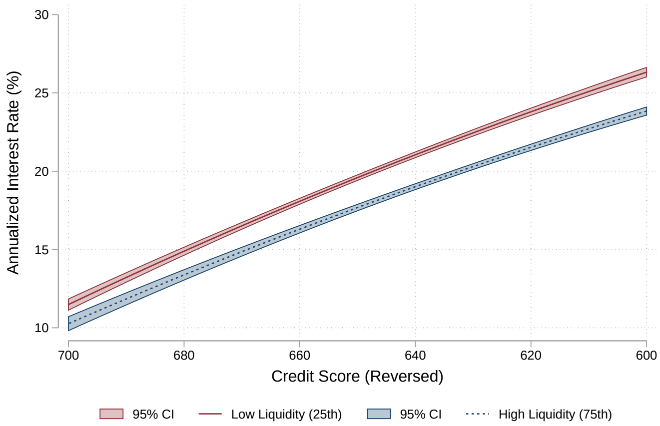


Figure A5: Risk-return Relationship by Liquidity Conditions



Note: this figure is based on the estimates of quadratic regression $Rates_l = \text{Credit Score}_l + \text{Credit Score}_l^2 + \epsilon$, where l indicates each granted loan. The equation is separately estimated for the loans in the high liquidity period and that in the low liquidity period.

Table A2: Full Table: Baseline OLS Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Ln(Credit Score)	Ln(Credit Score)	Ln(Credit Score)	Ln(Credit Score)	Ln(Credit Score)	Ln(Credit Score)	Ln(Credit Score)	Ln(Credit Score)	Ln(Credit Score)	Ln(Credit Score)	Ln(Credit Score)	Ln(Credit Score)
Lagged Detrended DR007	0.04***	0.04***	0.04***		0.04***	-0.05***	0.02***	0.01***	0.02***		0.02***	-0.03**
	(0.000)	(0.000)	(0.000)		(0.000)	(0.001)	(0.000)	(0.000)	(0.000)		(0.000)	(0.030)
Log Lagged Liquidity				-0.39	-0.29	0.64*				-0.19	-0.10	0.43
				(0.213)	(0.367)	(0.072)				(0.530)	(0.748)	(0.216)
Lagged Detrended DR007 × Log Lagged Liquidity						20.54***						11.47***
						(0.000)						(0.000)
Log Loan Amount		0.22	1.27***	1.35***	1.23***	1.21***		0.90**	0.86**	0.87**	0.86**	0.85**
		(0.607)	(0.002)	(0.002)	(0.005)	(0.006)		(0.019)	(0.031)	(0.039)	(0.043)	(0.043)
Loan Maturity		-1.67***	-1.82***	-1.82***	-1.81***	-1.81***		-1.82***	-1.87***	-1.87***	-1.86***	-1.86***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Loan Interest Rate		-0.01***	-0.01***	-0.01***	-0.01***	-0.01***		-0.01***	-0.01***	-0.01***	-0.01***	-0.01***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of Mobile Phone Carriers		0.00	-0.00**	-0.00**	-0.00**	-0.00**		-0.00	-0.00	-0.00	-0.00	-0.00
		(0.537)	(0.014)	(0.025)	(0.038)	(0.044)		(0.299)	(0.162)	(0.220)	(0.238)	(0.245)
Number of calls In the Past 3 Months		-0.00***	-0.00*	-0.00	-0.00	-0.00		-0.00	-0.00	-0.00	-0.00	-0.00
		(0.000)	(0.097)	(0.170)	(0.146)	(0.162)		(0.118)	(0.110)	(0.183)	(0.178)	(0.191)
Longest Call Duration In The Past 12 Months		-0.00	-0.00	-0.00	-0.00	-0.00		-0.00	-0.00	-0.00	-0.00	-0.00
		(0.240)	(0.471)	(0.381)	(0.463)	(0.502)		(0.312)	(0.405)	(0.363)	(0.423)	(0.454)
Ratio of Frequent Calls In Contact Book In the Past 12 Months		-0.01***	0.00**	0.01**	0.01**	0.00**		0.00	0.00	0.00	0.00	0.00
		(0.001)	(0.032)	(0.011)	(0.026)	(0.027)		(0.849)	(0.924)	(0.592)	(0.685)	(0.649)
Number of Calls In the Black List In the Past 12 Months		-0.00	-0.00	-0.00	-0.01	-0.01		0.00	0.00	-0.00	-0.00	-0.00
		(0.943)	(0.694)	(0.189)	(0.108)	(0.113)		(0.689)	(0.875)	(0.377)	(0.323)	(0.325)
Number of Calls With Family In the Past 12 Months		0.00	-0.00	-0.00	-0.00	-0.00		0.00	-0.00	-0.00	-0.00	-0.00
		(0.602)	(0.787)	(0.570)	(0.589)	(0.604)		(0.920)	(0.870)	(0.676)	(0.694)	(0.701)
Number of Calls With Agents As Caller		-0.00***	-0.00***	-0.00***	-0.00***	-0.00***		-0.00***	-0.00***	-0.00***	-0.00***	-0.00***
		(0.000)	(0.002)	(0.000)	(0.000)	(0.000)		(0.004)	(0.009)	(0.002)	(0.001)	(0.001)
Number of Calls In the Past 3 Months As Caller		0.00***	0.00***	0.00***	0.00***	0.00***		0.00**	0.00**	0.00**	0.00**	0.00**
		(0.000)	(0.004)	(0.008)	(0.006)	(0.007)		(0.019)	(0.018)	(0.031)	(0.027)	(0.028)
Longest Call Duration In The Past 12 Months As Caller		-0.00	-0.00*	-0.00**	-0.00**	-0.00**		-0.00*	-0.00*	-0.00**	-0.00**	-0.00**
		(0.199)	(0.072)	(0.022)	(0.032)	(0.028)		(0.057)	(0.066)	(0.026)	(0.034)	(0.031)
Median Call Duration In The Past 12 Months As Caller		-0.00	-0.00	-0.00	-0.00	-0.00		-0.00	-0.00	-0.00	-0.00	-0.00
		(0.227)	(0.210)	(0.469)	(0.275)	(0.287)		(0.371)	(0.349)	(0.661)	(0.461)	(0.467)
Number of Calls To Agents in the Past 12 Months As Caller		-0.00	-0.00	-0.00	-0.00	-0.00		-0.00	-0.00	-0.00	-0.00	-0.00
		(0.293)	(0.310)	(0.319)	(0.399)	(0.430)		(0.260)	(0.371)	(0.450)	(0.481)	(0.495)
Number of Calls In the Black List In the Past 12 Months		-0.00	-0.00	0.00	0.01	0.00		-0.00	-0.00	0.00	0.00	0.00
		(0.875)	(0.991)	(0.389)	(0.285)	(0.308)		(0.492)	(0.648)	(0.716)	(0.680)	(0.695)
Ratio of Calls In Contact Book In the Past 12 Months As Caller		0.02***	0.01***	0.01***	0.01***	0.01***		0.01***	0.01***	0.01***	0.01***	0.01***
		(0.000)	(0.000)	(0.002)	(0.001)	(0.001)		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Average Times of Being Called Per Day In the Past 12 Months		0.00***	0.00***	0.00***	0.00***	0.00***		0.00***	0.00***	0.00***	0.00***	0.00***
		(0.000)	(0.004)	(0.008)	(0.007)	(0.008)		(0.004)	(0.004)	(0.009)	(0.008)	(0.009)
Average Times of Being Caller Per Day In the Past 12 Months		-0.00***	-0.00***	-0.00***	-0.00***	-0.00***		-0.00***	-0.00***	-0.00***	-0.00***	-0.00***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Average Mobile Bill In the Past 12 Months		-0.00	-0.00	-0.00	-0.00	-0.00		-0.00	-0.00*	-0.00	-0.00	-0.00
		(0.167)	(0.234)	(0.266)	(0.200)	(0.184)		(0.372)	(0.090)	(0.123)	(0.121)	(0.119)
Have Shortcuts for Family In the Past 12 Months		0.00*	0.00**	0.00**	0.00**	0.00**		0.00*	0.00*	0.00**	0.00**	0.00**
		(0.057)	(0.029)	(0.020)	(0.027)	(0.028)		(0.055)	(0.052)	(0.041)	(0.048)	(0.048)
Number of the Contacts In The Contact Book		0.00***	0.00***	0.00***	0.00***	0.00***		0.00***	0.00***	0.00***	0.00***	0.00***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Transaction Amount With Trading Companies In The Past 12 Months		0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00	0.00
		(0.617)	(0.177)	(0.201)	(0.205)	(0.185)		(0.210)	(0.151)	(0.177)	(0.182)	(0.169)
Transaction Number With Trading Companies In The Past 12 Months		0.00	-0.00	-0.00	-0.00	-0.00		-0.00	-0.00	-0.00	-0.00	-0.00
		(0.980)	(0.375)	(0.504)	(0.532)	(0.561)		(0.280)	(0.249)	(0.380)	(0.397)	(0.410)
Number of Active Credit Cards		0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00	0.00
		(0.628)	(0.286)	(0.286)	(0.272)	(0.314)		(0.533)	(0.494)	(0.445)	(0.429)	(0.452)
Number of Banks of the Credit Cards		0.00***	0.00***	0.00***	0.00***	0.00***		0.00***	0.00***	0.00***	0.00***	0.00***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of Cash Withdrawal in the Past 12 Months		-0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00	0.00
		(0.466)	(0.815)	(0.534)	(0.576)	(0.558)		(0.886)	(0.755)	(0.441)	(0.459)	(0.452)
Total Interest Charged In the Past 6 Months		-0.00	0.00	0.00*	0.00*	0.00*		0.00**	0.00*	0.00**	0.00**	0.00**
		(0.862)	(0.105)	(0.072)	(0.094)	(0.078)		(0.045)	(0.053)	(0.033)	(0.044)	(0.039)
Number of Interest Charged In the Past 12 Months		0.00***	0.00***	0.00**	0.00**	0.00**		0.00*	0.00*	0.00*	0.00*	0.00*
		(0.000)	(0.006)	(0.012)	(0.012)	(0.013)		(0.078)	(0.052)	(0.078)	(0.077)	(0.079)
Number of Transactions Over 5000 RMB in the Past 12 Months		0.00***	0.00**	0.00**	0.00**	0.00**		0.00***	0.00**	0.00**	0.00**	0.00**
		(0.003)	(0.022)	(0.047)	(0.046)	(0.047)		(0.007)	(0.012)	(0.027)	(0.027)	(0.028)
Highest Credit Line in the Past 12 Months		0.00***	0.00*	0.00*	0.00*	0.00*		0.00	0.00	0.00	0.00	0.00
		(0.000)	(0.091)	(0.072)	(0.056)	(0.062)		(0.100)	(0.273)	(0.230)	(0.199)	(0.206)
Repayment Rate in the Past 6 Months		0.00***	0.00***	0.00***	0.00***	0.00***		0.00***	0.00***	0.00**	0.00**	0.00**
		(0.004)	(0.002)	(0.005)	(0.003)	(0.002)		(0.004)	(0.009)	(0.019)	(0.011)	(0.010)
Minimum Repayment Rate in the Past 12 Months		-0.00	-0.00**	-0.00	-0.00	-0.00		-0.00	-0.00	-0.00	-0.00	-0.00
		(0.113)	(0.029)	(0.129)	(0.119)	(0.118)		(0.136)	(0.171)	(0.381)	(0.352)	(0.344)
Usage Rate of Credit Line in the Past 6 Months		-0.00***	-0.01***	-0.01***	-0.01***	-0.01***		-0.01***	-0.01***	-0.01***	-0.01***	-0.01***
		(0.003)	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number Of Bank Relationship In The Past 3 Months		-0.00	-0.00**	-0.00	-0.00*	-0.00*		-0.00**	-0.00***	-0.00**	-0.00**	-0.00**
		(0.180)	(0.022)	(0.126)	(0.099)	(0.088)		(0.016)	(0.006)	(0.041)	(0.034)	(0.033)
Number Of Active Deposit Cards In The Past 3 Months		0.00*	0.00**	0.00*	0.00*	0.00*		0.00**	0.00**	0.00**	0.00**	0.00**
		(0.097)	(0.034)	(0.087)	(0.069)	(0.058)		(0.018)	(0.015)	(0.035)	(0.031)	(0.029)
Online Shopping Address Entropy		0.01***	0.01***	0.01***	0.01***	0.01***		0.01***	0.01***	0.01***	0.01***	0.01***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Alipay Average Daily Consumption in The Past 12 Months		0.00***	0.01***	0.00***	0.00***	0.00***		0.01***	0.01***	0.00***	0.00***	0.00***
		(0.009)	(0.001)	(0.007)	(0.005)	(0.004)		(0.000)	(0.000)	(0.002)	(0.002)	(0.001)
Alipay Average Daily Transaction in The Past 12 Months		-0.00**	-0.00***	-0.00**	-0.00**	-0.00**		-0.00***	-0.00***	-0.00***	-0.00***	-0.00***
		(0.017)	(0.004)	(0.014)	(0.013)	(0.013)		(0.000)	(0.000)	(0.002)	(0.002)	(0.002)
Average Transfer Per Day In the Past 12 Months		0.00	0.00*	0.00*	0.00*	0.00*		0.00**	0.00**	0.00**	0.00**	0.00**
		(0.430)	(0.059)	(0.057)	(0.092)	(0.088)		(0.011)	(0.018)	(0.020)	(0.027)	(0.027)
Alipay Gamble Transaction Fees in The Past 12 Months		-0.00**	-0.00**	-0.00**	-0.00**	-0.00*		-0.00***	-0.00***	-0.00***	-0.00***	-0.00***
		(0.021)	(0.035)	(0.022)	(0.036)	(0.059)		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Alipay Implied Credit Lines In The Past 12 Months		0.00	0.00	-0.00	0.00	0.00		0.00	0.00	0.00	0.00	0.00
		(0.434)	(0.975)	(0.946)	(0.978)	(0.933)		(0.542)	(0.548)	(0.645)	(0.620)	(0.600)
Alipay Implied Number of Banks of Credit Cards In The Past 12 Months		-0.00	-0.00	-0.00	-0.00	-0.00		-0.00*	-0.00*	-0.00	-0.00	-0.00
		(0.111)	(0.290)	(0.568)	(0.477)	(0.437)		(0.060)	(0.092)	(0.240)	(0.215)	(0.205)
Alipay Implied Highest Credit Line In The Past 12 Months		-0.00**	-0.00	-0.00	-0.00	-0.00		-0.00*	-0.00*	-0.00	-0.00*	-0.00*
		(0.038)	(0.208)	(0.245)	(0.214)	(0.188)		(0.059)	(0.082)	(0.101)	(0.099)	(0.091)
Lagged Stock Market Return			0.04	-0.54	-0.20	-0.50			-0.54	-0.79	-0.62	-0.77
			(0.940)	(0.306)	(0.704)	(0.343)			(0.281)	(0.124)	(0.229)	(0.135)
Lagged Stock Market Return for SMEs			-0.30	0.66*	-0.35	-0.08			0.14	0.64*	0.11	0.24
			(0.413)	(0.065)	(0.351)	(0.834)			(0.699)	(0.072)	(0.764)	(0.515)
Lagged Yield Curve			0.02***	0.02***	0.02***	0.02***			0.01***	0.00	0.01***	0.01**
			(0.000)	(0.000)	(0.000)	(0.000)			(0.003)	(0.313)	(0.005)	(0.015)
P2P Industry Loan Rate Composite Index			0.70*	2.44***	1.43***	1.52***			0.58	1.33***	0.82*	0.90**
			(0.061)	(0.000)	(0.001)	(0.000)			(0.131)	(0.002)	(0.055)	(0.037)
P2P Industry Popularity Index			0.08***	0.10***	0.08***	0.07***			0.03*	0.04**	0.03*	0.03
			(0.000)	(0.000)	(0.000)	(0.001)			(0.056)	(0.022)	(0.074)	(0.169)
P2P Industry Investor Composite Return			0.65	0.86	-1.06	-0.67			-2.06	-2.20	-2.57	-2.43
			(0.695)	(0.624)	(0.547)	(0.704)			(0.222)	(0.226)	(0.156)	(0.178)
Lagged Change in Housing Price			-0.20**	-0.13	-0.17**	-0.15*			-0.14	-0.12	-0.13	-0.13
			(0.014)	(0.102)	(0.044)	(0.060)			(0.117)	(0.168)	(0.156)	(0.153)
Lagged Change in Banking Total Assets			0.05***	0.05***	0.05***	0.05***						
			(0.000)	(0.000)	(0.000)	(0.000)						
Lagged Change in Banking Leverage			-0.25***	-0.28***	-0.27***	-0.28***						
			(0.000)	(0.000)	(0.000)	(0.000)						
Lagged Change in PMI			-0.01***	-0.01***	-0.01***	-0.01***						
			(0.000)	(0.000)	(0.000)	(0.000)						
Lagged Change in CPI			-0.02***	-0.02***	-0.02***	-0.02***						
			(0.000)	(0.000)	(0.000)	(0.000)						
Constant	6.47***	6.55***	6.44***	6.37***	6.43***	6.41***	6.47***	6.56***	6.56***	6.53***	6.56***	6.55***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	11956	11956	10953	10008	9922	9922	11956	11956	10953	10008	9922	9922
Adjusted R-Squared	0.02	0.59	0.66	0.65	0.66	0.66	0.12	0.68	0.69	0.69	0.68	0.68
Loan Characteristics	NO	YES	YES	YES	YES	YES	NO	YES	YES	YES	YES	YES
Borrower Characteristics	NO	YES	YES	YES	YES	YES	NO	YES	YES	YES	YES	YES
Macro Characteristics	NO	NO	YES	YES	YES	YES	NO	NO	YES	YES	YES	YES
Borrower Province FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Month FE	NO	NO	NO	NO	NO	NO	YES	YES	YES	YES	YES	YES

p-values in parentheses

In this table the independent variable of Log Lagged Liquidity, Log Loan Amount, Loan Maturity, Lagged Stock Market Return, Lagged Stock Market Return for SMES,

P2P Industry Loan Rate Composite Index, P2P Industry Popularity Index, P2P Industry Investor Composite Return, Lagged Change in Housing Price and Lagged CHange in Banking Total Assets are rescaled by 10^{-3} times original value, for clear presentation of the estimates.

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

Table A3: Full Table: Baseline OLS Results Using Overdue History to Replace Credit Score

	Number of Overdue(6M)			Amount of Overdue(6M)			Number of Overdue Ratio(3M to 9M)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lagged Detrended DR007	-367.26***	-353.93***	-874.39*	-52.89*	-47.53	-182.52*	-685.49***	-712.15***	-1692.12
	(0.002)	(0.006)	(0.059)	(0.068)	(0.133)	(0.053)	(0.006)	(0.008)	(0.129)
Log Lagged Liquidity		16.95*	22.37**		3.22**	4.63***		-14.10	-3.90
		(0.091)	(0.046)		(0.047)	(0.009)		(0.583)	(0.881)
Lagged Detrended DR007 × Log Lagged Liquidity			117.39			30.45			221.04
			(0.247)			(0.102)			(0.358)
Log Loan Amount	42.45***	41.34**	41.32**	11.92***	12.24***	12.24***	8.07	6.82	6.78
	(0.007)	(0.017)	(0.017)	(0.002)	(0.005)	(0.005)	(0.747)	(0.800)	(0.801)
Loan Maturity	3.71**	4.29**	4.29**	-0.10	-0.02	-0.02	-1.32	-1.29	-1.29
	(0.040)	(0.027)	(0.027)	(0.804)	(0.963)	(0.964)	(0.720)	(0.745)	(0.745)
Loan Interest Rate	3.30**	3.11**	3.11**	0.45	0.45	0.45	0.74	0.48	0.48
	(0.019)	(0.032)	(0.033)	(0.110)	(0.121)	(0.122)	(0.798)	(0.873)	(0.875)
Number of Mobile Phone Carriers	-13.62	-17.71	-17.62	-7.72***	-8.79***	-8.77***	-19.23	-20.98	-20.82
	(0.233)	(0.160)	(0.162)	(0.002)	(0.002)	(0.002)	(0.213)	(0.209)	(0.213)
Number of calls In the Past 3 Months	0.09	0.07	0.07	0.03*	0.03*	0.03*	0.03	-0.03	-0.03
	(0.185)	(0.301)	(0.294)	(0.073)	(0.091)	(0.087)	(0.817)	(0.811)	(0.823)
Longest Call Duration In The Past 12 Months	0.00**	0.00**	0.00**	0.00	0.00	0.00	-0.00	-0.00	-0.00
	(0.023)	(0.022)	(0.022)	(0.277)	(0.408)	(0.342)	(0.813)	(0.725)	(0.745)
Ratio of Frequent Calls In Contact Book In the Past 12 Months	-78.94	-59.62	-58.49	5.42	9.28	9.57	-80.72	-52.94	-50.80
	(0.289)	(0.440)	(0.450)	(0.710)	(0.548)	(0.537)	(0.556)	(0.721)	(0.732)
Number of Calls In the Black List In the Past 12 Months	-75.32	-74.50	-74.35	3.34	3.67	3.71	-369.25	-245.30*	-245.02*
	(0.149)	(0.144)	(0.144)	(0.430)	(0.665)	(0.660)	(0.114)	(0.095)	(0.095)
Number of Calls With Family In the Past 12 Months	-0.03**	-0.03*	-0.03*	-0.01***	-0.01**	-0.01**	-0.06*	-0.05	-0.05
	(0.035)	(0.077)	(0.078)	(0.006)	(0.011)	(0.011)	(0.055)	(0.120)	(0.120)
Number of Calls With Agents As Caller	0.05	0.07	0.07	-0.01	-0.01	-0.01	0.25	0.32	0.32
	(0.702)	(0.637)	(0.627)	(0.615)	(0.637)	(0.653)	(0.673)	(0.613)	(0.609)
Number of Calls In the Past 3 Months As Caller	-0.14	-0.13	-0.13	-0.07*	-0.07	-0.07	0.00	0.09	0.09
	(0.303)	(0.367)	(0.363)	(0.097)	(0.109)	(0.107)	(0.995)	(0.734)	(0.740)
Longest Call Duration In The Past 12 Months As Caller	0.01*	0.01	0.01	-0.00	-0.00	-0.00	0.02**	0.02*	0.02*
	(0.056)	(0.137)	(0.140)	(0.965)	(0.673)	(0.662)	(0.043)	(0.071)	(0.073)
Median Call Duration In The Past 12 Months As Caller	-0.81	-0.88	-0.88	0.02	0.01	0.01	-1.03	-0.88	-0.87
	(0.111)	(0.103)	(0.103)	(0.789)	(0.912)	(0.908)	(0.384)	(0.491)	(0.493)
Number of Calls To Agents in the Past 12 Months As Caller	-0.45	-0.37	-0.37	-0.07	-0.07	-0.06	-0.34	-0.21	-0.20
	(0.153)	(0.264)	(0.269)	(0.429)	(0.500)	(0.506)	(0.587)	(0.752)	(0.760)
Number of Calls In the Black List In the Past 12 Months	151.47	148.83	148.00	-7.96	-9.02	-9.24	801.25	663.09**	661.53**
	(0.187)	(0.118)	(0.121)	(0.355)	(0.475)	(0.462)	(0.123)	(0.047)	(0.048)
Ratio of Calls In Contact Book In the Past 12 Months As Caller	-3.86	-43.26	-44.40	-3.13	-7.88	-8.18	-49.19	-54.36	-56.49
	(0.966)	(0.654)	(0.645)	(0.864)	(0.695)	(0.684)	(0.754)	(0.745)	(0.735)
Average Times of Being Called Per Day In the Past 12 Months	-3.42	-1.35	-1.43	-1.78	-1.73	-1.75	-3.79	0.81	0.65
	(0.561)	(0.836)	(0.826)	(0.320)	(0.390)	(0.383)	(0.768)	(0.954)	(0.963)
Average Times of Being Caller Per Day In the Past 12 Months	5.58	5.33	5.29	3.41	3.62	3.61	1.57	-1.29	-1.36
	(0.475)	(0.530)	(0.533)	(0.179)	(0.190)	(0.191)	(0.903)	(0.927)	(0.923)
Average Mobile Bill In the Past 12 Months	0.20*	0.18	0.18	-0.01	-0.01	-0.01	-0.26	-0.25	-0.25
	(0.077)	(0.126)	(0.127)	(0.722)	(0.649)	(0.647)	(0.198)	(0.251)	(0.250)
Have Shortcuts for Family In the Past 12 Months	-31.54	-31.61	-31.67	0.01	-2.27	-2.29	109.80	125.57	125.45
	(0.262)	(0.292)	(0.290)	(0.998)	(0.712)	(0.710)	(0.128)	(0.107)	(0.107)
Number of the Contacts In The Contact Book	0.02	0.02	0.02	0.00	0.00	0.00	0.02	0.01	0.01
	(0.142)	(0.163)	(0.164)	(0.795)	(0.996)	(1.000)	(0.708)	(0.848)	(0.850)
Transaction Amount With Trading Companies In The Past 12 Months	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.174)	(0.225)	(0.220)	(0.432)	(0.407)	(0.403)	(0.474)	(0.399)	(0.390)
Transaction Number With Trading Companies In The Past 12 Months	-1.72***	-1.64**	-1.64**	-0.39**	-0.42**	-0.42**	-1.36*	-1.50*	-1.48*
	(0.003)	(0.010)	(0.010)	(0.041)	(0.048)	(0.049)	(0.075)	(0.068)	(0.070)
Number of Active Credit Cards	2.86	3.49	3.45	-0.79	-0.96	-0.97	0.43	0.09	0.00
	(0.472)	(0.489)	(0.495)	(0.201)	(0.226)	(0.219)	(0.928)	(0.988)	(1.000)
Number of Banks of the Credit Cards	10.51	9.96	10.00	0.79	1.02	1.03	19.61**	21.59**	21.65**
	(0.166)	(0.257)	(0.256)	(0.766)	(0.724)	(0.722)	(0.042)	(0.042)	(0.041)
Number of Cash Withdrawal in the Past 12 Months	0.81	0.86	0.87	0.37	0.39	0.39	-0.44	-0.45	-0.45
	(0.251)	(0.243)	(0.243)	(0.172)	(0.170)	(0.170)	(0.418)	(0.432)	(0.434)
Total Interest Charged In the Past 6 Months	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	0.00	0.00	0.00
	(0.142)	(0.182)	(0.187)	(0.216)	(0.201)	(0.206)	(0.587)	(0.731)	(0.721)
Number of Interest Charged In the Past 12 Months	0.82**	0.71	0.70	-0.10	-0.12	-0.12	0.37	0.48	0.48
	(0.045)	(0.112)	(0.112)	(0.448)	(0.390)	(0.389)	(0.657)	(0.597)	(0.598)
Number of Transactions Over 5000 RMB in the Past 12 Months	0.59*	0.62*	0.62*	0.36	0.37	0.37	0.36	0.38	0.38
	(0.092)	(0.091)	(0.092)	(0.110)	(0.104)	(0.105)	(0.280)	(0.271)	(0.276)
Highest Credit Line in the Past 12 Months	-0.00***	-0.00***	-0.00***	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.005)	(0.009)	(0.009)	(0.872)	(0.914)	(0.911)	(0.659)	(0.752)	(0.746)
Repayment Rate in the Past 6 Months	-24.99	-26.68	-26.37	-7.50	-9.15	-9.07	6.51	-7.86	-7.27
	(0.590)	(0.589)	(0.594)	(0.598)	(0.541)	(0.545)	(0.929)	(0.920)	(0.926)
Minimum Repayment Rate in the Past 12 Months	-75.26**	-85.93**	-86.10**	-22.13**	-22.89**	-22.94**	30.80	28.50	28.17
	(0.034)	(0.025)	(0.025)	(0.013)	(0.020)	(0.019)	(0.594)	(0.646)	(0.650)
Usage Rate of Credit Line in the Past 6 Months	55.52	44.56	43.74	-9.71	-10.74	-10.95	22.89	17.99	16.43
	(0.261)	(0.396)	(0.405)	(0.637)	(0.618)	(0.610)	(0.771)	(0.827)	(0.842)
Number Of Bank Relationship In The Past 3 Months	8.72	7.35	7.16	-2.44	-2.08	-2.13	-9.46	-15.59	-15.95
	(0.809)	(0.852)	(0.856)	(0.802)	(0.848)	(0.845)	(0.854)	(0.782)	(0.778)
Number Of Active Deposit Cards In The Past 3 Months	-8.95	-8.76	-8.51	-4.08	-4.45	-4.39	-20.98	-21.89	-21.43
	(0.726)	(0.757)	(0.764)	(0.602)	(0.604)	(0.610)	(0.579)	(0.603)	(0.611)
Online Shopping Address Entropy	26.13	30.45	30.49	13.74	15.70	15.71	57.31	38.86	38.94
	(0.560)	(0.527)	(0.527)	(0.239)	(0.225)	(0.225)	(0.479)	(0.652)	(0.651)
Alipay Average Daily Consumption in The Past 12 Months	-12.28	-10.12	-9.64	-1.36	-0.90	-0.77	18.55	18.66	19.56
	(0.694)	(0.753)	(0.764)	(0.854)	(0.906)	(0.919)	(0.767)	(0.775)	(0.764)
Alipay Average Daily Transaction in The Past 12 Months	1.00	0.44	0.48	1.25	0.84	0.85	-5.57	-5.33	-5.25
	(0.947)	(0.977)	(0.975)	(0.650)	(0.766)	(0.763)	(0.791)	(0.807)	(0.809)
Average Transfer Per Day In the Past 12 Months	-0.02**	-0.02**	-0.02**	-0.01*	-0.01*	-0.01*	-0.03***	-0.03**	-0.03**
	(0.029)	(0.028)	(0.028)	(0.062)	(0.070)	(0.070)	(0.008)	(0.015)	(0.015)
Alipay Gamble Transaction Fees in The Past 12 Months	0.04***	0.04***	0.04***	0.01***	0.01***	0.01***	0.03**	0.03**	0.03**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.029)	(0.033)	(0.032)
Alipay Implied Credit Lines In The Past 12 Months	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.01	0.01
	(0.134)	(0.123)	(0.121)	(0.369)	(0.364)	(0.360)	(0.441)	(0.339)	(0.336)
Alipay Implied Number of Banks of Credit Cards In The Past 12 Months	-0.32	3.11	2.97	3.99	4.99	4.95	-8.73	-12.96	-13.22
	(0.988)	(0.894)	(0.899)	(0.405)	(0.334)	(0.337)	(0.783)	(0.709)	(0.704)
Alipay Implied Highest Credit Line In The Past 12 Months	-0.01	-0.01	-0.01	-0.00	-0.00	-0.00	-0.01*	-0.02**	-0.02**
	(0.402)	(0.378)	(0.375)	(0.352)	(0.302)	(0.298)	(0.065)	(0.030)	(0.029)
Lagged Stock Market Return	-4.82	-2.00	-3.54	1.50	2.51	2.10	33.97	26.40	23.49
	(0.792)	(0.915)	(0.851)	(0.625)	(0.432)	(0.511)	(0.253)	(0.389)	(0.450)
Lagged Stock Market Return for SMEs	35.38**	31.42**	32.78**	6.31**	5.84**	6.19**	19.54	22.98	25.53
	(0.014)	(0.032)	(0.026)	(0.018)	(0.035)	(0.027)	(0.338)	(0.270)	(0.230)
Lagged Yield Curve	-45.08	-32.16	-42.39	-22.03	-19.85	-22.50	-218.59	-258.28	-277.54
	(0.623)	(0.746)	(0.673)	(0.217)	(0.309)	(0.255)	(0.216)	(0.175)	(0.151)
P2P Industry Loan Rate Composite Index	7.68	14.79	15.57	3.56	3.83	4.03	21.50	48.01	49.46
	(0.468)	(0.263)	(0.242)	(0.121)	(0.181)	(0.157)	(0.367)	(0.115)	(0.104)
P2P Industry Popularity Index	-0.50	-0.64	-0.72	-0.10	-0.14	-0.16	-1.01	-0.45	-0.59
	(0.342)	(0.255)	(0.204)	(0.351)	(0.203)	(0.145)	(0.364)	(0.708)	(0.621)
P2P Industry Investor Composite Return	-37.28	-53.57	-52.14	-21.72*	-23.11*	-22.74*	-107.05	-164.49	-161.81
	(0.457)	(0.334)	(0.347)	(0.070)	(0.084)	(0.090)	(0.368)	(0.224)	(0.233)
Lagged Change in Housing Price	0.99	1.68	1.68	-0.75	-0.75	-0.75	4.47	3.19	3.18
	(0.760)	(0.611)	(0.613)	(0.393)	(0.402)	(0.401)	(0.274)	(0.446)	(0.448)
Constant	-272.46	-419.54	-485.81	-41.90	-48.96	-66.15	1082.60	580.47	455.69
	(0.552)	(0.399)	(0.343)	(0.673)	(0.644)	(0.548)	(0.217)	(0.540)	(0.638)
Observations	10953	9922	9922	10953	9922	9922	10953	9922	9922
Adjusted R-Squared	0.03	0.03	0.03	0.06	0.07	0.07	0.01	0.01	0.01
Loan Characteristics	YES	YES	YES	YES	YES	YES	YES	YES	YES
Borrower Characteristics	YES	YES	YES	YES	YES	YES	YES	YES	YES
Macro Characteristics	YES	YES	YES	YES	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

p-values in parentheses

In this table the dependent variable of Number of Overdue (6M) and Number of Overdue Ratio(3M to 9M) are rescaled by 1000 times original value, for clear presentation of the estimates.

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

Table A4: Full Table: Baseline Probit Model Results

	(1) Granted	(2) Granted	(3) Granted	(4) Granted	(5) Granted	(6) Granted	(7) Granted
Granted							
Lagged Detrended DR007	-0.14**	-36.30***		-93.67**	-83.15*	-87.73**	-74.95*
	(0.026)	(0.000)		(0.027)	(0.051)	(0.041)	(0.085)
Ln(Credit Score)		5.33***	8.56***	8.76***	8.38***	7.80***	8.15***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lagged Detrended DR007 × Ln(Credit Score)		5.58***		14.37**	12.72*	13.44**	11.64*
		(0.000)		(0.028)	(0.054)	(0.043)	(0.084)
Lagged Liquidity			4.65***	4.79***	4.84***	4.36***	2.96***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Lagged Liquidity × Ln(Credit Score)			-0.71***	-0.73***	-0.74***	-0.67***	-0.46***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Lagged Detrended DR007 × Lagged Liquidity				13.48	10.92	12.90	14.32
				(0.150)	(0.248)	(0.175)	(0.137)
Lagged Detrended DR007 × Ln(Credit Score) × Lagged Liquidity				-2.07	-1.67	-1.97	-2.24
				(0.154)	(0.255)	(0.180)	(0.134)
Log Loan Amount					-0.19***	-0.25***	-0.27***
					(0.000)	(0.000)	(0.000)
Loan Maturity					-0.03***	-0.03***	-0.02***
					(0.000)	(0.000)	(0.000)
Loan Interest Rate					-0.01***	-0.01***	-0.01***
					(0.000)	(0.000)	(0.001)
Male						0.01	0.03*
						(0.376)	(0.062)
Age						0.01***	0.01***
						(0.000)	(0.000)
Number of Mobile Phone Carriers						-0.05***	-0.03***
						(0.000)	(0.000)
Number of calls In the Past 3 Months						-0.00**	-0.00
						(0.012)	(0.102)
Longest Call Duration In The Past 12 Months						-0.00	-0.00
						(0.566)	(0.513)
Ratio of Frequent Calls In Contact Book In the Past 12 Months						0.22***	0.17***
						(0.000)	(0.000)
Number of Calls In the Black List In the Past 12 Months						0.02	0.01
						(0.458)	(0.690)
Number of Calls With Family In the Past 12 Months						-0.00	-0.00
						(0.138)	(0.143)
Number of Calls With Agents As Caller						-0.00***	-0.00***
						(0.000)	(0.000)
Number of Calls In the Past 3 Months As Caller						0.00**	0.00
						(0.033)	(0.231)
Longest Call Duration In The Past 12 Months As Caller						0.00***	0.00***
						(0.002)	(0.004)
Median Call Duration In The Past 12 Months As Caller						-0.00***	-0.00***
						(0.000)	(0.000)
Number of Calls To Agents in the Past 12 Months As Caller						-0.00***	-0.00***
						(0.000)	(0.000)
Number of Calls In the Black List In the Past 12 Months						-0.04	-0.04
						(0.188)	(0.224)
Ratio of Calls In Contact Book In the Past 12 Months As Caller						0.24***	0.39***
						(0.000)	(0.000)
Average Times of Being Called Per Day In the Past 12 Months						0.00	0.00
						(0.324)	(0.491)
Average Times of Being Caller Per Day In the Past 12 Months						-0.00	-0.00
						(0.272)	(0.716)
Average Mobile Bill In the Past 12 Months						0.00	-0.00
						(0.670)	(0.753)
Have Shortcuts for Family In the Past 12 Months						-0.04**	-0.05**
						(0.041)	(0.019)
Number of the Contacts In The Contact Book						-0.00***	-0.00***
						(0.000)	(0.000)
Transaction Amount With Trading Companies In The Past 12 Months						0.00*	0.00
						(0.055)	(0.200)
Transaction Number With Trading Companies In The Past 12 Months						-0.00	-0.00
						(0.527)	(0.670)
Number of Active Credit Cards						-0.02***	-0.02***
						(0.000)	(0.000)
Number of Banks of the Credit Cards						0.02***	0.02***
						(0.000)	(0.001)
Number of Cash Withdrawal in the Past 12 Months						0.00	0.00
						(0.158)	(0.112)
Total Interest Charged In the Past 6 Months						0.00***	0.00***
						(0.000)	(0.000)
Number of Interest Charged In the Past 12 Months						-0.00***	-0.00***
						(0.000)	(0.000)
Number of Transactions Over 5000 RMB in the Past 12 Months						0.00	0.00**
						(0.112)	(0.045)
Highest Credit Line in the Past 12 Months						0.00***	0.00***
						(0.000)	(0.000)
Repayment Rate in the Past 6 Months						0.11***	0.11***
						(0.000)	(0.000)
Minimum Repayment Rate in the Past 12 Months						0.05**	0.04*
						(0.031)	(0.076)
Usage Rate of Credit Line in the Past 6 Months						-0.37***	-0.31***
						(0.000)	(0.000)
Number Of Bank Relationship In The Past 3 Months						-0.11***	-0.10***
						(0.000)	(0.000)
Number Of Active Deposit Cards In The Past 3 Months						0.03**	0.02
						(0.020)	(0.242)
Online Shopping Address Entropy						-0.01	-0.01
						(0.738)	(0.800)
Alipay Average Daily Consumption in The Past 12 Months						-0.02	-0.02
						(0.266)	(0.367)
Alipay Average Daily Transaction in The Past 12 Months						0.00	0.00
						(0.751)	(0.939)
Average Transfer Per Day In the Past 12 Months						0.00	0.00
						(0.771)	(0.671)
Alipay Gamble Transaction Fees in The Past 12 Months						0.00	0.00
						(0.809)	(0.767)
Alipay Implied Credit Lines In The Past 12 Months						-0.00	0.00
						(0.745)	(0.766)
Alipay Implied Number of Banks of Credit Cards In The Past 12 Months						-0.01	-0.01
						(0.438)	(0.480)
Alipay Implied Highest Credit Line In The Past 12 Months						0.00	0.00
						(0.168)	(0.449)
Lagged Change in Housing Price							0.01***
							(0.001)
Lagged Change in Banking Total Assets							-0.00***
							(0.000)
Lagged Change in Banking Leverage							3.45***
							(0.000)
Lagged Stock Market Return							-0.04***
							(0.000)
Lagged Stock Market Return for SMEs							0.01*
							(0.092)
Lagged Yield Curve							0.06
							(0.217)
P2P Industry Loan Rate Composite Index							-0.02*
							(0.077)
P2P Industry Popularity Index							0.00
							(0.167)
P2P Industry Investor Composite Return							0.01
							(0.725)
Lagged Change in PMI							0.21***
							(0.000)
Lagged Change in CPI							0.46***
							(0.000)
Constant	-0.92***	-35.32***	-56.49***	-57.76***	-53.02***	-48.85***	-49.29***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	72861	72861	66639	66236	66236	66236	54113
Loan Characteristics	NO	NO	NO	NO	YES	YES	YES
Borrower Characteristics	NO	NO	NO	NO	NO	YES	YES
Macro Characteristics	NO	NO	NO	NO	NO	NO	YES
Borrower FE	NO	NO	NO	NO	NO	NO	NO
Time FE	NO	NO	NO	NO	NO	NO	NO

p-values in parentheses

Table A5: Consecutive Days of Low Monetary Policy

	(1) OLS Model	(2) Probit Model
Ln(Credit Score)		9.0778***
		(0.000)
Days of Consecutive Low Monetary Policy		3.4286**
		(0.017)
Log Lagged Liquidity		4529.6841***
		(0.000)
Days of Consecutive Low Monetary Policy=1	-0.0022**	
	(0.020)	
Days of Consecutive Low Monetary Policy=2	-0.0029**	
	(0.017)	
Days of Consecutive Low Monetary Policy=3	-0.0008	
	(0.521)	
Days of Consecutive Low Monetary Policy=4	-0.0005	
	(0.747)	
Days of Consecutive Low Monetary Policy=5	-0.0012	
	(0.345)	
Days of Consecutive Low Monetary Policy=6	-0.0045***	
	(0.002)	
Days of Consecutive Low Monetary Policy=7	-0.0056***	
	(0.000)	
Days of Consecutive Low Monetary Policy=8	-0.0070***	
	(0.000)	
Days of Consecutive Low Monetary Policy × Ln(Credit Score)		-0.5253**
		(0.018)
Days of Consecutive Low Monetary Policy × Log Lagged Liquidity		-677.0992**
		(0.020)
Ln(Credit Score) × Log Lagged Liquidity		-698.3784***
		(0.000)
Days of Consecutive Low Monetary Policy × Ln(Credit Score) × Log Lagged Liquidity		103.6361**
		(0.021)
Constant	6.3931***	-54.9583***
	(0.000)	(0.000)
Observations	10953	54113
Adjusted R-Squared	0.6541	
Loan Characteristics	YES	YES
Borrower Characteristics	YES	YES
Macro Characteristics	YES	YES
Province FE	YES	NO
Borrower FE	NO	NO
Month FE	NO	NO

p-values in parentheses

In this table the independent variable of Log Lagged Liquidity, Log Loan Amount, Loan Maturity, Lagged Stock Market Return, Lagged Stock Market Return for SMES, P2P Industry Loan Rate Composite Index, P2P Industry Popularity Index, P2P Industry Investor Composite Return, Lagged Change in Housing Price and Lagged Change in Banking Total Assets are rescaled by 10^{-3} times original value, for clear presentation of the estimates.

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