Peer effects in the online P2P lending market: Ex-ante selection and ex-post learning

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Abstract

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Keywords: P2P lending, peer effect, ex-ante selection, ex-post learning, information asymmetry
JEL classification：G23, G30, G32

1. Introduction

In recent years, FinTech, which integrates cutting-edge information technologies such as artificial intelligence, big data, cloud computing, and blockchain, has completely reshaped the traditional financial industry (Banna et al., 2022; Murinde et al., 2022). FinTech not only dramatically improved the efficiency of financial services, but also greatly expanded its service scope. One example is the peer-to-peer (P2P) lending (Balyuk, 2018; Philippon, 2016). Unlike traditional credit businesses based on financial intermediaries, P2P lending facilitates lenders to lend funds to borrowers directly. Relevant information, like the type of business and transaction fees, assuming zero credit risk, is displayed on the platform. Compared with traditional lending through banks, P2P lending generally has lower access requirements and fewer restrictions on borrowers, and the borrowing rate is relatively higher (Chen et al., 2020). Therefore, P2P lending has been highly favored by the market ever since its launch. Borrowers with poor credit qualifications, excluded from traditional bank credit, can obtain financing through P2P lending, whereas investors can obtain relatively higher returns by investing in P2P lending.

In contrast to the traditional credit market in which financial intermediaries take deposits and provide loans, the P2P lending market consists of lenders lending funds directly to borrowers. Therefore, the behavior of lenders and borrowers has been the focus of research on P2P lending (Herzenstein et al., 2008; Duarte et al., 2012). In this regard, a large body of literature has explored the determinants of borrowers' successfully attained loans and defaulting in P2P markets, as well as the phenomena of discrimination and market efficiency in P2P markets (Pope and Sydnor, 2011; Chen et al., 2020). Considering that the P2P lending market is characterized by big data, with a small size for a single transaction and delivering a large number of loans involving research methods based on artificial intelligence, it has been particularly favored in recent years (Zhou et al., 2019). Moreover, as the lenders in the P2P lending market are more immature than the traditional financial intermediaries, there is a serious problem of information asymmetry between lenders and borrowers. Thus, the influences of other lenders' and borrowers' behavior on the lenders' and borrowers' decision-making have received special attention, and one of them is the learning effect (Freedman and Jin, 2011; Iyer et al., 2016).

This study also focuses on the learning effect of the lenders and borrowers in the P2P lending market for the following three reasons. First, existing research on the learning behavior of the P2P lending market mainly focuses on the lender, that is, whether the lenders can improve their lending efficiency through learning (Freedman and Jin, 2011; Iyer et al., 2016), and seldom explores the aspects from the borrowers. Second, in the face of information asymmetry between borrowers and lenders in this market, existing research mainly focuses on the adverse selection problem faced by lenders when deciding whether to provide a loan and rarely considers the moral hazard problem when borrowers decide whether to default after obtaining a loan (Zhu, 2018). Third, prior discussions on the lenders' learning behavior mainly focus on the herding effect (Herzenstein et al., 2011a; Zhang and Liu, 2012; Caglayan et al., 2021), while few have considered other types of learning behavior. Therefore, unlike previous literature that has always investigated the lenders' learning behavior, especially for the herding effect, this study further examines the peer effect in the P2P lending market from the perspectives of learning behavior from both lenders and borrowers.

Based on a database of nearly 500 thousand loans from Renrendai, a large Chinese P2P lending platform, this study finds that there are both peer effects of lending and defaulting in the P2P lending market. The former refers to the positive relationship between the loan success rate of the borrowers and their peers, while the latter refers to the positive relationship between the default rate of the borrowers and their peers. These results hold after addressing the endogeneity problem and performing several robustness tests. We further find that it is more pronounced in high-risk cities for peer effects of lending and among borrowers who have difficulty obtaining loans for peer effects of defaulting, indicating ex-ante selection and ex-post learning mechanisms, respectively. Finally, the results of economic consequences show a promoting effect for the peer effects of lending on P2P lending market efficiency and an inhibitory effect for the peer effects of defaulting on the market efficiency.

Compared to the existing literature, this study's contribution is reflected in two aspects. First, this study expands the research on the learning behavior in the P2P lending market from the perspective of the peer effects. Existing studies mainly focus on the herding effect of lenders when investigating the learning behavior in the P2P lending market (Herzenstein et al., 2011a; Zhang and Liu, 2012; Caglayan et al., 2021). This study finds that in the P2P lending market, lenders can also get obscure information through the peers' lending decisions in the same city, and borrowers will make contingent defaulting decisions after attaining loans through the peers' defaulting decisions. Second, this study further explores the impact of peer effects on P2P lending market efficiency and expands research on the economic consequences of learning behaviors in the P2P lending market. We find that the peer effects of lending based on ex-ante selection promote the efficiency of the P2P lending market, whereas the peer effects of defaulting based on ex-post learning inhibit the market efficiency.

The remainder of this paper is organized as follows. Section 2 addresses the relevant literature and the hypotheses. Section 3 discusses the data, methodologies, and summary statistics. Section 4 presents our empirical results. Section 5 concludes.

2. Literature Review and Hypotheses Development

Prior research on the P2P lending market has been carried out in three directions. The first involves examining the factors that affect borrowers' borrowing success and default rates, which is the earliest and most relevant direction in P2P lending. Based on classic adverse selection and moral hazard theory (Stiglitz and Weiss, 1981), the literature has explored the characteristics of lending (Herzenstein et al., 2008), the demographic characteristics of borrowers (Pope and Sydnor, 2011), unstructured information of borrowers (Dorfleitner et al., 2016), and other factors that affect the rate of loan success and default, such as geographical characters (Lin & Viswanathan, 2016; Günther et al., 2018), culture and institutional distance (Galak et al., 2011; Burtch et al., 2014). Some studies discuss discrimination and market efficiency in P2P lending (Pope and Sydnor, 2011; Chen et al., 2020). The second objective is to study the behavior of lenders (or investors) in the P2P lending market. Among them, the herding effect has attracted the most attention. Based on samples from different P2P lending platforms, Herzenstein et al. (2011a), and Zhang and Liu (2012) found an obvious herding effect among lenders, suggesting that lenders like to participate in projects in which other lenders have participated. In addition, local preferences and real estate market performance can affect lenders' decisions (Lin and Viswanathan, 2016; Paravisini et al., 2017). The third objective is to examine the operational performance and governance of P2P lending platforms. Chinese Regulators stipulate that P2P lending platforms only act as information intermediaries, meaning that the lender bears the loss from the borrower's default. However, because of hidden rigid payments, poor governance, and other reasons, many P2P lending platforms have suffered serious losses and recently shut down their operations. In this regard, the relevant literature explores the determinants of operational efficiency and risk, such as market liquidity, managerial background (Gao et al., 2021; Gong et al., 2020), and risk contagion among different platforms (Zhao et al., 2021).

This study contributes to the first two aspects of the above literature. Owing to information asymmetry in lending through traditional financial intermediaries and emerging P2P lending markets, it is always a challenge for lenders to choose a suitable project. Although the borrower information provided by P2P lending platforms is almost the same for different lenders due to differences in experience and ability, the final returns obtained by different lenders differ substantially. In this regard, lenders will continue to learn and optimize their decision-making models based on their past investment experience and lessons to reduce incorrect decisions and improve their return on investment (Freedman and Jin, 2011; Li et al., 2021).

In P2P lending markets, because of the lack of high-quality data, lenders need to learn from other lenders. On the one hand, borrower information in the P2P lending market is disclosed voluntarily by the borrower, and it is difficult for the platform to confirm whether the information disclosure is sufficient and accurate (Wang et al., 2023). However, because of the anonymity settings of the platform, it is difficult for the lender to contact the borrower for additional information privately; considering that other lenders may have unknown important information or experience, they will also learn and adjust based on the lender's behavior to help improve investment decisions. Numerous studies show that lenders in P2P lending markets prefer to follow other lenders' decisions (Herzenstein et al., 2011a; Zhang and Liu, 2012). However, the herding effect may be irrational when other lenders are indiscriminately imitated. For example, Zhang and Liu (2012) found that the herding effect is more prominent in underperforming projects.

For lenders in the P2P lending market, rather than investing in a project that other lenders recognize, it may be a good idea to choose a project with some implicit features that other lenders recognize, and location is one such feature (Lin & Viswanathan, 2016; Günther et al., 2018). Generally, people in the same region have similar living habits and cultures. These factors are difficult to observe directly but can significantly affect people's behavioral decisions. For example, Lu et al. (2020) point out that regional social capital can reduce the borrowing difficulty and borrowing costs of P2P lending market borrowers. Similarly, Jin et al. (2021) found that P2P lending market borrowers from regions with high levels of trust are more likely to obtain loans. For lenders in the P2P lending market, if a borrower comes from a city where other borrowers are more likely to obtain loans, providing a loan to this borrower should be a better option. Thus, we propose the following hypothesis:

H1: The borrower's success rate of getting loans is higher if the success rate is higher for the borrower's peers.

The first step for borrowers in the P2P lending market is to maximize the probability of success in obtaining loans. Borrowers with low credit levels use more complex language descriptions, improving their borrowing success rate but resulting in a higher default rate (Herzenstein et al., 2011b). Simultaneously, because of information asymmetry, borrowers in the P2P lending market are likely to actively choose to default after successfully obtaining loans (Zhu, 2018), which is mainly influenced by penalty costs. If the probability of other borrowers defaulting increases, the borrower is more likely to evade punishment, as "everyone does it." In other words, as the penalty cost of defaulting decreases, borrowers with loans are more likely to evade punishment, which may be beneficial in actively increasing the probability of default. Thus, we propose the following hypothesis:

H2: The default rate of the borrower is higher if the default rate is higher for the borrower's peers.

For lenders in the P2P lending market, decisions should be made more cautiously when facing a higher-risk cohort of borrowers, which requires more information. At this point, auxiliary information provided by the borrower's peer group becomes more important. Therefore, when faced with a high-risk cohort of borrowers, lenders pay more attention to information about borrowers, including the characteristics of their peers, when making loan decisions. If the borrower's peers are more likely to obtain a loan, lenders will be more inclined to lend to them. Thus, we propose the following hypothesis:

H3: The peer effect of lending is more pronounced if the borrower is at higher risk.

Finally, for borrowers in the P2P lending market, the major penalty for defaulting increases the difficulty of future borrowing. These results must be given significant attention. If the borrower cannot easily obtain a loan, even if many people around him default, the borrower should not mindlessly follow and choose to default. Conversely, if the borrower easily obtains a loan, it may be a good choice to follow the behavior of the people around them. Thus, we propose the following hypothesis:

H4: The peer effect of defaulting is more pronounced if the borrower has more difficulty obtaining loans.

3. Research Design

3.1 Sample

The research sample and data were obtained from the Renren Dai platform in China. Established in May 2010, Renrendai was China's earliest P2P lending platform. Its service scope covers more than 2,000 regions in more than 30 provinces. The Renrendai platform focuses on personal lending. It adopts online and offline business models and publishes quarterly operational data. In contrast to the quotation and inquiry strategy adopted by platforms such as Prosper.com, the Renrendai platform publishes the borrower's quotation, and the lender chooses whether to accept it. The Renrendai platform did not participate in the IRP. Before 2012, there was no lower limit on the order interest rate, but an upper limit was set according to the relevant state regulations on private lending. After 2012, the loan interest rate was limited to 7%-24%, and the loan period was 3-36 months. The repayment method adopts an equal principal and interest and repays monthly. For an order initiated by the borrower, the investor can choose to bid, and the minimum is not less than 50 yuan. Multiple investors can jointly participate in the same order, and each investor's participation differs.

The primary sample in this study comprised all orders on the Renrendai platform from 2013 to 2015. This interval was selected because the scale of Renrendai was small in the early days of its establishment, and there was some experimental data. After 2013, the lending market for the Renrendai platform began to develop rapidly. In 2013 alone, the number of loans issued on the platform doubled in the previous three years. After 2016, the Renrendai platform imposed stricter restrictions on borrowers and borrowing targets and introduced a large number of institutional investors, resulting in a rapid decline in the proportion of ordinary investors and a substantial increase in the success rate of borrowings, even close to 100%. Therefore, we chose the interval from 2013 to 2015, consistent with most prior studies based on the Renrendai platform (Chen et al., 2020; Jin et al., 2021). For the initial data, we further screened the following: (1) samples with missing key information, such as the location of the borrower; (2) abnormal data, such as the borrower's age being greater than 65 or less than 18; (3) violation of relevant regulations, for example, the loan period exceeding 36 months; and (4) situations in which the borrower could not repay, mainly the sample with a loan-to-income ratio exceeding 20. A total of 492,142 samples were obtained.

3.2 Model setting and variable definition

First, we construct the following empirical model to test our benchmark hypothesis: to verify whether the peer effect exists in the P2P market.

$$\begin{aligned} Success = \Pr(&\alpha_0 + \alpha_1 Success\_Peers + \alpha_2 Term + \alpha_3 Amount + \alpha_4 Interest \\ &+ \alpha_5 Loan\_to\_Income + \alpha_6 Education + \alpha_7 Age + \alpha_8 Sex \\ &+ \alpha_9 Marriage + \alpha_{10} House + \alpha_{11} Positive + \alpha_{12} Negative + \sum_{i=13}^{6} \alpha_i Credit + \varepsilon) \end{aligned} \tag{1}$$

$$\begin{aligned} Default = \Pr(&\beta_0 + \beta_1 Default\_Peers + \beta_2 Term + \beta_3 Amount + \beta_4 Interest \\ &+ \beta_5 Loan\_to\_Income + \beta_6 Education + \beta_7 Age + \beta_8 Sex \\ &+ \beta_9 Marriage + \beta_{10} House + \beta_{11} Positive + \beta_{12} Negative + \sum_{i=10}^{6} \beta_i Credit + \varepsilon) \end{aligned} \tag{2}$$

Model (1) tests the peer effect of borrowing behavior, where the explained variable *Success* in Model (1) represents the borrowing success rate. If the borrower applied and received a loan, the borrowing success rate is 1; otherwise, it is 0. The explanatory variable *Success_Peers* in Model (1) represents the borrowing success rate of peers; that is, the average borrowing success rate of all borrowers in the same city, except for the borrower.

Model (2) tests the peer effect of the default behavior, where the explained variable *Default* in Model (2) represents the default rate. If the loan status is overdue or bad debt, the default rate is 1; if the loan status is repayment or has been paid, it is 0. The explanatory variable *Default_Peers* in Model (2) represents the default rate of peers, the average default rate of all borrowers who have successfully obtained loans in the same city, except for the borrower.

In terms of the control variables, Models (1) and (2) simultaneously control for the characteristics of loans and borrowers, including the loan term (*Term*), loan amount (*Amount*), loan interest rate (*Interest*), loan-to-income ratio (*Loan_to_Income*), education level (*Education*), age (*Age*), gender (*Sex*), marriage (*Marriage*), with houses or not (*House*), Emotion (*Positive* and *Negative*), and credit rating dummy variables (*AA&A*, *B*, *C*, *D*, *E*, *HR*). Table 1 presents definitions of the variables. The coefficient of *HR* will be omitted for linear combination.

Considering that the explained variable is a dummy variable, we used both Probit and Logit models for the regression. According to the theoretical analyses of H1 and H2, we expect the regression coefficients (α_1 and β_1) of the explanatory variables for Models (1) and (2) to be significantly positive.

Second, we construct the following model to test H3:

$$
\begin{aligned}
Success = \Pr(&\alpha_0 + \alpha_1 Success\_Peers \times Risk + \alpha_2 Risk + \alpha_3 Success\_Peers + \alpha_4 Term \\
&+\alpha_5 Amount + \alpha_6 Interest + \alpha_7 Loan\_to\_Income + \alpha_8 Education + \alpha_9 Age \\
&+\alpha_{10} Sex + \alpha_{11} Marriage + \alpha_{12} House + \alpha_{13} Positive + \alpha_{14} Negative \sum_{i=15}^{6} \alpha_i Credit + \varepsilon)
\end{aligned} \tag{3}
$$

Where *Risk* represents the risk of lenders not being paid back by the target borrower. Specifically, we construct three metrics, namely *Default_of_City*, *AA&A_of_City*, and *HR_of_City*, representing the city's average rate of defaulted borrowers, AA&A-level borrowers, and HR-level borrowers, respectively. The variable definitions are shown in Table 1. By definition, higher (lower) values for *Default_of_City* and *HR_of_City* (*AA&A_of_City*) indicate a higher risk of lenders and vice versa. The remaining variables are defined in Models (1) and (2).

According to the theoretical analysis of H3, when the target borrower has a higher default risk, the lender is more likely to conduct ex-ante selection through the peer effect to help decide whether to provide loans to the target borrower. Therefore, when the average risk of the target borrower group is higher, the peer effect on borrowing behavior is more significant. In other words, the coefficients of interaction terms *Success_of_Peers* × *Default_of_City* and *Success_of_Peers* × *HR_of_City* are expected to be significantly positive, whereas the coefficient of the interaction term *Success_of_Peers* × *AA&A_of_City* is expected to be significantly positive. Their expectations were negative.

Third, we construct the following model to test H4:

$$
\begin{aligned}
Default = \Pr(&\beta_0 + \beta_1 Default\_Peers \times Difficulty + \beta_2 Difficulty + \beta_3 Default\_Peers \\
&+\beta_4 Term + \beta_5 Amount + \beta_6 Interest + \beta_7 Loan\_to\_Income + \beta_8 Education + \beta_9 Age \\
&+\beta_{10} Sex + \beta_{11} Marriage + \beta_{12} House + \beta_{13} Positive + \beta_{14} Negative \sum_{i=15}^{6} \beta_i Credit + \varepsilon)
\end{aligned} \tag{4}
$$

Where *Difficulty* represents borrowers' difficulty in obtaining loans. Specifically, we construct two metrics, *Success_City* and *Historical_Success_Rate*, to represent the city's average borrowing success rate and the borrower's historical success rate, respectively. Table 1 provides the definitions of these variables. By definition, the higher the values of *Success_City* and *Historical_Success_Rate*, the lower the difficulty of borrowing, and vice versa. The remaining variables are defined in Models (1) and (2).

According to the theoretical analysis of H4, when it is easier for the borrower to obtain a loan, the borrower is more likely to perform ex-post learning through the peer effect to help decide whether to default. Therefore, when a borrower's difficulty in obtaining loans is low, the peer effect of borrowing becomes more significant. In other words, the coefficients of the interaction terms, *Default_Peers* × *Success_City* and *Default_Peers* × *Historical_Success_Rate,* are expected to be significantly positive.

[Insert Table 1 here]

3.3 Summary statistics

Table 2 reports the descriptive statistics of the main variables in this study. It can be observed that the average success rate of getting loans in the sample is 0.0836, and the average default rate of successful borrowers is 0.0564. The borrowers' peers had similar borrowing success and default rates, with an average of 0.0812 and 0.0557, respectively. In terms of control variables, the average loan period is 20.572 months, the average loan amount is 35,277 (=e^10.471) yuan, the average loan interest rate is 12.94%, and the average loan-to-income ratio is 6.102, which is significantly higher than the maximum loan period of 3 years. Generally, the loan amount in the P2P market is smaller, the loan period is shorter, the loan interest rate is higher, and the borrower's repayment pressure is higher. Regarding demographic characteristics, the educational background and age of the sample population are relatively low, more than half of them have a college education or below, and the average age is less than 33. The borrowers are mainly male and married, with males accounting for more than 80% and married people accounting for more than 60%. Additionally, nearly half of the borrowers own at least one house.

[Insert Table 2 here]

4. Empirical Results

4.1 Baseline regression

We test for peer effects in the P2P market, and Columns 1 and 2 of Table 3 report the regression results based on Model (1) corresponding to the Probit and Logit models, respectively. The coefficient of the explanatory variable *Success_Peers* is significantly positive at the 1% level, indicating that as the peers' borrowing success rates increase, the borrowing success rate of the borrower also increases significantly. We further analyze their economic significance because large samples can easily be statistically significant. According to the regression results of the Logit model in Column 2, when the explanatory variable *Success_Peers* increases by one standard deviation, the odds ratio of the explained variable *Success* increases by 52% (=$e^{(0.0648\times6.456)}$-1). This is a relatively great effect according to the average success rate of only 8.4%. Overall, there is a peer effect on borrowing behavior in the P2P lending market.

Columns 3 and 4 of Table 3 report the regression results based on Model (2), which also corresponds to the Probit and Logit models. The coefficient of the explanatory variable *Default_Peers* is also significantly positive at the 1% level, indicating that, as the peers' default rates increase, the borrowers' default rate also increases significantly. In terms of economic significance, according to the regression results of the Logit model in Column 4, when the explanatory variable *Success_Peers* increases by one standard deviation, the odds ratio of the explained variables will increase by 13% (=$e^{(0.0892\times1.355)}$-1). According to the average default rate, which is only 5.6%, this is still a relatively great effect. Overall, there is also a peer effect on defaulting behavior in the P2P lending market.

In summary, the empirical results in Table 3 show two kinds of peer effects on borrowing and defaulting behavior in the P2P market, which is consistent with H1 and H2. For the control variables, a long loan period and large loan amount indicate that it is difficult for borrowers to repay, thus the coefficients of them are significantly negative in columns 1 and 2, and significantly positive in columns 3 and 4. These results are consistent with the findings of Herzenstein et al. (2008) and Chen et al. (2020). In addition, the higher the borrower's credit level, the higher the success rate of borrowing and the lower the possibility of defaulting, which are also consistent with theoretical expectations.

[Insert Table 3 here]

4.2 Endogeneity

Endogeneity must be addressed when studying peer effects as unobservable city-level factors may simultaneously affect the borrowers and their peers' behavior. Moreover, there will be an interaction between the borrowers' behavior and their peers' behavior. In this regard, we follow Duflo and Saez's (2002) instrumental variable construction method, and use the average rate of AA&A for the borrowers who applied and successfully obtained the loan at the city level (*AA&A_Success_City*) as the instrumental variable, which indicates the social trust at the city level. Theoretically, high social trust will lead to high success rates and low default rates for the borrower's peers in the same city (Ho et al., 2020). Meanwhile, as we control the borrowers' credit, it excludes the channel for social trust affecting the borrower's success rate and default rate through their own credit, which suggests the instrumental variable satisfies the exclusion restriction hypothesis.

Table 4 reports the results of the instrumental variable regression. In the first-stage regression results of Columns 1 and 3, the coefficients of the instrumental variable AA&A_Success_City are significantly positive and negative, respectively, which is consistent with the theoretical logic. Meanwhile, the test results of LM statistics and Wald F statistics also show that IV regression passes the weak IV test and underidentification test. The second-stage regression results in Columns 2 and 4 show that the coefficients of the explanatory variables *Success_Peers_esitmate* and *Default_Peers_esitmate* are still significantly positive, indicating that after controlling for endogenous interference, the peer effect of borrowing behavior and the peer of default effects still exist. Overall, the results of the instrumental variable regression indicate that there is a causal effect that the behavior of peers will affect the behavior of borrowers and lenders.

[Insert Table 4 here]

4.3 Robustness check

We conducted the following robustness tests on the results of the main hypothesis test.

First, we use standard errors clustered at the city level. By definition, the explained and explanatory variables of Models (1) and (2) are individual-level variables, and we use only robust standard errors. However, as each city contains many borrowing events, intra-city differences in the explanatory variables remain minimal. Therefore, we regress the Models (1) and (2) with standard clustering errors at the city level. Panel A of Table 5 presents the results. Compared to the results in Table 3, the standard error of city-level clustering is larger than the robust standard error. Still, the coefficients of the explanatory variables *Success_Peers* and *Default_Peers* remain significant at the 1% level, indicating that the peer effects still exist.

Second, we exclude the effect of look-ahead bias. The explanatory variables of Models (1) and (2) were constructed based on the total sample of the entire three-year sample period. However, when considering whether to provide a loan or default, lenders and borrowers cannot observe their peers' decisions, which have not yet occurred. Therefore, to exclude the possible effect of look-ahead bias, we construct explanatory variables based on the peers' decisions that happen at or before the year. Based on the new explanatory variables, we recalculated Models (1) and (2), and panel B of Table 5 reports the test results. The coefficients of the explanatory variables *Success_Peers* and

Default_Peers remain significantly positive, indicating that the peer effect still exists after excluding the effect of look-ahead bias.

Third, we exclude the sample with zero city default rate. High default risk is a crucial feature of the P2P market, which is especially important for investing in the behavior of lenders and borrowers. Considering that there are a few cities without default events, those with zero default rates show excellent credit environments and are atypical. Therefore, we removed these urban samples and retested Models (1) and (2). The test results are listed in Panel C of Table 5. The coefficients of the explanatory variables *Success_Peers* and *Default_Peers* remained significantly positive, indicating that the results regarding peer effects remained robust.

Fourth, we add other control variables. The macroeconomic environment and regional differences may be important influencing factors, for which we include province and month-fixed effects to control for their effects. Panel D of Table 5 reports the test result after adding these control variables. The coefficients of the explanatory variables *Success_Peers* and *Default_Peers* remained significantly positive, indicating that the results regarding peer effects remained robust.

[Insert Table 5 here]

Finally, we conduct subsample tests according to the ratio of loans to income. The borrower's income level is important in the P2P lending market because income is closely related to repayment ability. Here, we divide the sample into low *Loan_to_Income* and high *Loan_to_Income* groups according to whether the loan-to-income ratio is greater than five. Panel A and panel B of Table 6 present the test results for the two subsamples. The coefficients of the explanatory variables *Success_Peers* and *Default_Peers* remained significantly positive in both subsamples, indicating that the results regarding peer effects remained robust. Moreover, the coefficients are larger in the subsample with high *Loan_to_Income*, which is consistent with the logic that both lenders and borrowers are more likely to learn through their peers when facing greater risk.

[Insert Table 6 here]

4.4 Other hypothesis tests

After confirming the existence of the peer effect in the P2P market, we test other hypotheses. Table 7 reports the results of H3 testing based on model (3). The coefficients of the interaction terms *Success_Peers* × *Default_City* and *Success_Peers* × *HR_City* are both significantly positive, while the coefficients of the interaction terms *Success_Peers* × *AA&A_City* are significantly negative. These results were expected for H3. The peer effect of borrowing behavior is more pronounced in higher-risk cities, suggesting that lenders are more likely to make lending decisions following their peers when faced with higher risk. In conclusion, the empirical results in Table 7 show an ex-ante selection phenomenon for lenders in the P2P lending market.

Table 8 reports the results of the H4 testing based on Model (4). The coefficients of the interaction terms *Default_Peers* × *Success_City* and *Default_Peers* × *Historical_Success_Rate* are both significantly positive, and the results are exactly as expected in H4. The peer effect of default behavior is more significant in the group of borrowers who find it easier to obtain loans, suggesting that borrowers are more likely to make defaulting decisions following their peers when borrowing difficulty is lower. In conclusion, the empirical results in Table 8 indicate an ex-post learning phenomenon for the borrowers in the P2P lending market.

[Insert Tables 7 and 8 here]

4.5 Economic consequences of peer effects

Finally, we explore the economic consequences of the peer effect in the P2P lending market through its effects on market efficiency. First, we construct the following model to measure the P2P lending market efficiency:

$$Default\_City = \gamma_0 + \gamma_1 Success\_City + \sum_{k=2}^{K} \beta_k Credits\_Ctiy + \varepsilon \tag{5}$$

where the explained variable *Default_City* is the default rate at the city level, which is the average defaulting rate of all borrowers who successfully borrowed in the city. The explanatory variable *Success_City* is the average borrowing success rate of all borrowers in the city. To avoid the bias of bad controls, we include the city-level average credits (*AA&A_City*, *B_City*, *C_City*, *D_City*, *E_City*, and *HR_City*) as control variables. The variable definitions are shown in Table 1. As the value of the explained variable was 0-1, we used the Tobit model for testing. Considering an efficient P2P lending market, the city's default rate should be lower if its borrowing success rate is higher. Therefore, we expect the coefficient of *Success_City* to be significantly negative.

We further examine the impact of peer effect on the efficiency of the P2P market. First, we constructed a measure of peer effects. Considering the huge differences across different provinces in China, we regress the samples of each province to Models (1) and (2). The coefficient of *Success_Peers* (*Default_Peers*) is the peer effect of lending (defaulting) behavior in a province, denoted as *Peer_Effects_Success* (*Peer_Effects_Default*). The larger the value of *Peer_Effects_Success* (*Peer_Effects_Default*), the larger the peer effect of lending (defaulting) behavior. We construct the following model to examine the economic consequences of peer effects–the impacts of peer effects on P2P market efficiency.

$$\begin{aligned} Default\_City = \gamma_0 &+ \gamma_1 Success\_City + \gamma_2 Success\_City \times Peer\_Effects\_Success \\ &+ \gamma_3 Peer\_Effects\_Success + \gamma_4 Success\_City \times Peer\_Effects\_Default \\ &+ \gamma_5 Peer\_Effects\_Default + \sum_{k=6}^{K} \beta_k Credits\_City + \varepsilon \end{aligned} \tag{6}$$

where we mainly focus on coefficients γ_2 of the interaction *Success_City* × *Peer_Effects_Success* and coefficient γ_4 of the interaction *Success_City* × *Peer_Effects_Default*. If coefficient γ_2 (γ_4) is significantly negative (positive), the peer effect of lending (defaulting) behavior improves the efficiency of the P2P lending market and vice versa.

Table 9 reports the results of the tests for the economic consequences of peer effects. The first column is the regression result of model (5). The coefficient of the explanatory variable *Success_City* is significantly negative, indicating that China's P2P lending market is still effective overall. Columns 2-4 are the test results of the economic consequences of the peer effect based on Model (6). In this column, 2 (3) only tests the economic consequences of the peer effect of lending (defaulting) behavior. Column 4 examines the economic consequences of both peer effects of lending behavior and defaulting behavior.

The results show that the coefficients of the interaction term *Success_City* × *Peer_Effects_Success* in Columns 2 and 4 are significantly negative, indicating that the city with a higher peer effect of lending behavior has a greater negative correlation between the city's borrowing success rate and default rate. That is, the peer effect of lending significantly improves the efficiency of the P2P lending market. Meanwhile, the coefficients of the interaction term *Success_City* × *Peer_Effects_Success* in Columns 3 and 4 are significantly positive, indicating that the higher the peer effects of defaulting behavior in the city, the weaker the negative correlation between the borrowing success rate and the default rate in the city. That is, the peer effect of defaulting behavior significantly reduces the efficiency of the P2P lending market. In conclusion, for the P2P lending market efficiency, the peer effect of lending behavior has a promotional effect, whereas the peer effect of defaulting behavior has an inhibitory effect.

[Insert Table 9 here]

5. Conclusion

P2P lending has recently emerged as an important financial technology business. The hot market enthusiasm and credit model, which differs from traditional financial institutions, has attracted widespread attention from researchers. Compared to the previous literature, which mainly focuses on the herd effects of lenders in the P2P lending market, this study expands the research on learning behavior from a new perspective of peer effect. Using a database of nearly five million loans from Renrendai, a large P2P lending platform in China, we find that there are peer effects of lending and defaulting in the P2P lending market. The peer effect of lending is more pronounced in high-risk cities, whereas the peer effect of defaulting is more pronounced for borrowers with more difficulty obtaining loans, indicating an ex-ante selection mechanism for lenders and an ex-post learning mechanism for borrowers, respectively. Finally, the peer effects of lending promote P2P lending market efficiency, and the peer effects of defaulting inhibit the market efficiency.

The results expand the existing literature on the learning behaviors in the P2P lending market from the perspective of peer effects of lenders and borrowers. In particular, the peer effects of lending suggest that lenders adjust their decisions based on other lenders to learn about borrowers' hidden information that is not disclosed on the P2P lending platforms. The peer effects of defaulting show that borrowers adjust their default decisions according to the behavior of other borrowers, which increases their moral hazard to a certain extent. In summary, this study shows that individual decision-making in the P2P lending market is affected by similar groups' decision-making, as the information on the P2P lending platforms is transparent but not fully verified enough. Therefore, the peer effects need to be considered when formulating and improving the supervision of P2P lending markets, and reducing the disclosure of borrowers' decisions to other borrowers may be worth exploring. Finally, it should be noted that the analysis conducted in this study is based only on the data of one Chinese P2P lending platform. In determining whether the relevant conclusions are still applicable in other regions and platforms, it is necessary to consider different institutional backgrounds, information environments, cultures, and other factors. Research on these influencing factors in the P2P lending market is also an interesting topic worthy of further discussion.

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Table 1 Variable definitions

Variable	Definition
Success	Dummy variable: 1 if the borrower applied and received a loan, and 0 otherwise.
Success_Peers	The average borrowing success rate of other borrowers in the city.
Default	Dummy variable: 1 if the borrower defaulted or was overdue, and 0 if the borrower paid the loan back in full.
Default_Peers	The average loan default rate of other borrowers in the city.
Term	The loan period the borrower applies them is months.
Amount	The borrower applies the value of the loan in a natural logarithm.
Interest	The borrower applies the loan interest rate.
Loan_to_Income	The loan value applied is divided by the borrower's annual income.
Education	Level of education: 1 if high school or below, 2 if junior college, 3 if undergraduate degree, and 4 if postgraduate or above.
Age	Age of the borrower.
Sex	The dummy variable is 1 if male and 0 if female.
Marriage	Dummy variable, 1 if married, and 0 if unmarried.
House	Dummy variable, 1 if with a house or more, and 0 if without one
Positive	The number of positive emotional expressions in personal statements.
Negative	The number of negative emotional expressions in personal statements.
AA&A	Dummy variable: 1 if the borrower's credit rating is AA or A; otherwise, 0.
B	Dummy variable: 1 if the borrower's credit rating is B; otherwise, 0.
C	Dummy variable: 1 if the borrower's credit rating is C; otherwise, 0.
D	Dummy variable: 1 if the borrower's credit rating is D; otherwise, 0.
E	Dummy variable: 1 if the borrower's credit rating is E; otherwise, 0.
HR	Dummy variable: 1 if the borrower's credit rating is HR; otherwise, 0.
AA&A_Ctiy	The average rate of *AA&A* for all borrowers at the city level.
B_Ctiy	The average rate of *B* for all borrowers at the city level.
C_Ctiy	The average rate of *C* for all borrowers at the city level.
D_Ctiy	The average rate of *D* for all borrowers at the city level.
E_Ctiy	The average rate of *E* for all borrowers at the city level.
HR_Ctiy	The average rate of *HR* for all borrowers at the city level.

Table 2 Summary statistics of variables used in benchmark regressions

Variable	Obs	Mean	Median	1st Quantile	3rd Quantile	STD
Success	492,142	0.0836	0	0	0	0.277
Success_Peers	492,142	0.0812	0.0590	0.0336	0.120	0.0648
Default	41,140	0.0564	0	0	0	0.231
Default_Peers	41,140	0.0557	0.0179	0.0072	0.0503	0.0892
Term	492,142	20.572	24	12	24	10.790
Amount	492,142	10.471	10.760	9.903	11.112	1.039
Interest	492,142	12.940	12.6	12	13	2.436
Loan_to_Income	492,142	6.102	5.333	2.143	8.571	4.752
Education	492,142	1.904	2	1	2	0.767
Age	492,142	32.785	31	27	37	7.856
Gender	492,142	0.824	1	1	1	0.381
Marriage	492,142	0.638	1	0	1	0.481
House	492,142	0.461	0	0	1	0.498
Positive	492,142	1.819	1	0	3	1.724
Negative	492,142	0.0738	0	0	0	0.302
AA&A	492,142	0.345	0	0	1	0.475
B	492,142	0.0011	0	0	0	0.0329
C	492,142	0.0023	0	0	0	0.0481
D	492,142	0.0090	0	0	0	0.0946
E	492,142	0.0135	0	0	0	0.115
HR	492,142	0.629	1	0	1	0.483

Table 3 Peer effects in the P2P lending market

This table reports the benchmark results for the peer effects in the P2P lending market. The dependent variable in Columns (1) and (2) is *Success*, which takes the value of 1 for the borrower who applied and successfully obtained the loan, and 0 otherwise. The dependent variable in Columns (3) and (4) is *Default*, which takes the value of 1 if the borrower has defaulted or is overdue, and 0 otherwise. Definitions of the variables are provided in Table 1. Robust standard errors are indicated in the parentheses. Superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	Probit	Logit	Probit	Logit
	Success	*Success*	*Default*	*Default*
Success_Peers	**3.368*** **	**6.456*** **		
	(0.0437)	**(0.0852)**		
Default_Peers			**0.827*** **	**1.355*** **
			(0.128)	**(0.221)**
Term	-0.0415***	-0.0880***	0.0708***	0.125***
	(0.0005)	(0.0009)	(0.0027)	(0.0050)
Amount	-0.169***	-0.335***	0.168***	0.285***
	(0.0039)	(0.0077)	(0.0243)	(0.0417)
Interest	0.0545***	0.135***	-0.0052	-0.0094
	(0.0010)	(0.0022)	(0.0091)	(0.0163)
Loan_to_Income	-0.0135***	-0.0165***	-0.0453***	-0.0813***
	(0.0008)	(0.0015)	(0.0107)	(0.0189)
Education	0.0707***	0.116***	-0.252***	-0.460***
	(0.0041)	(0.0078)	(0.0217)	(0.0380)
Age	0.0130***	0.0223***	0.0062**	0.0112**
	(0.0004)	(0.0008)	(0.0027)	(0.0049)
Gender	0.0186**	0.0343**	0.0958*	0.168*
	(0.0076)	(0.0140)	(0.0518)	(0.0905)
Marriage	0.0871***	0.116***	0.0132	0.0278
	(0.0083)	(0.0161)	(0.0404)	(0.0704)
House	-0.144***	-0.278***	-0.0407	-0.0781
	(0.0067)	(0.0125)	(0.0359)	(0.0630)
Positive	-0.0958***	-0.251***	0.0322***	0.0588***
	(0.0042)	(0.0084)	(0.0109)	(0.0186)
Negative	0.0337**	0.0928***	-0.0104	-0.0083
	(0.0131)	(0.0261)	(0.0502)	(0.0889)
AA&A	1.983***	4.442***	-4.549***	-10.46***
	(0.0191)	(0.0400)	(0.206)	(0.604)
B	1.900***	3.863***	-2.370***	-4.820***
	(0.0606)	(0.111)	(0.367)	(1.001)
C	1.676***	3.448***	-1.440***	-2.722***
	(0.0427)	(0.0805)	(0.137)	(0.274)
D	1.563***	3.239***	-1.893***	-3.754***
	(0.0223)	(0.0421)	(0.112)	(0.245)

E	1.293***	2.798***	-1.466***	-2.820***
	(0.0197)	(0.0379)	(0.0819)	(0.176)
Constant	-1.207***	-2.419***	-2.669***	-4.497***
	(0.0391)	(0.0804)	(0.258)	(0.445)
Pseudo R^2	0.266	0.277	0.565	0.567
Observations	492,142	492,142	41,140	41,140

Table 4 Endogeneity tests by IV regression

This table reports the results of the endogeneity tests using an IV regression. The instrumental variable is *AA&A_Success_Peers*, which is the average rate of AA&A for the borrowers who applied and successfully obtained the loan at the city level. Control variables are the same as models (1) and (2), and are abbreviated as CTLs. Definitions of the variables are provided in Table 1. Robust standard errors are indicated in the parentheses. Superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	1^{st} stage	2^{nd} stage	1^{st} stage	2^{nd} stage
	Success_Peers	*Success*	*Default_Peers*	*Default*
AA&A_Success_City	**0.107*** **		**-0.105*** **	
	(0.0050)		**(0.0032)**	
Success_Peers_esitmate		**0.173*** **		
		(0.0204)		
Default_Peers_esitmate				**0.159** **
				(0.0773)
CTLs	Yes	Yes	Yes	Yes
F test	46043***		1086.6***	
LM statistics	34929***		992.6***	
Wald F statistics (10%)	39708 (16.38)		1697.9 (16.38)	
Pseudo R^2	0.147		0.323	
Observations	492,142		41,140	

Table 5 Robustness tests

This table reports the results of the robustness tests. The dependent variable in Columns (1) and (2) is *Success*, which takes the value of 1 for the borrower who applied and successfully obtained the loan and 0 otherwise. The dependent variable in Columns (3) and (4) is *Default*, which takes 1 if the borrower has defaulted or is overdue, and 0 otherwise. Control variables are the same as models (1) and (2), abbreviated as CTLs. Definitions of the variables are provided in Table 1. Robust standard errors are indicated in the parentheses. Superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	Probit	Logit	Probit	Logit
	Success	*Success*	*Default*	*Default*
Panel A. Standard errors clustered in city-level				
Success_Peers	**3.368*** **	**6.456*** **		
	(0.273)	**(0.656)**		
Default_Peers			**0.827*** **	**1.355*** **
			(0.190)	**(0.334)**
CTLs	Yes	Yes	Yes	Yes
Pseudo R^2	0.266	0.277	0.565	0.567
Observations	492,142	492,142	41,140	41,140
Panel B. Look-ahead bias controlled				
Success_Peers	**3.377*** **	**6.269*** **		
	(0.0207)	**(0.0386)**		
Default_Peers			**1.187*** **	**1.976*** **
			(0.126)	**(0.221)**
CTLs	Yes	Yes	Yes	Yes
Pseudo R^2	0.326	0.339	0.569	0.570
Observations	492,124	492,124	41,087	41,087
Panel C. Zero default rate cities eliminated				
Success_Peers	**3.368*** **	**6.456*** **		
	(0.0437)	**(0.0852)**		
Default_Peers			**0.827*** **	**1.355*** **
			(0.128)	**(0.221)**
CTLs	Yes	Yes	Yes	Yes
Pseudo R^2	0.266	0.277	0.565	0.567
Observations	492,142	492,142	41,140	41,140
Panel D. Other control variables included				
Success_Peers	**1.380*** **	**2.198*** **		
	(0.0587)	**(0.111)**		
Default_Peers			**0.482*** **	**0.769*** **
			(0.145)	**(0.253)**
CTLs	Yes	Yes	Yes	Yes
Province & Month FEs	Yes	Yes	Yes	Yes
Pseudo R^2	0.413	0.430	0.612	0.614
Observations	492,142	492,142	41,134	41,134

Table 6 Subsample tests with low (high) *Loan_to_Income*

This table reports the results of the subsample tests with low (high) *Loan_to_Income*. The dependent variable in Columns (1) and (2) is *Success*, which takes the value of 1 for the borrower who applied and successfully obtained the loan and 0 otherwise. The dependent variable in Columns (3) and (4) is *Default*, which takes the value of 1 if the borrower has defaulted or is overdue, and 0 otherwise. Control variables are the same as models (1) and (2), abbreviated as CTLs. Definitions of the variables are provided in Table 1. Robust standard errors are indicated in the parentheses. Superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	Probit	Logit	Probit	Logit
	Success	Success	Default	Default
Panel A. Low *Loan_to_Income*				
Success_Peers	**2.626*** **	**5.009*** **		
	(0.0545)	**(0.106)**		
Default_Peers			**0.796*** **	**1.304*** **
			(0.135)	**(0.233)**
CTLs	Yes	Yes	Yes	Yes
Pseudo R^2	0.214	0.225	0.510	0.512
Observations	240,033	240,033	25,538	25,538
Panel B. High *Loan_to_Income*				
Success_Peers	**4.324*** **	**7.807*** **		
	(0.0786)	**(0.152)**		
Default_Peers			**1.269*** **	**2.111*** **
			(0.390)	**(0.714)**
CTLs	Yes	Yes	Yes	Yes
Pseudo R^2	0.360	0.382	0.729	0.732
Observations	252,109	252,109	15,581	15,581

Table 7 Mechanism tests for ex-ante selection

This table reports the mechanism tests for ex-ante selection in the P2P lending market. The dependent variable is *Success*, which takes the value of one for the borrower who applied and successfully obtained the loan, and zero otherwise. Control variables are the same as models (1) and (2), abbreviated as CTLs. Definitions of the variables are provided in Table 1. Robust standard errors are indicated in the parentheses. Superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable: Success	(1) Probit	(2) Logit	(3) Probit	(4) Logit	(5) Probit	(6) Logit
Success_Peers × Default_City	**22.84*** **	**51.57*** **				
	(1.617)	**(3.460)**				
Default_City	-0.194***	-1.127***				
	(0.0722)	(0.157)				
Success_Peers × AA&A_City			**-1.164*** **	**-3.607*** **		
			(0.220)	**(0.423)**		
AA&A_City			-0.469***	-0.725***		
			(0.0258)	(0.0511)		
Success_Peers × HR_City					**1.330*** **	**4.030*** **
					(0.225)	**(0.435)**
HR_City					0.480***	0.737***
					(0.0265)	(0.0525)
Success_Peers	2.761***	5.162***	4.788***	9.696***	3.570***	5.964***
	(0.112)	(0.216)	(0.113)	(0.218)	(0.125)	(0.241)
CTLs	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.267	0.278	0.271	0.282	0.271	0.282
Observations	490,627	490,627	492,142	492,142	492,142	492,142

Table 8 Mechanism tests for ex-post learning

This table reports the results of the mechanism tests for ex-post learning in the P2P lending market. The dependent variable is *Default*, which takes 1 if the borrower has defaulted or is overdue, and 0 otherwise. Control variables are the same as models (1) and (2), abbreviated as CTLs. Definitions of the variables are provided in Table 1. Robust standard errors are indicated in the parentheses. Superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable: Default	(1)	(2)	(3)	(4)
	Probit	Logit	Probit	Logit
Default_Peers* × *Success_City	**14.83*** **	**26.19*** **		
	(5.588)	**(9.789)**		
Success_City	-0.0821	-0.228		
	(0.397)	(0.693)		
Default_Peers* × *Historical_Success_Rate			**1.122*** **	**1.684** **
			(0.432)	**(0.753)**
Historical_Success_Rate			0.444***	0.822***
			(0.0884)	(0.154)
Default_Peers	0.342	0.489	0.0273	0.159
	(0.258)	(0.449)	(0.335)	(0.589)
CTLs	Yes	Yes	Yes	Yes
Pseudo R^2	0.566	0.568	0.572	0.574
Observations	41,140	41,140	41,140	41,140

Table 9 Economic consequences of peer effects

This table reports the empirical tests that examine the economic consequences of peer effects. The dependent variable is *Default_City*, defined as the average default rate of the city. Definitions of the variables are provided in Table 1. Robust standard errors are indicated in the parentheses. Superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable: Default_City	(1) Tobit	(2) Tobit	(3) Tobit	(4) Tobit
Success_City	**-0.862***** **(0.147)**	-0.0955 (0.337)	-0.788*** (0.146)	-0.140 (0.348)
Success_City* × *Peer_Effects_Success		**-0.179**** **(0.0815)**		**-0.150*** **(0.0828)**
Peer_Effects_Success		0.0155*** (0.00430)		0.00954* (0.00532)
Success_City* × *Peer_Effects_Default			**0.0444***** **(0.0134)**	**0.0440***** **(0.0140)**
Peer_Effects_Default			-0.00303*** (0.00110)	-0.00294** (0.00118)
AA&A_City	28.211 (18.275)	36.331* (20.642)	30.529* (17.120)	34.415* (18.31)
B_City	26.327 (18.533)	35.159* (20.950)	30.438* (17.304)	34.006* (18.581)
C_City	25.651 (18.371)	33.811 (20.739)	27.639* (17.218)	31.630* (18.410)
D_City	27.594 (18.246)	35.406* (20.627)	29.385* (17.075)	33.178* (18.269)
E_City	27.955 (18.162)	36.038* (20.532)	29.993* (16.993)	33.904* (18.173)
HR_City	28.454 (18.281)	36.593* (20.647)	30.796* (17.127)	34.688* (18.312)
F Statistics	18.15***	17.70***	15.83***	15.39***
Observations	446	446	442	442