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**Working Paper**

## Naïve or sophisticated? Information disclosure and investment decisions in peer-to-peer lending

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## **ADB Working Paper Series**

### **NAÏVE OR SOPHISTICATED? INFORMATION DISCLOSURE AND INVESTMENT DECISIONS IN PEER-TO-PEER LENDING**

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Xiao Chen, Bihong Huang,  
and Mohamed Shaban

No. 1069  
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**Asian Development Bank Institute**

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**Abstract**

Despite the explosive growth of peer-to-peer lending in the People's Republic of China (PRC), information asymmetry remains a critical issue and is likely to be amplified in such an evolving credit market compared to a traditional credit market. This paper studies how investors screen the nonstandard, voluntary, and often unverifiable information disclosed by borrowers in making their investment decisions. Using data from the Renrendai P2P platform, one of the leading lending platforms in the PRC, we find that an additional item of disclosure increases the funding probability by 23.6%. The impact is even more remarkable for borrowers with a lower credit rating. However, investment in loan listings with more disclosures turns out to be riskier. An additional item of disclosure is accompanied by an incremental default probability of 11.7%. The puzzle that lenders remain attracted by such loan listings is explained by the higher profitability offered by the borrowers. Further investigation shows that investors can infer the real risk of borrowers marked by the disclosure.

**Keywords:** voluntary information disclosure, manipulation, information asymmetry, P2P lending

**JEL Classification:** G14, G23

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# 1. INTRODUCTION

Online peer-to-peer (P2P) lending platforms have emerged as an alternative to traditional lending institutions around the world (Sorenson et al. 2016). These platforms bypass banks by capitalizing on the advance of digital technology. Online P2P lending is a particular type of credit market in which individuals engage in lending practices. The lenders provide microloans to borrowers without collateral or the mediation of financial intermediaries (Lin, Prabhala, and Viswanathan 2013). P2P lending facilitates access to credit for small borrowers (Paravisini, Rappoport, and Ravina 2017) and offers a higher rate of return for investors (Duarte, Siegel, and Young 2012). Information asymmetry seems to be a critical and somewhat magnified issue in such an evolving market, relative to the traditional credit market (Herzenstein, Sonenshein and Dholakia 2011). In the latter, financial intermediaries' role is to evaluate and monitor borrowers' creditworthiness and accordingly make professional lending decisions, while in the former the platforms act as the matchmaker refraining from conducting any function that implies financial intermediation. The lenders make the investment decision mainly based on standard financial information as well as nonstandard information voluntarily disclosed by the borrowers (Iyer et al. 2016). There is a sizable literature that has extensively investigated the role of disclosure, particularly mandated and audited financial reports, in mitigating information asymmetry in the financial markets (Balakrishnan et al. 2014; Brockman, Khurana, and Martin 2008; Brockman, Martin, and Puckett 2010; Chung, Judge, and Li 2015; Goldstein and Yang 2019; Zhao, Allen, and Hasan 2013). Nonetheless, little is known about the role of information disclosure by individuals in a peer-to-peer context. Disclosure in such an information-opaque market is likely to influence the investment decisions made by peer lenders and indeed may shape the future of this new but rapidly growing fintech market.

This study fills the gap in the literature by capitalizing on the opulence of the Chinese P2P lending market. We use unique data from Renrendai, one of the leading P2P lending platforms in the PRC, to study the voluntary disclosures by borrowers and their impact on market efficiency. The PRC has developed the most prominent and fastest-growing market for online P2P lending. In 2016, the transaction volume of P2P lending nationwide exceeded 2.8 trillion yuan (US\$ 403 billion), with an increase of 138% from a year earlier.<sup>1</sup> Figure 1 plots the volume of transactions in the Chinese P2P lending market from 2013 to 2017. The government has encouraged the development of online finance to promote alternative sources of funding for consumers and small businesses that have long struggled to access finance from stodgy state-owned banks (SOBs). In the PRC, SOBs lean toward lending to large companies or those borrowers with sufficient tangible assets to pledge as collateral. Despite the explosive growth of fintech, the social credit system remains underdeveloped in the PRC and other emerging economies. As of 2014, the People's Bank of China maintained credit histories for around 350 million citizens, less than a third of the adult population, while in America 89% of adults have credit scores.<sup>2</sup> The well-established credit system in high-income countries can provide hard and solid information to support P2P lending. For example, Smava, the P2P platform in Germany, only allows loan applications from borrowers with a specific minimum credit score (Dorfleitner et al. 2016). On such platforms, investors rely heavily on hard information like credit scores, while the effect of soft information on funding success and the default rate is limited. At their inception, most of the Chinese

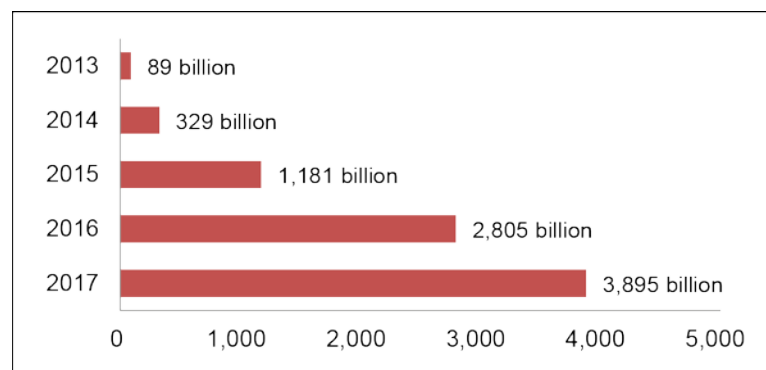
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<sup>1</sup> [http://www.chinadaily.com.cn/business/2017-01/05/content\\_27866083.htm](http://www.chinadaily.com.cn/business/2017-01/05/content_27866083.htm).

<sup>2</sup> <https://www.economist.com/news/finance-and-economics/21710292-chinas-consumer-credit-rating-culture-evolving-fastand-unconventionally-just>.

platforms did not have credit scores for borrowers. Voluntary disclosure by borrowers is the primary information source for investors to infer credit quality and make investment decisions. Under such conditions, the information asymmetry in the P2P lending market is amplified. Therefore, it is essential to explore the various mechanisms through which the information asymmetry between borrowers and lenders could be moderated (Strausz 2017).

**Figure 1: Volume of P2P Lending in the PRC, 2013–2017**



Analyzing 604,885 loan listings posted on Renrendai, we find that voluntary disclosure plays a significant role in forming lenders' investment decision. A single item of voluntary information disclosure enhances the funding success rate by 23.6%. The impact is even more remarkable for borrowers with a lower credit rating. We further compare the influence of verified and unverified information on the probability of funding. Our findings show that borrowers with more verified information are more likely to get a loan. However, investment in loan listings with more disclosures turns out to be riskier. Borrowers who list an additional item of disclosure are likely to increase their incremental default probability by 11.7%. Our results imply the possibility of information manipulation by borrowers in the Chinese P2P market. In other words, the results reveal a dark side of P2P lending, confirming borrowers' moral hazard behavior. Poor-quality borrowers exploit the high level of information asymmetry and the lack of hard information by disclosing more information to capture funding, but with a premeditated intention to default. These poor-quality borrowers may choose to disclose false information to mimic good-quality borrowers in order to acquire loans. Such manipulation of disclosure exacerbates the market inefficiency arising from information asymmetry. We find that factors such as education, work experience, and income play a much more significant role in affecting investors' choice than other information. The well-educated borrower may choose to disclose his or her degree while concealing other relevant information that may reflect material financial risk.

There is an important question that seems to impose itself in our study: Are investors sophisticated enough to infer the real credit quality of borrowers, considering the amount and quality of information voluntarily disclosed by borrowers? We find that lenders can infer the real risks that are not reflected by disclosures. They are reluctant to invest in loan listings with a higher level of default risk. It takes more time and needs more bids for such loan listings to get funded. A possible explanation for the puzzle that lenders remain attracted by loan listings with more disclosures but a higher default risk is the higher profitability offered by the borrowers (higher interest rate). The empirical evidence suggests that although loan listings with more voluntary information disclosures are more likely to default, the borrowers offer a higher interest rate as compensation for such a risk. At the same time, those loans with more voluntary information disclosures

have less loss when they are defaulted. Therefore, it appears to be an appealing choice for lenders to invest in loans with more voluntary information disclosures.

To infer the causal impact of disclosure on investment choice, there are a number of important endogeneity concerns to be addressed. First, as default depends on success, we can only observe the defaults among borrowers who have successfully had their loan requests funded and cannot observe defaults by those who fail to raise the funds. Hence, our estimation on the default might be susceptible to sample selection bias. Moreover, some unobservable or omitted variables may contaminate our estimation results. For example, social networks and investor sentiment may change the funding success rate (Grinblatt, Keloharju, and Linnainmaa 2011). We employ several empirical strategies to address these challenges, including the Heckman selection model and the instrumental variable probit model. In particular, we employ the widely recognized peer effect as the instrument for information disclosure (Adhikari and Agrawal 2018; Chen 2015; Eom 2018; Hasan and Cheung 2018; Huang and Mazouz 2018; Jiang and Yuan 2018; Kim, Patro, and Pereira 2017; Ward, Yin, and Zeng 2018; Zhang et al. 2016). The empirical results show that our conclusions are robust across different estimations after controlling for endogeneity.

Our study is an indispensable addition to the limited yet growing literature on P2P lending (Chen, Huang, and Ye 2019; Duarte, Siegel, and Young 2012; Lin, Prabhala, and Viswanathan 2013; Lin and Viswanathan 2016; Pope and Sydnor 2011). Our work is different from the study of Michels (2012) that investigates the effect of information disclosure on funding cost using the data from the Prosper platform in the US. His study focuses on the role of nonvoluntary disclosure by borrowers in reducing borrowing cost. Our study rather emphasizes the role of voluntary disclosure and unverifiable information. We argue that both voluntary disclosure and unverifiable information might be used by borrowers as a signal of creditability, thereby providing incentives to lenders to invest. The moral hazard behavior of borrowers manifested in such deceptive signaling is likely to lead to a higher probability of default and hence the loss of investors' wealth. The long-term policy implication of such acts may result in a loss of confidence and a slowing down of the industry. Our results reveal that borrowers strategically disclose in the market where the social credit system is underdeveloped in order to affect the investment decision. The implications of nonvoluntary and unverifiable information are likely to be augmented in the Chinese market given the relatively high level of information opaqueness compared to a developed market.

Disclosure plays a vital role in improving the efficiency of financial markets. Previous literature indicates that disclosure is associated with stock performance, bid-ask spreads, cost of capital, analyst coverage, and institutional ownership. Empirical evidence shows that imposing minimum disclosure requirements attenuates the information asymmetry between informed and uninformed investors (Ball, Jayaraman, and Shivakumar 2012; Bertomeu and Magee 2015; Hirshleifer and Teoh 2003). Our research enriches the existing literature on information asymmetry that is detrimental to the efficiency of financial markets. We provide evidence from the evolving P2P market that is little known about. Despite the current belief that disclosure is a valuable tool for reducing the adverse implications of information asymmetry, this study reveals that investors' moral hazard offsets the benefits of involuntary disclosure and leads to market inefficiency. In a market that can be described as being both evolving and information-opaque, investors should investigate the quality of information and demand verification of what is disclosed by borrowers.

The literature from psychology and behavioral economics claims that uninformative material influences behavior and choices significantly (Bertrand and Morse 2011).



Nonetheless, the role of voluntary and unverifiable information in screening the credit quality of borrowers and its impact on investment decisions is still ambiguous (Bernardo, Cai, and Luo 2004). Our study provides compelling evidence in this regard by showing that voluntary and unverifiable information has a significant influence on lenders' inference of borrowers' creditworthiness even when standard financial information like credit scores is not available.

The remainder of this paper is organized as follows. Section 2 reviews related literature; Section 3 describes our data set and measurement of key variables; Section 4 reports the main results; Section 5 addresses the endogeneity concerns; Section 6 summarizes the various robustness checks; and Section 7 concludes the paper.

## 2. RELATED LITERATURE

Since the seminal contributions of Akerlof (1970), Spence (1973), and Stiglitz and Weiss (1981), the link between lemon theory and disclosure has been widely investigated in the literature (Bhattacharya and Ritter 1983; Ghose 2009; Hughes 1986; Leftwich, Watts, and Zimmerman 1981; Lewis 2011; Pae 2002; Pownall and Waymire 1989; Tadelis and Zettelmeyer 2015; Teoh and Hwang 1991). Disclosure is seen as the primary solution to the information asymmetry that impedes the efficient allocation of resources in the capital market. Healy and Palepu (2001) show that financial accounting and reporting is a mechanism to moderate information asymmetry by converting inside information into public information. Kothari (2001) suggests that reducing information asymmetry has desirable effects on the cost of capital and the stability of security prices, which motivate regulators to strive for high-quality accounting standards. Examining the ex ante effects of public information quality on market prices, Barron and Qu (2014) conclude that high-quality public disclosure leads to increased price efficiency and decreased cost of capital in the pre-announcement period when information asymmetry is high. Studying the information-gathering role of a startup accelerator, Kim and Wagman (2014) demonstrate that when some signals are uninformative, and the portfolio consists of mostly high-quality ventures, the accelerator may choose to disclose only positive signals (and conceal negative signals) about its portfolio. Cheng, Liao, and Zhang (2013) find that firms that are eligible to reduce their disclosure, but voluntarily maintain their disclosure level, experience an increase in market illiquidity. Vashishtha (2014) shows that firms reduce disclosure following covenant violations and part of this decline in disclosure reflects a delegation of monitoring to banks by shareholders who consequently demand less disclosure.

The existing literature suggests that although most information accessible to investors in traditional lending markets is nonstandard, unverifiable, or "soft," it is valuable as far as borrower creditworthiness is concerned (Agarwal and Hauswald 2010; Bertomeu and Marinovic 2016; Inderst and Mueller 2007; Keys et al. 2010; Keys, Seru, and Vig 2012; Rajan, Seru, and Vig 2015). Early research on information asymmetry and disclosures has typically assumed that disclosures must be made truthfully and signals are costless and verifiable (Bagnoli and Watts 2007). However, the seminal paper of Crawford and Sobel (1982) triggered more and more researchers to explore scenarios where the disclosures are not necessarily truthful. In "cheap-talk" games, disclosures can even be false. Gigler (1994) shows that even when disclosures are unverifiable, the cost associated with disclosures lends them credibility. Analyzing self-reported anti-corruption efforts, Healy and Serafeim (2016) conclude that on average, firms' disclosures signal real efforts to combat corruption.

In other words, while traditional theory argues that unverifiable disclosures should be irrelevant, more and more evidence indicates that unverifiable information affects investment decisions. Without intermediation from financial institutions, P2P lending platforms provide a decentralized and market-based mechanism that makes it easier for investors to screen the creditworthiness of borrowers by aggregating information disclosed by borrowers. Besides the standard and hard financial information commonly used by banks, such as the borrower's income and credit report, lenders can view nonstandard, unverifiable, and less quantifiable information, such as the maximum interest rate the borrower is willing to pay, a textual description of the borrowing purpose, and the borrower's personal information like age, employment, marriage status, living place, etc. If investors are influenced by the voluntary and unverifiable disclosures made by borrowers in their loan listings, the funding probability will increase with more disclosures.

However, the impact of information disclosure on funding success hasn't reached consensus yet. According to Wittenberg-Moerman (2008) research on the secondary market transactions of syndicated loans, investors are more sensitive to the economic returns of discount loans than those of flat loans. In other words, when investors evaluate the claims of these borrowers, the good news will be more critical. Wittenberg-Moerman (2008) also confirm that the borrower's timely financial report does not have a significant impact on the bid-ask spread in loan transactions. His empirical evidence implies that more financial information does not necessarily enhance investors' trust in borrowers and the funding success rate because some particular information may trigger discrimination against these borrowers. For example, using data from Prosper.com, the leading P2P lending platform in the US, Pope and Sydnor (2011) find evidence of significant racial disparities. Loan listings by blacks are less likely to receive funding than those of whites with similar credit profiles, while the interest rate paid by blacks is higher than that paid by comparable whites. Another study by Duarte, Siegel, and Young (2012) employs similar data showing that borrowers that appear to be more trustworthy are more likely to have their borrowing requests funded. The empirical evidence produced by Lin and Viswanathan (2016) suggests that home bias is a robust phenomenon even in the context of a sizable online crowdfunding marketplace. Chen et al. (2019) discover a gender gap that discriminates against female borrowers on a Chinese P2P lending platform. This series of studies have shown that borrowers' voluntary disclosure of information does not necessarily lead to a higher probability of funding success. On the contrary, some information, such as gender, race, and low income, may even trigger discrimination toward borrowers and hence lower the funding probability.

Michels (2012) claims that voluntary information disclosure can reduce both the interest rate and the default rate. This argument is consistent with the theory of cheap talk and behavioral economics that people tend to believe whatever information they can get, and it is difficult to ignore the irrelevant information in decision-making. A large number of studies have shown that corporate voluntary information disclosure can moderate the cost of capital. Balakrishnan et al. (2014) find that voluntary disclosure is beneficial for a firm as it improves its liquidity, increases its market value, and reduces its capital cost. Dhaliwal et al. (2014) document that disclosing a company's corporate social responsibility can significantly reduce its cost of equity capital. The research of Jones (2007) also confirms that voluntary disclosure of R&D input could lower the proprietary cost. Francis, Nanda, and Olsson (2008) assert that companies with good earnings quality are likely to disclose sufficient information, thereby suggesting a complementary relationship between earnings quality and voluntary information disclosure. At the same time, voluntary information disclosure can reduce the cost of capital, increase stock liquidity, and reduce the operational risks. Francis, Khurana, and Pereira (2005) suggest

that enterprises that rely on external financing are more likely to make a higher level of information disclosure, which leads to a lower external financing cost. They confirm that their conclusion is independent of factors at the national level and can be generalized worldwide. In the lending market, high-quality borrowers have good reasons to voluntarily disclose more information to lower the borrowing rate and improve the funding probability.

Other studies find that companies are more likely to engage in manipulation when voluntary disclosure is closely related to the response of capital market (Evans 2016). Wen (2013) finds that management might disclose information beneficial to the company because voluntary disclosure affects its stock price. Roychowdhury and Sletten (2012) believe that management has strong incentives to avoid disclosing bad news. Also, the risk faced by the company affects the voluntary disclosure of information. Zechman (2010) claims that cash constraints may make managers reluctant to disclose the transaction information concerning financial assets. Nelson and Pritchard (2016) show that companies facing a high litigation risk would improve the quality of voluntary disclosure. Beyer and Guttman (2012) prove that management would manipulate voluntary information disclosure to obtain favorable conditions. In the credit market, borrowers have the best understanding of their ability and willingness to repay the loan. They may manipulate the content of disclosure in order to win the trust of lenders and acquire loans. Such manipulation, in turn, implies a potential positive relationship between default probability and the amount of voluntary disclosure.

Voluntary information disclosure is associated with impression management, the behavior through which people influence others' perception of themselves (McDonnell and King 2013). Individuals form impressions of others in social interactions and extend them accordingly (Bansal and Clelland 2004; Barsness, Diekmann, and Seidel 2005; Davidson et al. 2004; Hayward and Fitza 2017). Although the proverb says "don't judge a book by its cover," people still rely on the appearance of things to make decisions in most cases (Langlois et al. 2000). The study by Foulk and Long (2016) implies that newcomers use observed ingratiation, a common impression management strategy to form impressions of a supervisor's warmth. The existing literature on P2P lending suggests that borrowers design and form their image by using positive words in loan descriptions to show their strong willingness to repay (Herzenstein, Sonenshein, and Dholakia 2011). However, such impression management incentives can lead borrowers to disguise information that is relevant to the real credit risk (Leary and Kowalski 1990; Morrison and Bies 1991).

### **3. DATA SOURCE, KEY VARIABLE MEASUREMENT, AND SUMMARY STATISTICS**

#### **3.1 Data Source**

We obtained the data for this study from Renrendai, one of the largest peer-to-peer lending platforms in the PRC. Founded in 2010, it now has over one million members located in more than 2,000 cities or counties across the country. Moreover, the reputation of Renrendai has been well recognized in the PRC. In 2014 and 2015, it was awarded the status of AAA (the highest level) online lending platform by the Internet Society of China and the China Academy of Social Science. It ranked no. 53 in a list of the PRC's top 100 internet companies released by the Internet Society of China and the Ministry of Industry and Information in 2015.

Transactions taking place at Renrendai reflect typical P2P lending. On Renrendai, borrowers can post loan requests or listings with the required P2P information, i.e. the loan title, borrowing amount, interest rate, description of loan usage, and monthly installment. Renrendai only provides basic verification of borrowers' national identification cards, credit reports, and addresses. It assigns a credit score to each borrower according to his or her borrowing/lending history and the amount of verified information. As with Prosper.com, Renrendai's profit mainly comes from the borrower's closing fee and the lender's servicing fee. Since the verification and credit rating provided by Renrendai are limited, it is of critical importance for the lenders to identify the trustworthiness of the borrowers from the observable information disclosed on the platform. In particular, when creating loan listings, borrowers are encouraged to disclose additional information regarding the purpose of the loan and other personal information in a free-form text called the "loan description." Figure 2 shows a typical loan request on Renrendai. Once a loan listing has been posted online, lenders may place bids by stating the amount they want to fund. With a minimum bid amount of RMB 50, a listing typically requires dozens of bids to become fully funded. A listing that achieves 100% funding status is a "successful" listing; otherwise, the borrower receives zero funding.

**Figure 2: Example Loan Listing on Renrendai.com (Loan ID=469679)**

借款机器购买

借款协议 (范本)

50,000元

Loan Amount

13.00%

Annual Interest Rate

24Month

Duration

保障方式

本金 ①

提前还款费

1.00%

还款方式

按月还款/等额本息 ①

已流标

已流标

散标详情

投标记录

还款表现

债权信息

转让记录

借贷人信息

昵称 张轩博.rrd

信用评级 HR

基础信息

Age 28

Education --

Marital status --

信用信息

申请借款 1笔

信用额度 0.00元

逾期金额 0.00元

成功借款 0笔

借款总额 0.00元

逾期次数 0次

还清笔数 0笔

待还本息 0.00元

严重逾期 0笔

资产信息

Income --

房产 无房产

房贷 无房贷

车产 无车产

车贷 无车贷

工作信息

Industry --

Firm Size --

Position --

City --

Work Experience --

Source: <https://www.we.com/loan/469679>.

The transaction module of Renrendai is comparable to that of Prosper, the largest lending platform in the US and the main data source for most of the existing research (Duarte, Siegel, and Young 2012; Hildebrand, Puri, and Rocholld 2017; Iyer et al. 2016; Lin, Prabhala, and Viswanathan 2013; Lin and Viswanathan 2016; Michels 2012; Zhang

and Liu 2012). On Prosper, borrowers post personal loan requests while investors (individual or institutional) can fund anywhere from \$2,000 to \$35,000 per loan request. In addition to credit scores, ratings, and histories, investors can use borrowers' loan descriptions, endorsements from friends, and community affiliations to make an investment decision. Prosper handles the servicing of the loan and collects and distributes borrower payments and interest back to the loan investors. Prosper verifies borrowers' identities and personal data before funding loans and manages all stages of loan servicing.

This study uses all loan listings created on Renrendai between 1 January 2011 and 31 December 2015. We eliminate the data earlier and later than this period to avoid the initial launch period and truncation of loan repayments, respectively. The original sample includes 795,110 listings. We also eliminate 190,225 listings guaranteed by the platform because they are not typical P2P lending. In addition, we winsorize the loan listings whose AMOUNT and AGE are in the top or bottom one percentile of their respective distributions to eliminate outliers. As a result, our sample includes 604,885 loan listings, of which 27,112 were successfully funded while the rest were not funded. We track the repayment of all successful loan listings. By the end of September 2017, there were 4,094 defaulted listings and 414 samples in progress of repayment.

## 3.2 Key Variables

### 3.2.1 Measurement of Information Disclosure

To gauge the effects of voluntary information disclosure on loan outcome and loan performance, we construct an information disclosure measurement. There are two kinds of information disclosure at Renrendai: compulsory disclosure and voluntary disclosure. Compulsory information includes: (1) borrowing amount, interest rate, and term; (2) borrower's age and assets like ownership of housing or car; and (3) loan description, corresponding title, and borrower's nickname.

There are nine items of voluntary disclosure at Renrendai, including education, employment, income, marriage, living place, purpose of borrowing, etc. We award a point for each of them to construct the variable of voluntary disclosure. Detailed descriptions of all these nine items are listed below.

1. *Education*: a borrower's educational attainment. It is classified into four levels, namely high school or below, junior college, bachelor, and postgraduate and above.
2. *Working experience*: the length of time that a borrower has worked. It is classified into four categories, i.e. one year or less, one to three years, three to five years, and more than five years.
3. *Income*: a borrower's monthly income. It is classified into the following seven ranks: less than RMB1,000; 1,001–2,000; 2,001–5,000; 5,001–10,000; 10,001–20,000; 20,001–50,000; and more than 50,000.
4. *Marriage*: the marital status of borrowers, including divorced, widowed, single, or married.
5. *Living place*: the prefecture or district (of a municipality) that a borrower is living in.
6. *Firm size*: the size of the firm that a borrower is working for. It is classified into four categories as follows: less than 10 employees, 10–100 employees, 100–500 employees, and more than 500 employees.

7. *Loan purpose*: the usage of the fund described by the borrowers, including short-term turnover, personal consumption, auto loans, mortgage, wedding planning, education or training, investment, medical expenditure, home renovation, etc.
8. *Industry*: the industry that a borrower is working in, including IT, restaurant/hotel, real estate, public utilities, public welfare organizations, computer systems, construction, transportation, education/training, finance, law, retail/wholesale, media/advertising, energy, agriculture, sports/arts, medical/sanitation/health care, entertainment, government agencies, manufacturing, and other.
9. *Position*: the position that a borrower has in his working place, such as clerk, manager, etc.

We denote the abovementioned nine items of borrowers' voluntary disclosure as *Edu\_Disclosure*, *Worktime\_Disclosure*, *Income\_Disclosure*, *Marry\_Disclosure*, *City\_Disclosure*, *Firmsize\_Disclosure*, *Purpose\_Disclosure*, *Ind\_Disclosure*, and *Position\_Disclosure*, respectively. We then construct three indicators to measure the intensity of information disclosure, namely *DSCORE\_ALL*, *DSCORE*, and *DSCORE\_NOR*. We give a point to each item of information disclosed in a loan list. *DSCORE\_ALL* is the sum of the points that a loan listing is awarded for all the information voluntarily disclosed. *DSCORE* is a dummy that is equal to one if a borrower discloses all nine items of voluntary information, and zero otherwise. In our sample, almost all borrowers disclose the purpose of borrowing and marriage status. To avoid estimation bias, we construct the indicator of *DSCORE\_NOR* to calculate the amount of voluntary information disclosed, except purpose of borrowing and marriage status. For example, in Figure 2, borrower's *DSCORE\_ALL* equals 0, *DSCORE* equals 1 (only disclosed loan purpose), and *DSCORE\_NOR* equals 0.

In addition to the disclosure, we include two categories of control variables in the regression. The first is the information related to loan listings, including the term, interest rate, and borrowing amount, etc. The second is related to the credit risk of borrowers, including the credit score, if any, mortgage, auto loans, etc. Table 1 summarizes the definition of all variables used in this study.

### 3.2.2 Measurement of Loan Performance

In addition to the interest rate, we calculate the expected profit and expected loss of all loan listings to comprehensively measure the loan performance.

#### **Expected Profit**

Assume that each loan is for \$1, and if the borrower repays the loan, the lender receives  $(1 + r)$ , where  $r$  is the interest rate. This means that the lender earns a net profit of  $r$  if the borrower repays the loan, and loses the entire dollar if the borrower fails to repay the loan. If the default probability (DP) is  $\delta$ , a lender's expected profit (EP) on a loan listing is  $E[\pi] = (1 - \delta)r - \delta$ . To get the DP, the likelihood that a borrower defaults, we estimate the following equation using the probit model:

$$\Pr(\text{DEFAULT}_i) = \alpha_0 + \alpha_1 X_i + u_i \quad (1)$$

where the dependent variable indicates whether a loan listing  $i$  defaults after it is successfully funded. It equals 1 if the borrower defaults and 0 otherwise.  $X_i$  is a vector of control variables, including loan characteristics, borrower characteristics, and year effect.  $u_i$  refers to the error term. The coefficients estimated from Equation (1) are then

used to predict the default probability of each loan listing. With the default probability and interest rate, we are able to measure the expected profit for each loan listing.

**Table 1: Variables and Definitions**

<b>Name</b>	<b>Definition</b>
<i>SUCCESS</i>	1 if a loan listing is successfully funded, 0 otherwise
<i>INTEREST</i>	The annual interest rate that a borrower pays on the loan (%)
<i>DEFAULT</i>	1 if the funded loan has been defaulted, 0 otherwise
<i>BIDS</i>	The number of bids needed for a list to be successfully funded
<i>FundTime_M</i>	The amount of time needed for a list to be successfully funded (minutes)
<i>Ver_Numb</i>	The amount of information in a loan listing that has been verified by the platform
<i>EP</i>	Expected profit of a loan listing
<i>LRR</i>	Loan repayment ratio
<i>DL</i>	Default loss of a loan request
<i>DSCORE</i>	The amount of information disclosure
<i>DSCORE_ALL</i>	1 if borrower discloses all information, 0 otherwise
<i>DSCORE_NOR</i>	The amount of information disclosure, except marital status and borrowing purpose
<i>AMOUNT</i>	Loan amount requested by the borrower (RMB)
<i>MONTHS</i>	Loan term requested by the borrower (months)
<i>CREDIT</i>	Credit grade of a borrower at the time the listing was created. Values between 1 (high risk) and 7 (AA)
<i>POOR</i>	1 if a borrower's credit is high risk (HR), 0 otherwise
<i>AGE</i>	Age of the borrower (in years)
<i>HOUSE</i>	1 if a borrower owns a house, 0 otherwise
<i>CAR</i>	1 if a borrower owns a car, 0 otherwise
<i>T_Length</i>	The length of a loan title
<i>D_Length</i>	The length of a loan description (number of Chinese characters)
<i>N_Length</i>	The length of a borrower's nickname (number of Chinese characters)
<i>Year</i>	Year dummies for the period 2011–2015
<i>Edu_Disclosure</i>	1 if education level is disclosed, 0 otherwise
<i>Worktime_Disclosure</i>	1 if working experience is disclosed, 0 otherwise
<i>Income_Disclosure</i>	1 if income is disclosed, 0 otherwise
<i>Marry_Disclosure</i>	1 if marital status is disclosed, 0 otherwise
<i>City_Disclosure</i>	1 if residential city is disclosed, 0 otherwise
<i>FirmSize_Disclosure</i>	1 if company size is disclosed, 0 otherwise
<i>Purpose_Disclosure</i>	1 if purpose of loan is disclosed, 0 otherwise
<i>Ind_Disclosure</i>	1 if the working industry is disclosed, 0 otherwise
<i>Position_Disclosure</i>	1 if position is disclosed, 0 otherwise

### **Expected Loss**

Following the literature on credit risk management (Bessis 2015), we define the expected loss (EL) of a loan listing as the product of loss given default (LGD) and DP, i.e.

$$EL = LGD \times DP.$$

We define LGD as the fraction of the principal amount remaining if the borrower defaults at time  $t$ . In accordance with the common practice applied at Renrendai, we assume that all loan listings are fully amortized. The borrower pays off the debt with a fixed monthly repayment schedule in equal installments so that the loan will be fully paid off at maturity. Hence, according to Hayre and Mohebbi (1992), LGD can be computed as follows:

$$LGD = 1 - \frac{(1 + r^m)^t - 1}{(1 + r^m)^n - 1}$$

where  $r^m$  is the monthly rate (i.e. the note rate divided by 12) and the term  $n$  is quoted in months. For the loan listings fully repaid at maturity,  $t = n$ , and hence  $LGD = 0$ . After computing  $LGD$ , we can obtain the repayment ratio ( $RR$ ) for the problematic loans as  $RR = 1 - LGD$ .

### 3.3 Summary Statistics

Panel A of Table 2 shows the summary statistics for information disclosure. Among the nine items of voluntary information, almost all borrowers disclose their borrowing purpose and marital status, and around 70% disclose the city they live in, the size of the firm, the industry they are working in, and their positions. Overall, most borrowers are willing to disclose as much personal information as possible so as to get their loan requests funded.

Panel B of Table 2 tests for the mean differences between funded and unfunded listings, as well as whether loans default or not. In terms of information disclosure, the mean DSCORE for funded loan lists is 8.75, or 1.74 points significantly higher than that of unfunded loan lists. In addition, we also find that the mean DSCORE for default loans is 8.83, or 0.1 points significantly higher than that of a loan repaid on time. Compared with the loan lists that don't disclose all information, the lists with full information disclosure on average are 5% more likely to get their loan request funded and are 6% more likely to default. Their interest rates are also 0.93% higher.

Table 3 reports the correlation matrix of key variables. It is clear that borrowing rates, amounts, terms, and the lengths of nicknames are significantly and negatively correlated with funding success, whereas borrowers' credit rating, age, ownership of property and car, the lengths of borrowing title, and borrowing description are significantly and positively associated with funding success. More importantly, all nine items of voluntarily disclosed information are positively correlated with funding success, interest rate, and loan default.



**Table 2: Summary Statistics of Information Disclosure**

Panel A		Summary Statistics of Information Disclosure			
Variable	Mean	Sd		N	
Edu_Disclosure	0.881	0.324		604,885	
Worktime_Disclosure	0.700	0.458		604,885	
Income_Disclosure	0.755	0.430		604,885	
Marry_Disclosure	0.969	0.174		604,885	
City_Disclosure	0.698	0.459		604,885	
Firmsize_Disclosure	0.697	0.459		604,885	
Purpose_Disclosure	0.998	0.044		604,885	
Ind_Disclosure	0.697	0.459		604,885	
Position_Disclosure	0.694	0.461		604,885	

Panel B		Difference Test			
Variables	SUCCESS==0	Mean1	SUCCESS==1	Mean2	MeanDiff
DSCORE_ALL	577,723	0.63	27,111	0.9	−0.27***
DSCORE	577,723	7.01	27,111	8.75	−1.74***
DSCORE_NOR	577,723	5.05	27,111	6.75	−1.71***
Variables	DEFAULT==0	Mean1	DEFAULT==1	Mean2	MeanDiff
DSCORE_ALL	23,018	0.89	4094	0.93	−0.04***
DSCORE	23,018	8.74	4,094	8.83	−0.10***
DSCORE_NOR	23,018	6.74	4,094	6.83	−0.10***
Variables	DSCORE_ALL==0	Mean1	DSCORE_ALL==1	Mean2	MeanDiff
SUCCESS	218,823	0.01	386,062	0.06	−0.05***
INTEREST	218,823	12.76	386,062	13.70	−0.93***
DEFAULT	2,697	0.100	24,415	0.160	−0.06***

**Table 3: Correlation Matrix**

	<b>SUCCESS</b>	<b>INTEREST</b>	<b>DEFAULT</b>	<b>AMOUNT</b>	<b>MONTHS</b>	<b>CREDIT</b>	<b>AGE</b>		
SUCCESS	1								
INTEREST	-0.0513*	1							
DEFAULT	0.3811*	-0.0089*	1						
AMOUNT	-0.0807*	0.0513*	-0.0301*	1					
MONTHS	-0.0856*	0.1395*	0.0158*	0.2182*	1				
CREDIT	0.4686*	-0.0400*	0	-0.0163*	-0.0777*	1			
AGE	0.0922*	0.0472*	0.0385*	0.2348*	0.0442*	0.0995*	1		
	<b>SUCCESS</b>	<b>INTEREST</b>	<b>DEFAULT</b>	<b>HOUSE</b>	<b>CAR</b>	<b>T_Length</b>	<b>D_Length</b>	<b>N_Length</b>	
SUCCESS	1								
INTEREST	-0.0513*	1							
DEFAULT	0.3811*	-0.0089*	1						
HOUSE	0.1175*	0.0402*	0.0374*	1					
CAR	0.1268*	0.0039*	0.0266*	0.3634*	1				
T_Length	0.0730*	0.0521*	0.0176*	0.0647*	0.0607*	1			
D_Length	0.0727*	0.1215*	0.0193*	0.0991*	0.1024*	0.2416*	1		
N_Length	-0.1106*	-0.2143*	-0.0358*	-0.1337*	-0.0947*	-0.0232*	-0.1018*	1	
	<b>SUCCESS</b>	<b>INTEREST</b>	<b>DEFAULT</b>	<b>DSCORE_ALL</b>	<b>DSCORE</b>	<b>DSCORE_NOR</b>			
SUCCESS	1								
INTEREST	-0.0513*	1							
DEFAULT	0.3811*	-0.0089*	1						
DSCORE_ALL	0.1182*	0.1575*	0.0509*	1					
DSCORE	0.1273*	0.1533*	0.0509*	0.8974*	1				
DSCORE_NOR	0.1277*	0.1524*	0.0511*	0.9021*	0.9982*	1			

Note: \*  $p < 0.05$ .

Table 4 presents descriptive statistics of all variables used in this study. The average funding success rate is about 4.48%, among which 15.1% default, implying that the competition for funding is very tough in the P2P lending market where the credit risk is high. On average, it takes about 122 minutes for each loan to raise money successfully. The average loan has about 25 investors. The average borrower has only 2.5 items of certified information. A typical loan has an expected return of 19.82 yuan, a recovery rate of 0.421, and an average default loss of -709 yuan. Borrowers on average voluntarily disclose about 7.09 out of 9 information items. The borrowers who voluntarily disclose all information account for 63.8% of all borrowers, implying that most borrowers are willing to disclose as much information as possible so as to transmit signals of trustworthiness to investors. The average borrowing rate is approximately 13.36% and the average borrowing amount is RMB59,000 (around \$10,000), indicating the role of the P2P lending market in facilitating microfinance. The credit grades of borrowers are universally low with an average credit rating of 1.083. Most borrowers are young in the P2P lending market with an average age of around 32. Additionally, 30.7% of borrowers own houses and 17.8% have cars. The average loan title length is 13.72 Chinese characters and punctuation marks while the average loan description length is 92.49 Chinese characters. The average length of a borrower's nickname is 9.7 Chinese characters and punctuation marks.

**Table 4: Summary Statistics**

Variable	Obs	Mean	Std. Dev.	Min	Max
SUCCESS	604,885	0.0448	0.207	0	1
INTEREST	604,885	13.36	2.851	3	24.40
DEFAULT	27,112	0.151	0.358	0	1
DSCORE	604,885	7.090	2.827	0	9
DSCORE_NOR	604,885	5.123	2.764	0	7
DSCORE_ALL	604,885	0.638	0.481	0	1
FundTime_M	27,112	122.8	574.4	0	6,269
BIDS	27,112	25.19	44.04	0	747
Ver_Numb	604,885	2.547	1.392	0	11
EP	604,885	19.82	11.43	-20.60	187.4
LRR	4,094	0.421	0.284	0	0.967
DL	604,885	-709.3	64239	-3,108,765	878,353
AMOUNT	604,885	58,956	90,079	3,000	500,000
MONTHS	604,885	15.74	9.184	1	36
CREDIT	604,885	1.083	0.488	1	7
AGE	604,885	32.16	6.363	24	53
HOUSE	604,885	0.307	0.461	0	1
CAR	604,885	0.178	0.383	0	1
T_Length	604,885	13.72	7.128	1	108
D_Length	604,885	92.49	76.25	1	999
N_Length	604,885	9.706	3.184	1	32
YEAR=2011	604,885	0.0335	0.180	0	1
YEAR=2012	604,885	0.0468	0.211	0	1
YEAR=2013	604,885	0.0997	0.300	0	1
YEAR=2014	604,885	0.331	0.471	0	1
YEAR=2015	604,885	0.489	0.500	0	1

## 4. MAIN RESULTS

We first examine the extent to which information disclosure and its intensity affect investment decisions. We also compare the information disclosure by borrowers of different credit categories and its impact on funding probability. Next, we explore whether information revealed by borrowers reflects their creditworthiness. Given the unexpected relationship between disclosure and default, we further investigate whether investors are aware of the risks not reflected by disclosure. Finally, we focus on solving the puzzle that lenders remain attracted by loan listings with more disclosures but a higher default probability by looking at the profitability of such listings.

### 4.1 Disclosure and Funding Success

The summary statistics show the significantly positive correlation between borrowers' voluntary disclosure and funding success rate. This section reports the regression results estimated by the logit model. We first estimate the following model:

$$SUCCESS_i = \beta_0 + \beta_1 Vol\_Disclosure_i + \beta_2 Control_i + \varepsilon_i, \quad (2)$$

where the dependent variable *SUCCESS* denotes whether a borrower successfully gets their loan request funded. It equals one if a borrower's loan request is funded and zero otherwise. *Vol\_Disclosure* is a dummy variable indicating whether a borrower voluntarily discloses any of his or her personal information, including education, income, working time, living place, size or industry of the firm he or she is working for, position, or borrowing purposes. Because almost all borrowers disclose their marital status, we do not include them in the estimation. We control other variables that might affect funding probability, including the characteristics of loan listings, borrowers' age, financial assets, length of loan description, etc.  $\varepsilon_i$  is a random disturbance term.

Table 5 reports the estimation results. Column (1) summarizes the regression result on the variables that have been widely used to explain the probability of funding success. In line with existing researches, loan requests with lower interest rates or amounts, longer terms, and/or longer titles and loan descriptions are more likely to be funded (Dorfleitner et al. 2016; Iyer et al. 2016; Liu et al. 2015). Moreover, the funding probability is higher for borrowers with a higher credit rating, of older age, or who own houses or cars. Column (2) indicates that after adding the variable of *Edu\_Disclosure* into the regression, Pseudo  $R^2$  increases from 0.301 to 0.313. This means that borrowers' voluntary disclosure of educational achievement can explain the additional 1.2% of funding probability. In addition, the coefficient of *Edu\_Disclosure* is positive and significant at the 1% level, implying that disclosure of education can significantly improve funding success.

In Columns (3) to (9), we add the information items of *Worktime\_Disclosure*, *Income\_Disclosure*, *City\_Disclosure*, *Firmsize\_Disclosure*, *Purpose\_Disclosure*, *Ind\_Disclosure*, and *Position\_Disclosure*, respectively. Pseudo  $R^2$  is improved by degrees varying from 0% to 2.6%, and the coefficients are all significantly positive. These results indicate that borrowers' voluntary information disclosure is effective and has strong explanatory power on borrowing success rate. Among all items of information disclosure, living place, working time, and income play the most important roles in raising the funding probability.

**Table 5: Voluntary Disclosure and Funding Success**

	(1) SUCCE S	(2) SUCCE S	(3) SUCCE S	(4) SUCCE S	(5) SUCCE S	(6) SUCCE S	(7) SUCCE S	(8) SUCCE S	(9) SUCCE S
Edu_Disclosure		5.239*** (14.81)							
Worktime_Disclosure			5.535*** (26.51)						
Income_Disclosure				6.342*** (16.81)					
City_Disclosure					3.223*** (49.87)				
Firmsize_Disclosure						0.985*** (37.27)			
Purpose_Disclosure							0.394* (1.78)		
Ind_Disclosure								0.985*** (37.25)	
Position_Disclosure									0.921*** (36.43)
lnAMOUNT	-0.607*** (-87.19)	-0.605*** (-85.92)	-0.607*** (-84.60)	-0.603*** (-84.51)	-0.613*** (-85.47)	-0.601*** (-84.87)	-0.607*** (-87.18)	-0.601*** (-84.88)	-0.603*** (-85.19)
INTEREST	-0.109*** (-38.26)	-0.109*** (-38.80)	-0.110*** (-39.89)	-0.109*** (-39.46)	-0.110*** (-39.83)	-0.110*** (-39.19)	-0.109*** (-38.27)	-0.110*** (-39.19)	-0.110*** (-39.22)
MONTHS	0.008*** (7.87)	0.007*** (6.42)	0.004*** (3.66)	0.005*** (5.17)	0.004*** (4.24)	0.005*** (4.91)	0.008*** (7.87)	0.005*** (4.91)	0.005*** (5.00)
CREDIT	1.476*** (95.10)	1.453*** (95.57)	1.404*** (96.46)	1.422*** (96.16)	1.432*** (99.24)	1.451*** (95.19)	1.476*** (95.10)	1.450*** (95.19)	1.453*** (95.15)
AGE	0.047*** (44.54)	0.048*** (45.94)	0.052*** (48.28)	0.050*** (47.17)	0.051*** (47.95)	0.047*** (44.80)	0.047*** (44.55)	0.047*** (44.79)	0.047*** (44.36)
HOUSE	0.469*** (27.27)	0.361*** (21.43)	0.146*** (8.91)	0.228*** (13.83)	0.161*** (9.70)	0.316*** (18.24)	0.469*** (27.27)	0.316*** (18.25)	0.330*** (19.05)
CAR	0.600*** (32.02)	0.551*** (30.19)	0.449*** (25.72)	0.488*** (27.56)	0.471*** (26.78)	0.540*** (29.31)	0.600*** (32.02)	0.540*** (29.31)	0.543*** (29.41)
T_Length	0.026*** (26.02)	0.023*** (23.50)	0.020*** (19.76)	0.021*** (21.00)	0.021*** (20.69)	0.024*** (24.02)	0.026*** (25.99)	0.024*** (24.02)	0.024*** (23.80)
D_Length	0.002*** (24.03)	0.002*** (22.69)	0.002*** (20.97)	0.002*** (21.24)	0.002*** (21.06)	0.002*** (22.10)	0.002*** (24.01)	0.002*** (22.10)	0.002*** (22.23)
N_Length	-0.152*** (-57.16)	-0.141*** (-53.68)	-0.110*** (-42.57)	-0.122*** (-47.14)	-0.114*** (-43.53)	-0.137*** (-51.33)	-0.152*** (-57.15)	-0.137*** (-51.33)	-0.139*** (-52.09)
_cons	1.288*** (17.50)	-3.876*** (-10.76)	-3.998*** (-18.40)	-4.903*** (-12.84)	-1.672*** (-17.06)	0.478*** (6.19)	0.894*** (3.84)	0.479*** (6.20)	0.588*** (7.68)
N	604885	604885	604885	604885	604885	604885	604885	604885	604885
Year	YES	YES	YES	YES	YES	YES	YES	YES	YES
r2_p	0.301	0.313	0.337	0.328	0.332	0.309	0.301	0.309	0.308

Note: (1) This table reports logit regression results on funding success. The dependent variable is *SUCCESS*, a dummy variable taking the value of 1 if a loan listing is fully funded and 0 otherwise. The explanatory variables include: *Edu\_Disclosure* – a dummy variable taking the value of 1 if a borrower discloses the education level and 0 otherwise; *Worktime\_Disclosure* – a dummy variable taking the value of 1 if a borrower discloses the working experience and 0 otherwise; *Income\_Disclosure* – a dummy variable taking the value of 1 if a borrower discloses the income and 0 otherwise; *City\_Disclosure* – a dummy variable taking the value of 1 if a borrower discloses the residential city and 0 otherwise; *Firmsize\_Disclosure* – a dummy variable taking the value of 1 if a borrower discloses company size and 0 otherwise; *Purpose\_Disclosure* – a dummy variable taking the value of 1 if a borrower discloses loan purpose and 0 otherwise; *Ind\_Disclosure* – a dummy variable taking the value of 1 if a borrower discloses the working industry and 0 otherwise; *Position\_Disclosure* – a dummy variable taking the value of 1 if a borrower discloses the position and 0 otherwise; *lnAMOUNT* – natural log of loan amount (in RMB) requested by the borrower; *INTEREST* – the interest rate that a borrower pays on the loan; *MONTHS* – loan term (in months) requested by the borrower; *CREDIT* – credit grade of the borrower at the time the listing was created; *AGE* – the age of a borrower expressed in years; *HOUSE* – a dummy variable taking the value of 1 if the borrower is a homeowner and 0 otherwise; *CAR* – a dummy variable taking the value of 1 if a borrower owns a car and 0 otherwise; *T\_Length* – the number of characters in a loan title; *D\_Length* – the number of characters in a loan description; *N\_Length* – the number of characters in a borrower's nickname; and *Year* – Year dummy.

(2) \*, \*\*, and \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors are used and Z-statistics are reported in parentheses. N is the number of observations. r2\_p is Pseudo R-square.

We further explore the relationship between intensity of disclosure and funding probability with the following the equation:

$$SUCCESS_i = \beta_0 + \beta_1 Disclosure\_Int_i + \beta_2 Control_i + \varepsilon_i. \quad (3)$$

We use three indicators to measure the intensity of information disclosure (*Disclosure\_Int*), namely *DSCORE\_ALL*, *DSCORE*, and *DSCORE\_NOR*. *DSCORE\_ALL* is a dummy that is equal to one if a borrower discloses all nine items of voluntary information and zero otherwise; *DSCORE* is the sum of all points that a loan listing is awarded for all the information voluntarily disclosed by its borrower; and *DSCORE\_NOR* is the sum of all points that a loan listing is awarded for all the voluntary information disclosed, excluding purpose of borrowing and marriage status.

**Table 6: Voluntary Disclosure Intensity and Funding Success**

	(1) SUCCESS	(2) SUCCESS	(3) SUCCESS	(4) SUCCESS	(5) SUCCESS	(6) SUCCESS
DSCORE_ALL	1.110*** (43.80)	0.0343*** (42.33)				
DSCORE			0.344*** (65.80)	0.0106*** (61.03)		
DSCORE_NOR					0.346*** (65.68)	0.0107*** (60.93)
lnAMOUNT	-0.606*** (-84.97)	-0.0187*** (-78.93)	-0.602*** (-83.93)	-0.0186*** (-78.21)	-0.602*** (-83.95)	-0.0186*** (-78.22)
INTEREST	-0.111*** (-39.50)	-0.00343*** (-39.01)	-0.111*** (-39.89)	-0.00343*** (-39.39)	-0.111*** (-39.88)	-0.00342*** (-39.38)
MONTHS	0.004*** (3.77)	0.000122*** (3.768)	0.003*** (3.15)	0.000102*** (3.150)	0.003*** (3.16)	0.000102*** (3.156)
CREDIT	1.448*** (95.85)	0.0447*** (103.8)	1.428*** (95.85)	0.0441*** (104.2)	1.428*** (95.84)	0.0441*** (104.2)
AGE	0.048*** (44.91)	0.00148*** (43.82)	0.049*** (45.90)	0.00152*** (44.75)	0.049*** (45.87)	0.00151*** (44.72)
HOUSE	0.269*** (15.52)	0.00832*** (15.45)	0.204*** (12.12)	0.00630*** (12.09)	0.204*** (12.14)	0.00632*** (12.12)
CAR	0.519*** (28.39)	0.0161*** (28.09)	0.487*** (27.14)	0.0150*** (26.89)	0.487*** (27.15)	0.0151*** (26.90)
T_Length	0.023*** (23.08)	0.000710*** (22.94)	0.022*** (21.78)	0.000668*** (21.67)	0.022*** (21.84)	0.000670*** (21.73)
D_Length	0.002*** (21.89)	5.23e-05*** (21.81)	0.002*** (21.03)	5.02e-05*** (20.96)	0.002*** (21.05)	5.03e-05*** (20.98)
N_Length	-0.132*** (-49.15)	-0.00408*** (-48.01)	-0.123*** (-46.67)	-0.00380*** (-45.80)	-0.123*** (-46.69)	-0.00381*** (-45.81)
_cons	0.483*** (6.29)		-1.507*** (-17.55)		-0.836*** (-10.28)	
Year	YES	YES	YES	YES	YES	YES
N	604,885	604,885	604,885	604,885	604,885	604,885
r2_p	0.312		0.321		0.321	

Note: (1) This table reports logit regression results on funding success. The dependent variable is *SUCCESS*, a dummy variable taking the value of 1 if a loan listing is fully funded and 0 otherwise. The explanatory variables include: *DSCORE* – the borrower's disclosure score (see Table 2 for definition); *DSCORE\_ALL* – a dummy variable taking the value of 1 if a borrower's disclosure score is equal to 9 and 0 otherwise; *DSCORE\_NOR* – a borrower's disclosure score, excluding the disclosure on marital status and borrowing purpose; *lnAMOUNT* – natural log of loan amount (in RMB) requested by the borrower; *INTEREST* – the interest rate that a borrower pays on the loan; *MONTHS* – loan term (in months) requested by the borrower; *CREDIT* – credit grade of the borrower at the time the listing was created; *AGE* – the age of a borrower expressed in years; *HOUSE* – a dummy variable taking the value of 1 if the borrower is a homeowner and 0 otherwise; *CAR* – a dummy variable taking the value of 1 if a borrower owns a car and 0 otherwise; *T\_Length* – the number of characters in a loan title; *D\_Length* – the number of characters in a loan description; *N\_Length* – the number of characters in a borrower's nickname; and *Year* – Year dummy.

(2) \*, \*\*, and \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors are used and Z-statistics are reported in parentheses. N is the number of observations. r2\_p is Pseudo R-square.

(3) Columns (2), (4), and (6) in show the corresponding marginal effects.

Table 6 summarizes the estimation results. In Columns (1), (3), and (5) of Table 6, we separately estimate the impacts of *DSCORE\_ALL*, *DSCORE*, and *DSCORE\_NOR* on funding success and show the corresponding marginal effects in Columns (2), (4), and (6). Comparing with Column (1) in Table 5, we find that Pseudo R<sup>2</sup>s of Columns (1), (3), and (5) in Table 6 are improved by varying degrees, implying that the quantity of information disclosure generates incremental explanatory power on borrowing success rate. Column (2) shows that the marginal effect of *DSCORE\_ALL* is 0.0343 and significant at the 1% level. This means that after controlling for other factors, the funding success rate of a loan request with complete information disclosure is 76.5% higher than its counterpart with incomplete information disclosure (0.0343/0.0448). The marginal effect of *DSCORE* in Column (4) is 0.0106 and significant at the 1% level. This implies that one additional component of voluntarily disclosed information will enhance the borrowing success rate on average by 23.6% (0.0106/0.0448). These results indicate that borrowers' voluntary information disclosure plays a very important role in enhancing the funding probability.

The impact of voluntary information disclosure on funding success might differ across borrowers of different risks. It is easy for borrowers with good credit to signal their trustworthiness by virtue of verifiable and hard information such as a credit report issued by the crediting authorities. They can easily obtain bids and fund without disclosing much information. However, potential borrowers with poor credit have to rely more heavily on information disclosure to differentiate themselves from other competing borrowers (Michels 2012). This will induce them to disclose more information than borrowers with a high credit rating. To test the differentiated impacts of disclosure on funding success across borrowers of different levels of risk, we estimate the following model:

$$SUCCESS_i = \beta_0 + \beta_1 Disclosure_i + \beta_2 POOR_i + \beta_3 Disclosure_i \times POOR_i + \beta_4 Control_i + \varepsilon_i, \quad (4)$$

where *POOR* is a dummy variable that equals one if a borrower's credit rating is HR and zero otherwise. *Disclosure*×*POOR* is the interaction term between the intensity of borrowers' voluntary disclosure and credit rating.

Table 7 presents the corresponding regression results. In Columns (1), (3), and (5), we estimate the effect of the interaction terms *DSCORE\_ALL*×*POOR*, *DSCORE*×*POOR*, and *DSCORE\_NOR*×*POOR* on funding probability, respectively. Columns (2), (4), and (6) report the corresponding marginal effects. The estimation results reveal that the positive relationship between funding success rate and disclosures is stronger for borrowers of relatively low credit quality. Column (2) shows that the marginal effect of *DSCORE\_ALL*×*POOR* is 0.0422 and significant at the 1% level. This means that after controlling for other factors, the funding success rate for borrowers with complete information disclosure and a low credit rating is approximately 94% higher than that of those with a bad credit rating (0.0422/0.0448) but incomplete information disclosure. The marginal effect of *DSCORE*×*POOR* in Column (4) is 0.0123 and significant at the 1% level, indicating that all else being equal, one additional component of information voluntarily disclosed by a borrower of high risk will enhance his/her funding success rate by 27.4% (0.0123/0.0448). The marginal effect of *DSCORE\_NOR*×*POOR* in Column (6) is 0.0124 and significant at the 1% level, suggesting that all else being equal, one additional item of voluntary information, excluding borrowing purpose and marital status, will increase the funding success rate by 27.6% (0.0124/0.0448). These results imply that disclosure is highly valuable for borrowers of high risk because it helps to alleviate the negative effect of a low credit rating on funding success.

**Table 7: Credit Score, Disclosure, and Funding Probability**

	(1) SUCCESS	(2) SUCCESS	(3) SUCCESS	(4) SUCCESS	(5) SUCCESS	(6) SUCCESS
DSCORE_ALL	-0.128** (-2.51)	-0.00372** (-2.506)				
DSCORE_ALL*POOR	1.454*** (24.23)	0.0422*** (24.05)				
DSCORE			-0.034** (-1.99)	-0.00100** (-1.989)		
DSCORE_POOR			0.422*** (22.73)	0.0123*** (22.55)		
DSCORE_NOR					-0.036** (-2.10)	-0.00106** (-2.102)
DSCORE_NOR*POOR					0.426*** (22.90)	0.0124*** (22.73)
POOR	-4.719*** (-77.89)	-0.137*** (-75.41)	-7.023*** (-43.20)	-0.204*** (-42.50)	-6.214*** (-48.99)	-0.181*** (-48.06)
lnAMOUNT	-0.599*** (-82.42)	-0.0174*** (-76.50)	-0.596*** (-81.73)	-0.0173*** (-76.05)	-0.597*** (-81.74)	-0.0173*** (-76.06)
INTEREST	-0.113*** (-41.15)	-0.00329*** (-40.49)	-0.113*** (-41.45)	-0.00329*** (-40.78)	-0.113*** (-41.44)	-0.00329*** (-40.78)
MONTHS	0.004*** (3.77)	0.000115*** (3.766)	0.004*** (3.36)	0.000103*** (3.356)	0.004*** (3.37)	0.000103*** (3.366)
CREDIT	0.080*** (5.92)	0.00231*** (5.935)	0.091*** (6.78)	0.00263*** (6.791)	0.091*** (6.77)	0.00263*** (6.787)
AGE	0.048*** (42.64)	0.00140*** (41.78)	0.049*** (43.32)	0.00143*** (42.41)	0.049*** (43.31)	0.00143*** (42.40)
HOUSE	0.243*** (13.78)	0.00706*** (13.72)	0.196*** (11.40)	0.00570*** (11.37)	0.196*** (11.42)	0.00571*** (11.39)
CAR	0.478*** (25.67)	0.0139*** (25.41)	0.458*** (25.01)	0.0133*** (24.78)	0.458*** (25.01)	0.0133*** (24.78)
T_Length	0.022*** (21.25)	0.000625*** (21.12)	0.021*** (20.45)	0.000599*** (20.34)	0.021*** (20.47)	0.000600*** (20.37)
D_Length	0.002*** (19.44)	4.64e-05*** (19.37)	0.002*** (18.87)	4.49e-05*** (18.81)	0.002*** (18.88)	4.50e-05*** (18.83)
N_Length	-0.118*** (-42.89)	-0.00343*** (-41.93)	-0.112*** (-41.26)	-0.00325*** (-40.47)	-0.112*** (-41.28)	-0.00325*** (-40.48)
_cons	5.955*** (61.69)		6.069*** (35.47)		6.015*** (42.17)	
Year	YES	YES	YES	YES	YES	YES
N	604,885	604,885	604,885	604,885	604,885	604,885
r2_p	0.362		0.369		0.369	

Note: (1) This table reports logit regression results on funding success. The dependent variable is *SUCCESS*, a dummy variable taking the value of 1 if a loan listing is fully funded and 0 otherwise. The explanatory variables include: *DSCORE* – the borrower's disclosure score (see Table 2 for definition); *DSCORE\_ALL* – a dummy variable taking the value of 1 if a borrower's disclosure score is equal to 9 and 0 otherwise; *DSCORE\_NOR* – a borrower's disclosure score, excluding the disclosure on marital status and borrowing purpose; *POOR* – a dummy variable taking the value of 1 if a borrower's credit is high risk (HR) and 0 otherwise; *lnAMOUNT* – natural log of loan amount (in RMB) requested by the borrower; *INTEREST* – the interest rate that a borrower pays on the loan; *MONTHS* – loan term (in months) requested by the borrower; *CREDIT* – credit grade of the borrower at the time the listing was created; *AGE* – the age of a borrower expressed in years; *HOUSE* – a dummy variable taking the value of 1 if the borrower is a homeowner and 0 otherwise; *CAR* – a dummy variable taking the value of 1 if a borrower owns a car and 0 otherwise; *T\_Length* – the number of characters in a loan title; *D\_Length* – the number of characters in a loan description; *N\_Length* – the number of characters in a borrower's nickname; and *Year* – Year dummy.

(2) \*, \*\*, and \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors are used and Z-statistics are reported in parentheses. N is the number of observations. r2\_p is Pseudo R-square.

(3) Columns (2), (4), and (6) in show the corresponding marginal effects.

## 4.2 Disclosure and Default

The above empirical results imply that borrowers should be aware of the importance of disclosure. Given the low cost of disclosure, a borrower may manipulate the information he or she reveals to the investors to conceal bad credit information and acquire a loan. Hence, a natural question is whether voluntary disclosure truly reduces the informational disadvantages that lenders face on the P2P lending platform. We hence explore the relationship between disclosure and the probability of default with the following equation:

$$DEFAULT_i = \beta_0 + \beta_1 Disclosure\_Int_i + \beta_2 Control_i + \varepsilon_i, \quad (5)$$

where the dependent variable *DEFAULT* indicates whether a loan listing *i* defaults after it is successfully funded. It equals 1 if the borrower defaults and 0 otherwise. *Disclosure\_Int* is the indicator measuring the intensity of information disclosure, including *DSCORE\_ALL*, *DSCORE*, and *DSCORE\_NOR*. We control the variables that might affect funding probability, including the characteristics of loan listing, borrowers' age, financial assets, length of loan description, etc.  $\varepsilon_i$  is a random disturbance term.

Table 8 reports the regression results. In Columns (2), (4), and (6), we separately estimate the impacts of *DSCORE\_ALL*, *DSCORE*, and *DSCORE\_NOR* on the probability of default. Columns (3), (5), and (7) show the corresponding marginal effects. Comparing with Column (1), we find that Pseudo R<sup>2</sup>s of Columns (2), (4), and (6) are improved by varying degrees, implying that the quantity of information disclosure generates incremental explanatory power on default. Column (3) shows that the marginal effect of *DSCORE\_ALL* is 0.0447 and significant at the 1% level, meaning that after controlling for other factors, the probability of default of a loan with complete information disclosure is 29.6% higher than its counterpart with incomplete information disclosure (0.0447/0.151). The marginal effect of *DSCORE* in Column (5) is 0.0177 and significant at the 1% level, suggesting that one additional component of voluntarily disclosed information will enhance the probability of default on average by 11.7% (0.0177/0.151). The marginal effect of *DSCORE\_NOR* in Column (7) is 0.0179 and significant at the 1% level. This implies that all else being equal, one additional item of voluntary information, excluding borrowing purpose and marital status, will increase the probability of default on average by 11.8% (0.0179/0.151).

Our findings are different from those of Michels (2012), who found that disclosure has a strong and negative association with future defaults. Our results reflect the possibility of information manipulation by borrowers in the Chinese P2P market, with a high level of information asymmetry between lenders and borrowers due to a lack of hard information for most borrowers. In such a situation, lenders are more likely to depend on soft information disclosed by borrowers. However, the evidence we show here suggests that the extent to which such information is related to borrowers' fundamental default risk is questionable. On the one hand, borrowers may choose to disclose the information in their favor. For example, according to our estimation, disclosures regarding education, working experience, and income play a much larger role in affecting investors' choice than other information. Well-educated borrowers may choose to disclose their degree and conceal other important information that might reveal their real risks. On the other hand, the information disclosed by borrowers is hard to verify. Poor-quality borrowers may choose to disclose false information and mimic good-quality borrowers in order to acquire loans. Such manipulation of disclosure will exaggerate the market inefficiency arising from information asymmetry.



**Table 8: Voluntary Disclosure Intensity and Loan Default**

	(1) DEFAULT	(2) DEFAULT	(3) DEFAULT	(4) DEFAULT	(5) DEFAULT	(6) DEFAULT	(7) DEFAULT
DSCORE_ALL		0.459*** (6.30)	0.0447*** (6.318)				
DSCORE				0.182*** (6.84)	0.0177*** (6.860)		
DSCORE_NOR						0.184*** (6.90)	0.0179*** (6.922)
lnAMOUNT	0.301*** (10.64)	0.315*** (11.06)	0.0307*** (11.12)	0.319*** (11.19)	0.0311*** (11.25)	0.320*** (11.20)	0.0311*** (11.26)
INTEREST	0.120*** (10.21)	0.119*** (10.11)	0.0116*** (10.18)	0.119*** (10.07)	0.0116*** (10.14)	0.119*** (10.07)	0.0116*** (10.14)
MONTHS	0.060*** (24.57)	0.058*** (23.43)	0.00565*** (24.79)	0.058*** (23.28)	0.00562*** (24.63)	0.058*** (23.28)	0.00562*** (24.63)
CREDIT	-2.093*** (-27.54)	-2.098*** (-27.60)	-0.204*** (-30.86)	-2.100*** (-27.62)	-0.204*** (-30.88)	-2.099*** (-27.62)	-0.204*** (-30.88)
AGE	0.039*** (12.63)	0.038*** (12.17)	0.00370*** (12.33)	0.038*** (12.11)	0.00368*** (12.27)	0.038*** (12.10)	0.00368*** (12.26)
HOUSE	-0.180*** (-4.34)	-0.200*** (-4.82)	-0.0195*** (-4.833)	-0.204*** (-4.90)	-0.0198*** (-4.911)	-0.204*** (-4.91)	-0.0198*** (-4.915)
CAR	-0.139*** (-3.11)	-0.128*** (-2.87)	-0.0125*** (-2.874)	-0.127*** (-2.83)	-0.0123*** (-2.834)	-0.127*** (-2.83)	-0.0123*** (-2.837)
T_Length	0.003 (0.93)	0.004 (1.30)	0.000344 (1.304)	0.004 (1.37)	0.000361 (1.371)	0.004 (1.38)	0.000363 (1.378)
D_Length	0.001*** (3.02)	0.001*** (2.82)	5.94e-05*** (2.819)	0.001*** (2.83)	5.96e-05*** (2.830)	0.001*** (2.83)	5.95e-05*** (2.827)
N_Length	0.009 (1.26)	0.009 (1.18)	0.000844 (1.182)	0.009 (1.16)	0.000832 (1.165)	0.009 (1.17)	0.000833 (1.166)
_cons	-5.082*** (-15.24)	-5.537*** (-16.20)		-6.729*** (-16.34)		-6.380*** (-16.64)	
Year	YES	YES	YES	YES	YES	YES	YES
N	27,112	27,112		27,112		27,112	
r2_p	0.280	0.282		0.282		0.282	

Note: (1) This table reports logit regression results on default. The dependent variable is *DEFAULT*, a dummy variable taking the value of 1 if the funded loan has been defaulted and 0 otherwise. The explanatory variables include: *DSCORE* – the borrower's disclosure score (see Table 2 for definition); *DSCORE\_ALL* – a dummy variable taking the value of 1 if a borrower's disclosure score is equal to 9 and 0 otherwise; *DSCORE\_NOR* – a borrower's disclosure score, excluding the disclosure on marital status and borrowing purpose; *lnAMOUNT* – natural log of loan amount (in RMB) requested by the borrower; *INTEREST* – the interest rate that a borrower pays on the loan; *MONTHS* – loan term (in months) requested by the borrower; *CREDIT* – credit grade of the borrower at the time the listing was created; *AGE* – the age of a borrower expressed in years; *HOUSE* – a dummy variable taking the value of 1 if the borrower is a homeowner and 0 otherwise; *CAR* – a dummy variable taking the value of 1 if a borrower owns a car and 0 otherwise; *T\_Length* – the number of characters in a loan title; *D\_Length* – the number of characters in a loan description; *N\_Length* – the number of characters in a borrower's nickname; and *Year* – Year dummy.

(2) \*, \*\*, and \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors are used and Z-statistics are reported in parentheses. N is the number of observations. r2\_p is Pseudo R-square. (3) Columns (3), (5), and (7) in show the corresponding marginal effects.

### 4.3 Verified Information and Loan Outcome

In the financial market, verified financial information is the key signal to transmit information to the market, as generally speaking, verified information will be more credible (Ben-Porath, Dekel, and Lipman 2014; Brown et al. 2012; Greenwood, Sánchez, and Wang 2010). As mentioned before, Renrendai provides basic verification of borrowers' national identification cards along with credit reports. Borrowers can also provide some other information to be verified by the platform. Taking marriage certification as an example, the borrower usually takes photos of the marriage certificate

and uploads it to the platform. However, the uploaded certificate could be faked and Renrendai is not able to check every single detail of seemingly verifiable information. Even so, information certification can reflect the extent to which borrowers are trying to obtain loans. So how does information certification affect the loan outcome? We estimate the following model:

$$\text{Loan Outcome}_i = \beta_0 + \beta_1 \text{Disclosure}_i + \beta_2 \text{Ver\_Numb}_i + \beta_3 \text{Disclosure}_i \times \text{Ver\_Numb}_i + \beta_4 \text{Control}_i + \varepsilon_i, \quad (6)$$

where  $\text{Loan Outcome}_i$  is the variables measuring the outcome of loan listing  $i$ , including *SUCCESS*, *INTEREST*, and *DEFAULT*, respectively. *Disclosure* represents indicators measuring the intensity of information disclosure, including *DSCORE\_ALL* and *DSCORE*. *Ver\_Numb* is the amount of information verified by the platform, indicating whether any items, such as a borrower's national identification cards, credit reports, job or income, etc., have been verified by the platform.  $\text{Disclosure} \times \text{Ver\_Numb}$  is the interaction term between the intensity of borrowers' voluntary disclosure and the number of information verifications. We control other variables that might affect funding probability, interest rate, and the probability of default, including the characteristics of loan listing, borrowers' age, financial assets, length of loan description, etc.  $\varepsilon_i$  is a random disturbance term.

Table 9 presents the corresponding regression results. In Column (1) and Column (2), the estimated results of *Ver\_Numb* and its interaction with *Disclosure* relative to funding probability are presented. In Column (3) and Column (4), the estimated results of *Ver\_Numb* and its interaction with *Disclosure* relative to interest are presented. In Column (5) and Column (6), the estimated results of *Ver\_Numb* and its interaction with *Disclosure* relative to the probability of default are presented. According to the empirical results, the effect of *Ver\_Numb* on funding probability is positive and significant at the 1% confidence level, but *Ver\_Numb* does not have a significant impact on interest rate and the probability of default. This means that borrowers with more verified information are more likely to get a loan. The interaction between *Ver\_Numb* and *Disclosure* will only have a significant impact on funding probability. It can be seen from the results of Columns (1) and (2) that the impact of *Ver\_Numb\_DSCORE\_ALL* and *Ver\_Numb\_DSCORE* on funding probability is negative and significant at the 1% confidence level. This implies that there is a substitution relationship between the amount of verified information and voluntary information disclosure.

This is particularly important for the PRC, which doesn't have a widely accepted system to gauge creditworthiness among a fast-expanding middle class with growing paychecks, a huge demand for consumer products, but little or no credit history. In such a situation, the cost of default would be lower than that in industrial countries like the US where most adults rely on their credit score to reveal their creditworthiness and defaulting would significantly lower their credit score. Therefore, lenders in the Chinese P2P lending market tend to trust borrowers with more verified information. However, the uploaded certificate could be faked and Renrendai is not able to check every single detail of seemingly verifiable information. Without an effective social credit evaluation system, the creditability of unilateral information verification on the P2P lending platform is limited.

**Table 9: Verified Information and Loan Outcome**

	(1)	(2)	(3)	(4)	(5)	(6)
	SUCCESS	SUCCESS	INTEREST	INTEREST	DEFAULT	DEFAULT
DSCORE_ALL	1.888*** (30.18)		0.174*** (8.09)		0.162 (0.70)	
Ver_Numb	1.108*** (51.25)	2.010*** (32.34)	-0.007 (-0.76)	-0.005 (-0.18)	0.076 (1.61)	-0.279 (-1.41)
Ver_Numb*DSCORE_ALL	-0.337*** (-15.51)		-0.015 (-1.62)		0.043 (0.89)	
DSCORE		0.642*** (38.00)		0.024*** (3.64)		-0.045 (-0.47)
Ver_Numb*DSCORE		-0.139*** (-19.97)		-0.002 (-0.53)		0.044** (1.99)
lnAMOUNT	-0.732*** (-79.82)	-0.735*** (-79.94)	0.028*** (8.93)	0.028*** (8.94)	0.296*** (10.30)	0.298*** (10.39)
INTEREST	-0.133*** (-37.30)	-0.132*** (-37.64)			0.115*** (9.74)	0.114*** (9.70)
MONTHS	0.008*** (6.63)	0.008*** (6.78)	0.065*** (161.38)	0.066*** (162.05)	0.059*** (23.62)	0.058*** (23.47)
CREDIT	0.588*** (32.12)	0.587*** (32.58)	-0.464*** (-56.00)	-0.466*** (-56.22)	-2.113*** (-27.88)	-2.113*** (-27.87)
AGE	0.042*** (31.77)	0.043*** (32.58)	0.000 (0.77)	0.000 (0.90)	0.038*** (12.18)	0.038*** (12.12)
HOUSE	-0.178*** (-8.86)	-0.205*** (-10.43)	-0.111*** (-13.68)	-0.106*** (-13.07)	-0.248*** (-5.88)	-0.249*** (-5.90)
CAR	-0.060*** (-2.63)	-0.069*** (-3.05)	-0.221*** (-24.84)	-0.219*** (-24.60)	-0.196*** (-4.28)	-0.193*** (-4.23)
T_Length	0.013*** (11.29)	0.012*** (10.36)	0.027*** (52.88)	0.026*** (52.74)	0.003 (1.21)	0.003 (1.27)
D_Length	0.001*** (14.66)	0.001*** (14.45)	0.001*** (16.15)	0.001*** (16.15)	0.001** (2.38)	0.001** (2.40)
N_Length	-0.095*** (-30.45)	-0.088*** (-28.76)	-0.050*** (-50.34)	-0.051*** (-50.55)	0.019*** (2.61)	0.020*** (2.63)
_cons	-0.006 (-0.06)	-3.869*** (-22.51)	11.413*** (294.47)	11.348*** (167.62)	-5.607*** (-13.86)	-5.057*** (-5.49)
Year	YES	YES	YES	YES	YES	YES
N	604,885	604,885	604,885	604,885	27,112	27,112
r2_p/a	0.460	0.466	0.305	0.305	0.285	0.285

Note: (1) This table reports logit regression results on funding success in Columns (1) and (2), on default in Columns (5) and (6), and OLS regression results on interest rate in Columns (3) and (4). The dependent variables are (i) *SUCCESS*, a dummy variable taking the value of 1 if a loan listing is fully funded and 0 otherwise; (ii) *INTEREST*, the interest rate that the borrower pays on the loan; and (iii) *DEFAULT*, a dummy variable taking the value of 1 if the funded loan has been defaulted and 0 otherwise. The explanatory variables include: *DSCORE* – the borrower's disclosure score (see Table 2 for definition); *DSCORE\_ALL* – a dummy variable taking the value of 1 if a borrower's disclosure score is equal to 9 and 0 otherwise; *DSCORE\_NOR* – a borrower's disclosure score, excluding the disclosure on marital status and borrowing purpose; *Ver\_Numb* – the amount of information in a loan listing that has been verified by the platform; *lnAMOUNT* – natural log of loan amount (in RMB) requested by the borrower; *INTEREST* – the interest rate that a borrower pays on the loan; *MONTHS* – loan term (in months) requested by the borrower; *CREDIT* – credit grade of the borrower at the time the listing was created; *AGE* – the age of a borrower expressed in years; *HOUSE* – a dummy variable taking the value of 1 if the borrower is a homeowner and 0 otherwise; *CAR* – a dummy variable taking the value of 1 if a borrower owns a car and 0 otherwise; *T\_Length* – the number of characters in a loan title; *D\_Length* – the number of characters in a loan description; *N\_Length* – the number of characters in a borrower's nickname; and *Year* – Year dummy.

(2) \*, \*\*, and \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors are used and Z/T-statistics are reported in parentheses. N is the number of observations. r2\_a/p is adjusted R-square (Pseudo R-square).

#### 4.4 Disclosure and Risk Screening

The findings presented in the above two subsections reveal that borrowers might manipulate disclosures to acquire loans. An important question, therefore, is whether investors are sophisticated enough to infer the real credit quality that might be marked by information voluntarily provided by borrowers. To answer this question, we assume that the same amount of disclosure corresponds to the same level of default risk if the market is fully efficient (Fama 1970; Fama 1991). In other words, investors can infer the default probability of borrowers from the amount of information voluntarily disclosed by these borrowers. However, given that borrowers may disclose their information strategically under the premise of cheap talk, two loans with the same voluntary disclosure may contain different levels of risk. Investors thus have to infer the credit quality using information other than voluntary disclosures. To measure the risk of default reflected by disclosures, we first estimate the equation

$$DEFAULT_i = \beta_0 + \beta_1 Disclosure_i + \varepsilon_i. \quad (7)$$

The coefficients estimated by Equation (7) are used to predict the default risk captured by disclosures, i.e.  $\Pr(DEFAULT_i | Disclosure_i)$ . Similarly, using the coefficients estimated by Equation (5), we can measure the default risk captured by all information observable to the investors as  $\Pr(DEFAULT_i | Disclosure_i, Control_i)$ . Therefore, a default risk that is not reflected by voluntary information disclosure can be computed as

$$default\_risk_i \equiv \Pr(DEFAULT_i | Disclosure_i, Control_i) - \Pr(DEFAULT_i | Disclosure_i). \quad (8)$$

If lenders are sophisticated enough, they can screen out the default risk not revealed by the voluntary information disclosure and make a rational investment choice. Given that smart investors will be reluctant to invest in loan listings with a higher level of default risk, such loan listings need more bids and a longer time to get their loan funded. This assumption can be tested with the following two equations:

$$FundTime_i = \beta_0 + \beta_1 default\_risk_i + \beta_2 Control_i + \varepsilon_i \quad (9)$$

and

$$BIDS_i = \beta_0 + \beta_1 default\_risk_i + \beta_2 Control_i + \varepsilon_i. \quad (10)$$

The empirical results are shown in Table 10. Column (1) and Column (2) report the coefficients estimated for Equation (7) and (5), respectively. The Pseudo  $R^2$  of Model (1) is just 0.2%, meaning that in the P2P lending market, voluntary information disclosure only reflects a limited amount of default risk. In Column (2), information other than disclosure is added, including the characteristics of loan listings, borrowers' age, financial assets, length of loan description, etc. The Pseudo  $R^2$  of Model (2) increases to 28.2%, suggesting that information other than disclosures is important to infer the credit quality.

We further estimated the impact of  $default\_risk_i$  on  $FundTime$  and  $BIDS$ . The empirical results reported in Columns (3) and (4) show that the influence of  $default\_risk_i$  on the number of bids and the funding time are both positive and significant at a confidence level of 1%. For a successful loan listing, a 10% increase in  $default\_risk_i$  will raise the funding time by 72 minutes, and the number of bids by 18. Our results confirm that lenders are aware of the risks not reflected by voluntary disclosures.

**Table 10: Voluntary Disclosure Intensity and Risk Identification**

	(1) DEFAULT	(2) DEFAULT	(3) FundTime_M	(4) BIDS
default_risk			721.161** (2.02)	180.129*** (7.81)
DSCORE	0.174*** (6.84)	0.182*** (6.84)		
lnAMOUNT		0.319*** (11.19)	-125.241 (-1.11)	-28.884*** (-4.00)
INTEREST		0.119*** (10.07)	-94.612** (-2.20)	-21.753*** (-7.92)
MONTHS		0.058*** (23.28)	-40.808** (-1.97)	-10.732*** (-8.03)
CREDIT		-2.100*** (-27.62)	1,498.271** (2.00)	378.442*** (7.82)
AGE		0.038*** (12.11)	-26.603** (-1.96)	-6.653*** (-7.59)
HOUSE		-0.204*** (-4.90)	123.664* (1.72)	34.505*** (7.38)
CAR		-0.127*** (-2.83)	69.978 (1.51)	20.808*** (7.08)
T_Length		0.004 (1.37)	-3.379** (-2.50)	-0.760*** (-8.75)
D_Length		0.001*** (2.83)	-0.207 (-0.91)	-0.088*** (-6.01)
N_Length		0.009 (1.16)	-1.824 (-0.55)	-1.166*** (-5.51)
_cons	-3.259*** (-14.46)	-6.729*** (-16.34)	1,527.449 (1.26)	355.500*** (4.59)
Year	NO	YES	YES	YES
N	27,112	27,112	27,112	27,112
r2_p/a	0.002	0.282	0.153	0.476

Note: (1) This table reports logit regression results on default in Columns (1) and (2), and OLS regression results on funding time and bids in Columns (3) and (4). The dependent variables are (i) *DEFAULT*, a dummy variable taking the value of 1 if the funded loan has been defaulted and 0 otherwise; (ii) *FundTime\_M*, the amount of time needed for a list to be successfully funded (minutes); (iii) *BIDS*, the number of bids needed for a list to be successfully funded. The explanatory variables include: *DSCORE* – the borrower's disclosure score (see Table 2 for definition); *default\_risk* – estimated default risk defined by Equation (8); *lnAMOUNT* – natural log of loan amount (in RMB) requested by the borrower; *INTEREST* – the interest rate that a borrower pays on the loan; *MONTHS* – loan term (in months) requested by the borrower; *CREDIT* – credit grade of the borrower at the time the listing was created; *AGE* – the age of a borrower expressed in years; *HOUSE* – a dummy variable taking the value of 1 if the borrower is a homeowner and 0 otherwise; *CAR* – a dummy variable taking the value of 1 if a borrower owns a car and 0 otherwise; *T\_Length* – the number of characters in a loan title; *D\_Length* – the number of characters in a loan description; *N\_Length* – the number of characters in a borrower's nickname; and *Year* – Year dummy.

(2) \*, \*\*, and \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors are used and Z/T-statistics are reported in parentheses. N is the number of observations. r2\_a/p is adjusted R-square (Pseudo R-square).

## 4.5 Disclosure and Profitability

One possible explanation for the puzzle that lenders remain attracted by loan listings with more disclosures but high default risks is the higher profitability offered by the borrowers. To test this hypothesis, we first explore the relationship between intensity of disclosure and interest rate with the following equation:

$$Interest\ Rate_i = \beta_0 + \beta_1 Disclosure_i + \beta_2 Control_i + \varepsilon_i, \quad (11)$$

where *Interest Rate* denotes the interest rate offered by a borrower. *Disclosure* represents indicators measuring the intensity of information disclosure, including *DSCORE\_ALL*, *DSCORE*, and *DSCORE\_NOR*. We control other variables, including the characteristics of loan listings, borrowers' age, financial assets, length of loan description, etc.  $\varepsilon_i$  is a random disturbance term.

**Table 11: Voluntary Disclosure Intensity and Interest Rate**

	(1) INTEREST	(2) INTEREST	(3) INTEREST	(4) INTEREST
DSCORE_ALL		0.133*** (19.19)		
DSCORE			0.020*** (17.72)	
DSCORE_NOR				0.020*** (17.12)
lnAMOUNT	0.025*** (8.17)	0.028*** (9.07)	0.028*** (9.08)	0.028*** (9.05)
MONTHS	0.066*** (164.01)	0.065*** (161.37)	0.066*** (162.20)	0.066*** (162.24)
CREDIT	-0.493*** (-68.54)	-0.492*** (-68.61)	-0.493*** (-68.70)	-0.493*** (-68.70)
AGE	-0.000 (-0.24)	0.000 (0.27)	0.000 (0.44)	0.000 (0.43)
HOUSE	-0.074*** (-9.86)	-0.115*** (-14.30)	-0.111*** (-13.71)	-0.110*** (-13.61)
CAR	-0.207*** (-23.73)	-0.229*** (-25.83)	-0.227*** (-25.58)	-0.226*** (-25.53)
T_Length	0.027*** (53.87)	0.026*** (52.62)	0.026*** (52.46)	0.026*** (52.52)
D_Length	0.001*** (16.96)	0.001*** (16.01)	0.001*** (16.02)	0.001*** (16.05)
N_Length	-0.053*** (-55.94)	-0.050*** (-50.33)	-0.050*** (-50.44)	-0.050*** (-50.48)
_cons	11.537*** (348.91)	11.429*** (340.63)	11.369*** (329.53)	11.408*** (335.66)
Year	YES	YES	YES	YES
N	604,885	604,885	604,885	604,885
r2_a	0.3047	0.3051	0.3050	0.3050

Note: (1) This table reports OLS regression results on interest rate. The dependent variable is *INTEREST*, the interest rate that the borrower pays on the loan. The explanatory variables include: *DSCORE* – the borrower's disclosure score (see Table 2 for definition); *DSCORE\_ALL* – a dummy variable taking the value of 1 if a borrower's disclosure score is equal to 9 and 0 otherwise; *DSCORE\_NOR* – a borrower's disclosure score, excluding the disclosure on marital status and borrowing purpose; *lnAMOUNT* – natural log of loan amount (in RMB) requested by the borrower; *INTEREST* – the interest rate that a borrower pays on the loan; *MONTHS* – loan term (in months) requested by the borrower; *CREDIT* – credit grade of the borrower at the time the listing was created; *AGE* – the age of a borrower expressed in years; *HOUSE* – a dummy variable taking the value of 1 if the borrower is a homeowner and 0 otherwise; *CAR* – a dummy variable taking the value of 1 if a borrower owns a car and 0 otherwise; *T\_Length* – the number of characters in a loan title; *D\_Length* – the number of characters in a loan description; *N\_Length* – the number of characters in a borrower's nickname; and *Year* – Year dummy.

(2) \*, \*\*, and \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors are used and T-statistics are reported in parentheses. N is the number of observations. r2\_a is adjusted R-square.

Table 11 lists the regression results. In Columns (2), (3), and (4), we separately estimate the impacts of *DSCORE\_ALL*, *DSCORE*, and *DSCORE\_NOR* on interest rate. Comparing with Column (1), we find that the Adjusted  $R^2$  of Columns (2), (3), and (4) are higher by varying degrees, implying that the quantity of information disclosure generates incremental explanatory power on the borrowing rate. Column (2) shows that the coefficient of *DSCORE\_ALL* is 0.133 and significant at the 1% confidence level. This means that after controlling for other factors, the interest rate of a loan request with complete information disclosure is 1% higher than its counterpart with incomplete information disclosure (0.133/13.36). The coefficient of *DSCORE* in Column (3) is 0.02 and significant at the 1% level. This implies that one additional component of voluntarily disclosed information will enhance the loan interest rate on average by 0.14% (0.02/13.36). The estimates in Column (4) are similar to those in Column (3).

Our result is contrary to that of Michels (2012), who finds that more disclosures result in lower funding cost. We believe that this also reflects the borrowers' disclosure manipulation. In the P2P lending market, the borrowing rate is the key indicator for lenders, because it is related to the return on investment. Therefore, borrowers who tend to manipulate information disclosure are more likely to set a higher interest rate to attract the lenders to invest.

We further examine the effect of voluntary disclosure on loan performance with the following model:

$$Loan\ Performance_i = \beta_0 + \beta_1 Disclosure_i + \beta_2 Control_i + \varepsilon_i, \quad (12)$$

where *Loan Performance<sub>i</sub>* is measured by the three indicators of expected profit (*EP*), loan repayment ratio (*LRR*), and default loss (*DL*), respectively. *Disclosure* represents indicators measuring the intensity of information disclosure, including *DSCORE\_ALL*, *DSCORE*, and *DSCORE\_NOR*. We control other variables that might affect funding probability, interest rate, and the probability of default, including the characteristics of loan listings, borrowers' age, financial assets, length of loan description, etc.  $\varepsilon_i$  is a random disturbance term.

Table 12 presents the corresponding regression results. In Columns (1) to (9), we separately estimate the impacts of *DSCORE\_ALL*, *DSCORE*, and *DSCORE\_NOR* on expected profit, loan repayment ratio, and default loss. We find that *Disclosure* can have a significant impact on expected profit and default loss, but not on loan repayment ratio. The coefficient of *DSCORE* reported in Column (4) is 0.003 and significant at the 1% confidence level, meaning that the more voluntary information disclosures there are, the higher the expected profit will be. The coefficient of *DSCORE* is negative and significant at the 1% confidence level. All these results suggest that although the loan listings with more voluntary information disclosure are more likely to be defaulted, the higher interest rate offered by the borrowers can compensate for the risk. At the same time, those loan listings with more voluntary information disclosure have less loss when they default. Therefore, it is still the best choice for lenders to invest in loan listings with more voluntary information disclosure.

**Table 12: Voluntary Disclosure Intensity and Loan Performance**

	(1) EP	(2) LRR	(3) DL	(4) EP	(5) LRR	(6) DL	(7) EP	(8) LRR	(9) DL
DSCORE_ALL	0.013** (1.96)	-0.021 (-1.19)	-2.8e+03*** (-17.54)						
DSCORE				0.003*** (2.75)	-0.009 (-1.46)	-467.853*** (-17.92)			
DSCORE_NOR							0.003*** (2.94)	-0.010 (-1.46)	-482.712*** (-18.08)
lnAMOUNT	-2.424*** (-827.47)	-0.008 (-1.18)	-487.777*** (-3.44)	-2.424*** (-827.19)	-0.008 (-1.22)	-497.684*** (-3.51)	-2.424*** (-827.25)	-0.008 (-1.22)	-497.734*** (-3.51)
INTEREST	0.782*** (218.69)	-0.007** (-2.55)	2,270.494*** (67.48)	0.782*** (218.75)	-0.007** (-2.53)	2,268.830*** (67.43)	0.782*** (218.75)	-0.007** (-2.54)	2,268.664*** (67.43)
MONTHS	-0.493*** (-1,230.01)	0.001 (1.07)	2,054.188*** (177.55)	-0.493*** (-1,230.38)	0.001 (1.11)	2,051.611*** (177.60)	-0.493*** (1,230.42)	0.001 (1.11)	2,051.664*** (177.61)
CREDIT	12.729*** (353.63)	0.052*** (4.37)	-2.2e+04*** (-31.42)	12.729*** (353.55)	0.052*** (4.39)	-2.2e+04*** (-31.41)	12.729*** (353.55)	0.052*** (4.39)	-2.2e+04*** (-31.40)
AGE	-0.320*** (-565.46)	-0.001 (-1.58)	1,944.035*** (115.91)	-0.320*** (-564.20)	-0.001 (-1.57)	1,941.069*** (115.74)	-0.320*** (-564.17)	-0.001 (-1.57)	1,940.977*** (115.74)
HOUSE	1.416*** (175.72)	-0.033*** (-3.55)	-6.5e+03*** (-36.49)	1.415*** (174.92)	-0.033*** (-3.51)	-6.4e+03*** (-36.03)	1.414*** (174.73)	-0.033*** (-3.52)	-6.4e+03*** (-35.96)
CAR	1.117*** (112.00)	0.056*** (5.42)	-3.5e+03*** (-14.19)	1.117*** (111.84)	0.056*** (5.42)	-3.5e+03*** (-14.11)	1.117*** (111.81)	0.056*** (5.42)	-3.5e+03*** (-14.09)
T_Length	-0.012*** (-21.42)	0.000 (0.26)	126.619*** (11.31)	-0.012*** (-21.44)	0.000 (0.24)	129.433*** (11.53)	-0.012*** (-21.45)	0.000 (0.24)	129.349*** (11.52)
D_Length	-0.005*** (-91.18)	0.000 (0.77)	48.472*** (28.92)	-0.005*** (-91.15)	0.000 (0.79)	48.601*** (28.97)	-0.005*** (-91.16)	0.000 (0.79)	48.602*** (28.97)
N_Length	-0.033*** (-34.74)	0.002 (1.12)	39.578 (1.51)	-0.033*** (-34.77)	0.002 (1.12)	34.305 (1.31)	-0.033*** (-34.71)	0.002 (1.12)	33.415 (1.28)
_cons	36.104*** (517.82)	0.529*** (7.06)	-9.2e+04*** (-46.78)	36.091*** (520.86)	0.594*** (6.31)	-9.0e+04*** (-45.73)	36.095*** (519.38)	0.575*** (6.65)	-9.1e+04*** (-46.25)
Year	YES	YES	YES	YES	YES	YES	YES	YES	YES
N	604,885	4,094	604,885	604,885	4,094	604,885	604,885	4,094	604,885
r2_a	0.956	0.022	0.189	0.956	0.023	0.189	0.956	0.023	0.189

Note: (1) This table reports OLS regression results. The dependent variables are (i) *EP*, expected profit of a loan listing; (ii) *LRR*, repayment ratio of a loan listing; and (iii) *DL*, default loss of a loan listing. The explanatory variables include: *DSCORE* – the borrower's disclosure score (see Table 2 for definition); *DSCORE\_ALL* – a dummy variable taking the value of 1 if a borrower's disclosure score is equal to 9 and 0 otherwise; *DSCORE\_NOR* – a borrower's disclosure score, excluding the disclosure on marital status and borrowing purpose; *lnAMOUNT* – natural log of loan amount (in RMB) requested by the borrower; *INTEREST* – the interest rate that a borrower pays on the loan; *MONTHS* – loan term (in months) requested by the borrower; *CREDIT* – credit grade of the borrower at the time the listing was created; *AGE* – the age of a borrower expressed in years; *HOUSE* – a dummy variable taking the value of 1 if the borrower is a homeowner and 0 otherwise; *CAR* – a dummy variable taking the value of 1 if a borrower owns a car and 0 otherwise; *T\_Length* – the number of characters in a loan title; *D\_Length* – the number of characters in a loan description; *N\_Length* – the number of characters in a borrower's nickname; and *Year* – Year dummy.

(2) \*, \*\*, and \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors are used and T-statistics are reported in parentheses. N is the number of observations. r2\_a is adjusted R-square.



## 5. ENDOGENEITY CONCERNS

In evaluating the impact of voluntary disclosure information on loan outcomes, there are a number of important methodological challenges that need to be addressed. First, as default depends on success, we can only observe the defaults among the borrowers who have successfully had their loan requests funded but cannot observe defaults by those who fail to raise the funds. Hence, our estimation on default might be susceptible to sample selection bias. The Heckman selection model is adopted to moderate this bias (Heckman 1979). Second, some unobservable or omitted variables may contaminate our estimation results. For example, social network and investor sentiment may change the funding success rate (Grinblatt, Keloharju, and Linnainmaa 2011). We employ the IV probit model and the 2SLS model to address this concern.

### 5.1 Heckman Selection Model

One methodological challenge of this study is that default is dependent on success. We employ the Heckman (1979) selection model to address this concern. In the first stage, we estimate the determinants of the probability of funding success (*SUCCESS*). In the second stage, the probit model is used to treat *DEFAULT* as the dependent variable and other information as the independent variable for regression. A convincing implementation of the Heckman selection model is to identify from the first-stage choice model at least one exogenous independent variable that can be validly excluded from the vector of explanatory variables in the second-stage regression (Bayar and Chemmanur 2012; Boubakri et al. 2018; Cole and Sokolyk 2018; Daher and Ismail 2018; Dutordoir, Strong, and Sun 2018; Hasan et al. 2018; Jiang et al. 2018; Lin and Su 2008; Little 1985; Lockhart and Unlu 2018; Signori and Vismara 2018; Yang, Guariglia, and Guo 2019; Yuan, Sun, and Cao 2016; Yuan and Wen 2018).

We leverage the peer effect for identification. The important role of peers in forming financial decisions has been well recognized in the literature. For example, Leary and Roberts (2014) acknowledge that firms' financing decisions are in large part responses to the financing decisions of peer firms. We borrow from these studies and develop an instrument named *Me\_SUCCESS* for the model identification. It is the average loan success rate of borrowers with a similar interest rate, borrowing amount, and loan description length. We believe that the loan success rate of peers with similar characteristics will affect the funding probability of an individual borrower, but not this borrower's probability of default.

The estimation results are shown in Table 13. Column (1) reports the first-step estimation on *SUCCESS*. The coefficient on *Me\_SUCCESS* is positively significant, implying that the higher the funding success rate of the peers, the higher the likelihood of a borrower getting their loan application funded. Column (2) presents the endogeneity-adjusted estimate on default where the inverse Mills ratio (IMR) estimated by the first stage is added. The coefficient on *IMR* is negative, but not significant, indicating that the influence of sample selection bias is not obvious. The coefficient on *DSCORE* is 0.177, which is significant and similar in size to the baseline estimation, meaning that our conclusions are robust after controlling for sample selection bias.

**Table 13: Endogenous Concern (Heckman Two-Step)**

	(1) SUCCESS	(2) DEFAULT
Me_SUCCESS	5.009*** (60.92)	
DSCORE	0.147*** (68.44)	0.177*** (6.21)
IMR		-0.034 (-0.42)
lnAMOUNT	-0.193*** (-53.87)	0.329*** (8.99)
INTEREST	-0.030*** (-22.71)	0.121*** (9.23)
MONTHS	0.002*** (3.41)	0.058*** (22.75)
CREDIT	0.690*** (90.94)	-2.118*** (-22.51)
AGE	0.024*** (46.41)	0.037*** (10.45)
HOUSE	0.104*** (12.99)	-0.206*** (-4.90)
CAR	0.245*** (28.05)	-0.134*** (-2.80)
T_Length	0.009*** (17.69)	0.003 (1.21)
D_Length	0.000* (1.86)	0.001*** (2.64)
N_Length	-0.059*** (-46.71)	0.010 (1.23)
_cons	-2.255*** (-50.06)	-6.705*** (-16.03)
Year	YES	YES
N	604,885	27,112
r2_p	0.350	0.282

Note: (1) This table reports the Heckman two-step regression results on the probability of default. Column (1) is estimated by probit regression while Column (2) is the Heckman two-step regression. In Column (1), the dependent variable is SUCCESS, taking a value of 1 if a loan listing is fully funded and 0 otherwise. In Column (2), the dependent variable is the DEFAULT dummy, taking a value of 1 if the funded loan has been defaulted and 0 otherwise. IMR is the inverse Mills ratio. Me\_SUCCESS is the average funding success rate of a borrower's peers. Other explanatory variables include: *lnAMOUNT* – natural log of loan amount (in RMB) requested by the borrower; *INTEREST* – the interest rate that a borrower pays on the loan; *MONTHS* – loan term (in months) requested by the borrower; *CREDIT* – credit grade of the borrower at the time the listing was created; *AGE* – the age of a borrower expressed in years; *HOUSE* – a dummy variable taking the value of 1 if the borrower is a homeowner and 0 otherwise; *CAR* – a dummy variable taking the value of 1 if a borrower owns a car and 0 otherwise; *T\_Length* – the number of characters in a loan title; *D\_Length* – the number of characters in a loan description; *N\_Length* – the number of characters in a borrower's nickname; and *Year* – Year dummy.

(2) \*, \*\*, and \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors are used and Z-statistics are reported in parentheses. N is the number of observations. r2\_p is Pseudo R-square.

## 5.2 Instrumental Variable Estimation

Our results may be affected by the omitted variables. For example, borrowers who need funds urgently may choose to disclose as much information as possible. In this paper, we employ instrumental variable (IV) regression to address these concerns. To mitigate the effect of omitted variables on our basic conclusion, first of all we need to find a suitable instrumental variable, which should not directly correlate to funding success and interest rate but can exert a direct impact on voluntary disclosure by borrowers. Given that peer effect plays an important role in financial decisions (Leary and Roberts 2014), we utilize peer-borrower effect as a candidate. Leary and Roberts (2014) find that listed firms are greatly affected by peers in the same industry regarding financial decisions. A large amount of corporate finance literature also uses the industrial average to construct the exogenous instrumental variable (Adhikari and Agrawal 2018; Chen 2015; Eom 2018; Hasan and Cheung 2018; Huang and Mazouz 2018; Jiang and Yuan 2018; Kim, Patro and Pereira 2017; Ward, Yin, and Zeng 2018; Zhang et al. 2016). Huang and Mazouz (2018) suggest that firms in the same industry tend to adopt a similar corporate policy and use the natural logarithm of the industry average excess cash as the instrumental variable of the firm's excess cash. Eom (2018) employs the industry average of the logarithm of oversubscription in the recent five IPOs as the instrument for oversubscription. Following the existing literature, we believe that a borrower's decision on information disclosure is largely affected by the amount of information disclosed by his or her peers. To define peers, we classify borrowers into different categories according to their borrowing rate (low, median, or high), the borrowing amount (low, median, or high) and the loan description length (low, median, or high). The average amount of information disclosure by each category (*Me\_DSCORE*) is then used as the instrument for the amount of information voluntarily disclosed by a borrower in this category.

Table 14 reports the IV probit and 2SLS regression results. The first-stage regression result shown in Column (1) indicates that the information disclosure by peers is a strong predictor of the information disclosed by an individual borrower. Moreover, the F-statistic shown at the bottom is 18,233. According to Staiger and Stock (1994), the suggested critical F-value is 8.96 when the number of instruments is one. With the F-statistic much greater than 10, we can reject the null hypothesis that the coefficient on the instrument is insignificantly different from zero at the 1% level, excluding the weak instrument concern. The second-stage regression results shown in Columns (2) to (3) are in line with the baseline estimations. The Wald test implies the need to address the endogeneity of *DSCORE*. Borrowers with more voluntary information disclosures have a significantly higher success rate of borrowing and a higher interest rate.

**Table 14: Endogenous Concern (2SLS and IV probit)**

	(1) DSCORE	(2) INTEREST	(3) SUCCESS
Me_DSCORE	0.396*** (66.78)		
DSCORE		3.668*** (63.30)	0.253*** (18.04)
lnAMOUNT	−0.131*** (−42.88)	0.554*** (39.39)	−0.265*** (−43.08)
INTEREST	−0.007*** (−5.92)		−0.054*** (−42.21)
MONTHS	0.019*** (46.79)	−0.027*** (−13.06)	−0.002*** (−2.72)
CREDIT	0.022*** (5.02)	−0.535*** (−21.45)	0.682*** (65.17)
AGE	−0.018*** (−35.63)	0.066*** (29.21)	0.025*** (51.01)
HOUSE	1.827*** (329.75)	−6.832*** (−61.85)	−0.102*** (−3.37)
CAR	0.991*** (163.01)	−3.865*** (−57.70)	0.129*** (6.56)
T_Length	0.027*** (63.43)	−0.087*** (−34.98)	0.007*** (9.25)
D_Length	0.001*** (14.60)	−0.007*** (−35.09)	0.001*** (10.49)
N_Length	−0.163*** (−155.87)	0.555*** (53.37)	−0.038*** (−11.17)
_cons	6.141*** (123.76)	−19.999*** (−38.95)	−1.732*** (−13.88)
N	604,885	604,885	604,885
F statistics	18,233		
Wald test			0.00
r2_a	0.269		

Note: (1) This table reports 2SLS and IV probit regression results. This table reports the IV probit regression results on funding success probability, and 2SLS regression results on interest rate. Column (1) is estimated by OLS regression; Column (2) is estimated by 2SLS regression; and Column (3) is estimated by IV probit regression. *Me\_DSCORE* is the average amount of information disclosed by peers. Other explanatory variables include: *lnAMOUNT* – natural log of loan amount (in RMB) requested by the borrower; *INTEREST* – the interest rate that a borrower pays on the loan; *MONTHS* – loan term (in months) requested by the borrower; *CREDIT* – credit grade of the borrower at the time the listing was created; *AGE* – the age of a borrower expressed in years; *HOUSE* – a dummy variable taking the value of 1 if the borrower is a homeowner and 0 otherwise; *CAR* – a dummy variable taking the value of 1 if a borrower owns a car and 0 otherwise; *T\_Length* – the number of characters in a loan title; *D\_Length* – the number of characters in a loan description; *N\_Length* – the number of characters in a borrower's nickname; and *Year* – Year dummy.

(2) \*, \*\*, and \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors are used and T/Z-statistics are reported in parentheses. N is the number of observations. r2\_a is adjusted R-square.

## 6. ROBUSTNESS CHECK

In this section, we perform several robustness checks to further prove the validity of our findings reported in the previous sections.

### 6.1 Probit and Poisson Estimation

Given that the probit model is also suitable for binary variable estimation and has been widely used in economic research (Blundell and Powell 2004; Nyberg 2012), we re-estimate the impact of information disclosure on funding success and the probability of default with the probit model. At the same time, the interest rate limit set by Renrendai for borrowers is “no more than four times the benchmark interest rate of the central bank in the same period.” Therefore, we also use the tobit model to re-estimate the impact of information disclosure on interest rate. In the tobit model we set the upper bound on the interest rate to 24%. As shown in Table 15, after controlling for other factors, borrowers’ voluntary information disclosure is still positively and significantly related to funding success, interest rate, and the probability of default. A larger amount of disclosure is associated with a higher probability of funding success, loan interest rate, and the probability of default.

### 6.2 Sample Adjustment

In this subsection, we adjust the sample to exclude the loan listings with extreme values of borrowing amount and borrowing rate. According to the regulation<sup>3</sup> recently issued by the China Banking Regulatory Commission, a person cannot borrow over 200,000 yuan on the same P2P lending platform. Moreover, the highest annual borrowing rate of P2P lending cannot exceed four times the bank annual interest rate. According to our calculation, the maximum borrowing rate is 24% under the current regulation framework. Thus, in robustness tests, we exclude loan listings that don’t match the regulation requirements. Table 16 reports the estimation results for loan listings whose borrowing amount is less than 200,000 yuan and whose borrowing rate is lower than 24%. We find that voluntary information disclosures are still positively and significantly associated with funding success, interest rate, and probability of default.

### 6.3 The Quality of Voluntary Information Disclosure

From the logic of this paper, we assume that the quality of information provided by borrowers will have a differentiated impact on investment, and different information will reflect the quality of borrowers to different degrees. If the impacts of different types of information disclosure are the same, lenders will be indifferent about investing in listings with or without disclosure, while borrowers will have no incentive to manipulate the information disclosure. To test this assumption, we examine the differentiated impacts of different items of information on loan outcomes under the condition of full disclosure of information. The results reported in Tables 17–19 indicate that different types of information do have differentiated impacts on funding success, interest rate, and probability of default.

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<sup>3</sup> On 24 August 2016, the Chinese government released the Interim Measures on Administration of the Business Activities of Peer-to-Peer Lending Information Intermediaries to crack down on illegal fundraising activities through online finance so as to prevent financial risks and potential social unrest.

**Table 15: Robust Check 1: Probit and Tobit Model**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	SUCCESS	INTEREST	DEFAULT	SUCCESS	INTEREST	DEFAULT	SUCCESS	INTEREST	DEFAULT
DSCORE_ALL	0.492*** (46.52)	0.135*** (19.15)	0.249*** (6.06)						
DSCORE				0.149*** (71.08)	0.020*** (17.68)	0.100*** (6.78)			
DSCORE_NOR							0.150*** (71.03)	0.020*** (17.08)	0.101*** (6.84)
lnAMOUNT	-0.289*** (-86.33)	0.027*** (8.55)	0.181*** (11.21)	-0.291*** (-85.29)	0.027*** (8.57)	0.183*** (11.34)	-0.291*** (-85.30)	0.027*** (8.54)	0.183*** (11.35)
INTEREST	-0.053*** (-40.20)		0.063*** (9.37)	-0.053*** (-40.68)		0.063*** (9.33)	-0.053*** (-40.67)		0.063*** (9.33)
MONTHS	0.001*** (2.63)	0.065*** (158.49)	0.034*** (23.31)	0.001* (1.95)	0.065*** (159.31)	0.034*** (23.11)	0.001* (1.95)	0.065*** (159.35)	0.034*** (23.10)
CREDIT	0.717*** (93.21)	-0.498*** (-68.91)	-0.946*** (-22.06)	0.710*** (93.05)	-0.498*** (-69.01)	-0.948*** (-22.10)	0.710*** (93.05)	-0.498*** (-69.00)	-0.948*** (-22.10)
AGE	0.023*** (46.50)	0.000 (0.22)	0.022*** (12.13)	0.024*** (47.55)	0.000 (0.39)	0.021*** (12.07)	0.024*** (47.52)	0.000 (0.38)	0.021*** (12.06)
HOUSE	0.133*** (16.59)	-0.116*** (-14.21)	-0.111*** (-4.68)	0.101*** (12.89)	-0.112*** (-13.62)	-0.113*** (-4.78)	0.102*** (12.91)	-0.111*** (-13.52)	-0.113*** (-4.78)
CAR	0.262*** (30.29)	-0.231*** (-25.69)	-0.064** (-2.52)	0.246*** (28.84)	-0.229*** (-25.44)	-0.063** (-2.48)	0.246*** (28.84)	-0.229*** (-25.39)	-0.063** (-2.48)
T_Length	0.011*** (23.74)	0.027*** (52.22)	0.002 (1.48)	0.011*** (22.23)	0.027*** (52.06)	0.002 (1.55)	0.011*** (22.29)	0.027*** (52.11)	0.002 (1.55)
D_Length	0.001*** (21.05)	0.001*** (15.95)	0.000*** (2.61)	0.001*** (20.17)	0.001*** (15.95)	0.000*** (2.60)	0.001*** (20.19)	0.001*** (15.98)	0.000*** (2.60)
N_Length	-0.061*** (-49.62)	-0.050*** (-49.78)	0.004 (0.95)	-0.058*** (-46.78)	-0.050*** (-49.89)	0.004 (0.94)	-0.058*** (-46.80)	-0.050*** (-49.93)	0.004 (0.95)
_cons	-0.032 (-0.89)	11.446*** (334.91)	-3.431*** (-18.06)	-0.859*** (-22.13)	11.385*** (324.00)	-4.094*** (-17.82)	-0.568*** (-15.17)	11.425*** (330.01)	-3.901*** (-18.25)
sigma									
_cons		2.417*** (527.69)			2.417*** (527.66)			2.417*** (527.66)	
Year	YES	YES	YES	YES	YES	YES	YES	YES	YES
N	604885	604885	27112	604885	604885	27112	604885	604885	27112
r2_p	0.318	0.072	0.272	0.326	0.072	0.272	0.326	0.072	0.272

Note: (1) This table reports probit and tobit regression results. The dependent variables are (i) *SUCCESS*, a dummy variable taking the value of 1 if a loan listing is fully funded and 0 otherwise; (ii) *INTEREST*, the interest rate that the borrower pays on the loan; and (iii) *DEFAULT*, a dummy variable taking the value of 1 if the funded loan has been defaulted and 0 otherwise. The explanatory variables include: *DSCORE* – the borrower's disclosure score (see Table 2 for definition); *DSCORE\_ALL* – a dummy variable taking the value of 1 if a borrower's disclosure score is equal to 9 and 0 otherwise; *DSCORE\_NOR* – a borrower's disclosure score, excluding the disclosure on marital status and borrowing purpose; *lnAMOUNT* – natural log of loan amount (in RMB) requested by the borrower; *INTEREST* – the interest rate that a borrower pays on the loan; *MONTHS* – loan term (in months) requested by the borrower; *CREDIT* – credit grade of the borrower at the time the listing was created; *AGE* – the age of a borrower expressed in years; *HOUSE* – a dummy variable taking the value of 1 if the borrower is a homeowner and 0 otherwise; *CAR* – a dummy variable taking the value of 1 if a borrower owns a car and 0 otherwise; *T\_Length* – the number of characters in a loan title; *D\_Length* – the number of characters in a loan description; *N\_Length* – the number of characters in a borrower's nickname; and *Year* – Year dummy.

(2) \*, \*\*, and \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors are used and Z/T-statistics are reported in parentheses. N is the number of observations. r2\_a/p is adjusted R-square (Pseudo R-square).

**Table 16: Robust Check 2: Loan Listings with Borrowing Amount less than 200,000 Yuan and Loan Listings with Borrowing Rate lower than 24%**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	SUCCESS	INTEREST	DEFAULT	SUCCESS	INTEREST	DEFAULT	SUCCESS	INTEREST	DEFAULT
DSCORE_ALL	1.107*** (43.60)	0.133*** (18.98)	0.457*** (6.26)						
DSCORE				0.343*** (65.53)	0.020*** (17.40)	0.180*** (6.79)			
DSCORE_NOR							0.345*** (65.41)	0.019*** (16.81)	0.182*** (6.85)
lnAMOUNT	-0.557*** (-73.45)	0.036*** (10.30)	0.291*** (9.87)	-0.554*** (-72.60)	0.036*** (10.32)	0.295*** (10.00)	-0.554*** (-72.62)	0.036*** (10.30)	0.296*** (10.01)
INTEREST	-0.112*** (-38.90)		0.121*** (10.10)	-0.112*** (-39.25)		0.120*** (10.06)	-0.112*** (-39.24)		0.120*** (10.06)
MONTHS	0.002* (1.87)	0.066*** (155.63)	0.058*** (23.33)	0.001 (1.31)	0.066*** (156.44)	0.058*** (23.19)	0.001 (1.31)	0.066*** (156.48)	0.058*** (23.19)
CREDIT	1.466*** (93.14)	-0.490*** (-66.50)	-2.118*** (-27.50)	1.444*** (93.12)	-0.491*** (-66.60)	-2.120*** (-27.51)	1.445*** (93.11)	-0.491*** (-66.59)	-2.120*** (-27.51)
AGE	0.048*** (44.81)	-0.000 (-0.28)	0.038*** (12.09)	0.049*** (45.78)	-0.000 (-0.12)	0.038*** (12.03)	0.049*** (45.75)	-0.000 (-0.14)	0.038*** (12.02)
HOUSE	0.274*** (15.79)	-0.114*** (-13.93)	-0.204*** (-4.88)	0.209*** (12.39)	-0.109*** (-13.32)	-0.207*** (-4.96)	0.209*** (12.42)	-0.109*** (-13.22)	-0.207*** (-4.96)
CAR	0.522*** (28.56)	-0.218*** (-23.96)	-0.124*** (-2.77)	0.490*** (27.32)	-0.217*** (-23.72)	-0.122*** (-2.73)	0.490*** (27.32)	-0.216*** (-23.67)	-0.122*** (-2.73)
T_Length	0.023*** (22.98)	0.027*** (52.40)	0.004 (1.55)	0.022*** (21.68)	0.027*** (52.26)	0.004 (1.61)	0.022*** (21.73)	0.027*** (52.31)	0.004 (1.62)
D_Length	0.002*** (21.83)	0.001*** (15.80)	0.001** (2.40)	0.002*** (20.98)	0.001*** (15.81)	0.001** (2.41)	0.002*** (21.00)	0.001*** (15.84)	0.001** (2.41)
N_Length	-0.132*** (-49.13)	-0.048*** (-47.57)	0.008 (1.09)	-0.124*** (-46.66)	-0.048*** (-47.70)	0.008 (1.07)	-0.124*** (-46.68)	-0.048*** (-47.74)	0.008 (1.07)
_cons	0.037 (0.46)	11.322*** (308.57)	-5.286*** (-15.23)	-1.942*** (-21.83)	11.263*** (300.22)	-6.471*** (-15.52)	-1.271*** (-15.01)	11.302*** (304.96)	-6.125*** (-15.76)
Year	YES	YES	YES	YES	YES	YES	YES	YES	YES
N	576,423	576,423	26,822	576,423	576,423	26,822	576,423	576,423	26,822
r2_p/a	0.308	0.304	0.280	0.317	0.304	0.281	0.316	0.304	0.281

Note: (1) This table reports logit and OLS regression results. The dependent variables are (i) *SUCCESS*, a dummy variable taking the value of 1 if a loan listing is fully funded and 0 otherwise; (ii) *INTEREST*, the interest rate that the borrower pays on the loan; and (iii) *DEFAULT*, a dummy variable taking the value of 1 if the funded loan has been defaulted and 0 otherwise. The explanatory variables include: *DSCORE* – the borrower's disclosure score (see Table 2 for definition); *DSCORE\_ALL* – a dummy variable taking the value of 1 if a borrower's disclosure score is equal to 9 and 0 otherwise; *DSCORE\_NOR* – a borrower's disclosure score, excluding the disclosure on marital status and borrowing purpose; *lnAMOUNT* – natural log of loan amount (in RMB) requested by the borrower; *INTEREST* – the interest rate that a borrower pays on the loan; *MONTHS* – loan term (in months) requested by the borrower; *CREDIT* – credit grade of the borrower at the time the listing was created; *AGE* – the age of a borrower expressed in years; *HOUSE* – a dummy variable taking the value of 1 if the borrower is a homeowner and 0 otherwise; *CAR* – a dummy variable taking the value of 1 if a borrower owns a car and 0 otherwise; *T\_Length* – the number of characters in a loan title; *D\_Length* – the number of characters in a loan description; *N\_Length* – the number of characters in a borrower's nickname; and *Year* – Year dummy.

(2) \*, \*\*, and \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors are used and Z/T-statistics are reported in parentheses. N is the number of observations. r2\_a/p is adjusted R-square (Pseudo R-square).

**Table 17: Robust Check 3: Information Quality and Funding Success**

	(1)	(2)	(3)	(4)	(5)
	SUCCESS	SUCCESS	SUCCESS	SUCCESS	SUCCESS
EDUCATION	0.329*** (34.11)				
WORKTIME		0.320*** (38.27)			
INCOME			0.321*** (41.75)		
Firmsize				0.229*** (31.81)	
Marry_Married					0.205*** (11.53)
lnAMOUNT	-0.648*** (-83.79)	-0.646*** (-83.73)	-0.776*** (-94.90)	-0.618*** (-79.44)	-0.641*** (-82.96)
INTEREST	-0.103*** (-35.95)	-0.107*** (-37.40)	-0.108*** (-37.46)	-0.106*** (-37.05)	-0.107*** (-37.38)
MONTHS	0.007*** (6.74)	0.006*** (5.88)	0.017*** (14.95)	0.004*** (3.96)	0.007*** (6.79)
CREDIT	1.372*** (91.55)	1.376*** (91.81)	1.376*** (90.95)	1.397*** (93.69)	1.409*** (93.84)
AGE	0.055*** (48.12)	0.037*** (30.26)	0.047*** (40.84)	0.055*** (48.63)	0.049*** (41.19)
HOUSE	0.118*** (6.77)	0.080*** (4.59)	0.177*** (10.27)	0.150*** (8.66)	0.133*** (7.63)
CAR	0.407*** (22.15)	0.373*** (20.21)	0.237*** (12.42)	0.471*** (25.45)	0.380*** (20.55)
T_Length	0.015*** (14.22)	0.017*** (15.73)	0.016*** (15.23)	0.017*** (16.28)	0.017*** (15.92)
D_Length	0.002*** (20.57)	0.002*** (21.54)	0.002*** (18.49)	0.002*** (21.57)	0.002*** (20.88)
N_Length	-0.108*** (-38.98)	-0.108*** (-39.04)	-0.109*** (-39.38)	-0.108*** (-39.21)	-0.109*** (-39.91)
_cons	1.107*** (13.58)	1.594*** (19.82)	1.967*** (24.81)	0.872*** (10.52)	1.785*** (22.19)
Year	YES	YES	YES	YES	YES
N	386,062	386,062	386,062	386,062	386,062
r2_p	0.282	0.284	0.286	0.281	0.277

Note: (1) This table reports logit regression results for the sample with full information disclosure. The dependent variable is *SUCCESS*, a dummy variable taking the value of 1 if a loan listing is fully funded and 0 otherwise. The explanatory variables include: *DSCORE* – the borrower's disclosure score (see Table 2 for definition); *DSCORE\_ALL* – a dummy variable taking the value of 1 if a borrower's disclosure score is equal to 9 and 0 otherwise; *DSCORE\_NOR* – a borrower's disclosure score, excluding the disclosure on marital status and borrowing purpose; *lnAMOUNT* – natural log of loan amount (in RMB) requested by the borrower; *INTEREST* – the interest rate that a borrower pays on the loan; *MONTHS* – loan term (in months) requested by the borrower; *CREDIT* – credit grade of the borrower at the time the listing was created; *AGE* – the age of a borrower expressed in years; *HOUSE* – a dummy variable taking the value of 1 if the borrower is a homeowner and 0 otherwise; *CAR* – a dummy variable taking the value of 1 if a borrower owns a car and 0 otherwise; *T\_Length* – the number of characters in a loan title; *D\_Length* – the number of characters in a loan description; *N\_Length* – the number of characters in a borrower's nickname; and *Year* – Year dummy.

(2) \*, \*\*, and \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors are used and Z-statistics are reported in parentheses. N is the number of observations. r2\_p is Pseudo R-square.



**Table 18: Robust Check 3: Information Quality and Interest Rate**

	(1)	(2)	(3)	(4)	(5)
	INTEREST	INTEREST	INTEREST	INTEREST	INTEREST
EDUCATION	−0.136*** (−25.59)				
WORKTIME		0.005 (1.01)			
INCOME			0.066*** (14.82)		
Firmsize				−0.036*** (−8.66)	
Marry_Married					−0.058*** (−6.27)
lnAMOUNT	0.028*** (6.45)	0.020*** (4.65)	−0.007 (−1.46)	0.017*** (3.84)	0.022*** (4.94)
MONTHS	0.052*** (93.89)	0.052*** (94.14)	0.054*** (95.34)	0.053*** (94.52)	0.052*** (94.22)
CREDIT	−0.493*** (−65.25)	−0.515*** (−68.10)	−0.524*** (−69.13)	−0.510*** (−67.66)	−0.512*** (−68.06)
AGE	0.002** (2.41)	0.002** (2.49)	0.001 (1.06)	0.002*** (2.74)	0.003*** (4.75)
HOUSE	−0.101*** (−11.28)	−0.120*** (−13.33)	−0.119*** (−13.35)	−0.117*** (−13.08)	−0.109*** (−11.98)
CAR	−0.231*** (−23.88)	−0.234*** (−24.13)	−0.265*** (−26.97)	−0.242*** (−24.85)	−0.225*** (−22.94)
T_Length	0.030*** (46.05)	0.030*** (44.91)	0.029*** (44.50)	0.030*** (44.87)	0.030*** (44.86)
D_Length	0.001*** (11.51)	0.001*** (11.24)	0.001*** (10.61)	0.001*** (11.09)	0.001*** (11.17)
N_Length	−0.033*** (−25.92)	−0.033*** (−25.32)	−0.032*** (−25.20)	−0.033*** (−25.54)	−0.032*** (−25.24)
_cons	11.752*** (254.39)	11.593*** (252.99)	11.658*** (252.24)	11.715*** (243.83)	11.558*** (250.92)
Year	YES	YES	YES	YES	YES
N	386,062	386,062	386,062	386,062	386,062
r2_a	0.279	0.278	0.278	0.278	0.278

Note: (1) This table reports logit regression results for the sample with full information disclosure. The dependent variable is *INTEREST*, the interest rate that the borrower pays on the loan. The explanatory variables include: *DSCORE* – the borrower's disclosure score (see Table 2 for definition); *DSCORE\_ALL* – a dummy variable taking the value of 1 if a borrower's disclosure score is equal to 9 and 0 otherwise; *DSCORE\_NOR* – a borrower's disclosure score, excluding the disclosure on marital status and borrowing purpose; *lnAMOUNT* – natural log of loan amount (in RMB) requested by the borrower; *INTEREST* – the interest rate that a borrower pays on the loan; *MONTHS* – loan term (in months) requested by the borrower; *CREDIT* – credit grade of the borrower at the time the listing was created; *AGE* – the age of a borrower expressed in years; *HOUSE* – a dummy variable taking the value of 1 if the borrower is a homeowner and 0 otherwise; *CAR* – a dummy variable taking the value of 1 if a borrower owns a car and 0 otherwise; *T\_Length* – the number of characters in a loan title; *D\_Length* – the number of characters in a loan description; *N\_Length* – the number of characters in a borrower's nickname; and *Year* – Year dummy.

(2) \*, \*\*, and \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors are used and Z-statistics are reported in parentheses. N is the number of observations. r2\_p is Pseudo R-square.

**Table 19: Robust Check 3: Information Quality and Loan Default**

	(1)	(2)	(3)	(4)	(5)
	DEFAULT	DEFAULT	DEFAULT	DEFAULT	DEFAULT
EDUCATION	-0.559*** (-20.70)				
WORKTIME		-0.069*** (-3.10)			
INCOME			0.245*** (11.96)		
Firmsize				-0.210*** (-10.12)	
Marry_Married					0.076 (1.61)
lnAMOUNT	0.336*** (10.87)	0.315*** (10.50)	0.108*** (3.14)	0.285*** (9.44)	0.313*** (10.45)
INTEREST	0.117*** (9.16)	0.120*** (9.84)	0.119*** (9.80)	0.118*** (9.56)	0.120*** (9.86)
MONTHS	0.060*** (22.65)	0.057*** (22.42)	0.063*** (24.01)	0.060*** (23.21)	0.057*** (22.38)
CREDIT	-2.069*** (-26.75)	-2.101*** (-27.23)	-2.104*** (-27.26)	-2.103*** (-27.17)	-2.101*** (-27.30)
AGE	0.035*** (10.71)	0.042*** (12.21)	0.035*** (10.77)	0.036*** (11.21)	0.037*** (10.89)
HOUSE	-0.083* (-1.87)	-0.169*** (-3.87)	-0.173*** (-3.99)	-0.169*** (-3.90)	-0.202*** (-4.57)
CAR	-0.163*** (-3.42)	-0.138*** (-2.94)	-0.264*** (-5.48)	-0.196*** (-4.16)	-0.152*** (-3.21)
T_Length	0.008*** (2.67)	0.003 (1.18)	0.003 (0.89)	0.003 (1.08)	0.003 (1.22)
D_Length	0.001*** (3.10)	0.001*** (3.26)	0.001*** (2.82)	0.001*** (3.00)	0.001*** (3.38)
N_Length	0.010 (1.27)	0.007 (0.86)	0.008 (1.00)	0.009 (1.19)	0.006 (0.83)
_cons	-4.180*** (-11.60)	-5.023*** (-14.43)	-3.993*** (-11.27)	-4.170*** (-11.67)	-5.036*** (-14.47)
Year	YES	YES	YES	YES	YES
N	24,415	24,415	24,415	24,415	24,415
r2_p	0.305	0.285	0.291	0.289	0.284

Note: (1) This table reports logit regression results for the sample with full information disclosure. The dependent variable is *DEFAULT*, a dummy variable taking the value of 1 if the funded loan has been defaulted and 0 otherwise. The explanatory variables include: *DSCORE* – the borrower's disclosure score (see Table 2 for definition); *DSCORE\_ALL* – a dummy variable taking the value of 1 if a borrower's disclosure score is equal to 9 and 0 otherwise; *DSCORE\_NOR* – a borrower's disclosure score, excluding the disclosure on marital status and borrowing purpose; *lnAMOUNT* – natural log of loan amount (in RMB) requested by the borrower; *INTEREST* – the interest rate that a borrower pays on the loan; *MONTHS* – loan term (in months) requested by the borrower; *CREDIT* – credit grade of the borrower at the time the listing was created; *AGE* – the age of a borrower expressed in years; *HOUSE* – a dummy variable taking the value of 1 if the borrower is a homeowner and 0 otherwise; *CAR* – a dummy variable taking the value of 1 if a borrower owns a car and 0 otherwise; *T\_Length* – the number of characters in a loan title; *D\_Length* – the number of characters in a loan description; *N\_Length* – the number of characters in a borrower's nickname; and *Year* – Year dummy.

(2) \*, \*\*, and \*\*\* indicate significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors are used and Z-statistics are reported in parentheses. N is the number of observations. r2\_p is Pseudo R-square.

## 6.4 Additional Tests

To avoid estimation bias and ensure the solidness of our conclusion, we carry out some additional robustness checks. But we don't report the results due to space constraints. First, we exclude loan listings that are under repayment or defaulted from the sample, and redo the empirical analysis. Second, we divide the samples into several subgroups according to whether the borrower owns housing property or a car, and whether the borrowing rate, term, borrowers' age, and the lengths of the borrowing title and loan description are above or lower than the median value. Third, we re-estimate the models using the bootstrap (100) standard error. All the results are robust and consistent.

## 7. CONCLUSIONS

The information asymmetry in the online P2P lending market motivates us to explore the role of voluntary disclosures in moderating the information gap between borrowers and investors. Using data from Renrendai, one of the largest peer-to-peer lending platforms in the PRC, we investigate the impact of voluntary information disclosure on investment decisions. We find that voluntary information disclosure is positively associated with funding probability, as well as the probability of default. This finding suggests that borrowers may strategically disclose information in favor of themselves, which further strengthens the information asymmetry between the borrower and the lender. However, lenders are smart enough to recognize the default risk associated with voluntary information disclosure under the condition of "cheap talk," even though hard facts like credit scores are not available. It is still a good choice for lenders to invest in loan listings with more voluntary information disclosures, because these loan listings have higher expected profits but lower default losses.

Our study has strong implications for policy makers. Despite its substantial benefits, P2P lending also raises safety concerns. P2P lending shares all of the risks associated with traditional "bricks and mortar" lending, including lending fraud, identity theft, money laundering, consumer privacy, and data protection violations. These risks are then married to, and amplified by, the anonymity and ubiquity of the internet. Lax regulation has helped the industry to prosper, but as it approaches a significant size that may impact the financial markets, it would be wise for regulation to play a more influential role. Globally, the existing legal framework and regulations covering P2P lending are patchy at best. Our research confirms that the degree of information asymmetry will be strengthened in developing countries where the credit system is not developed, and the market environment is not perfect. For the financial authorities, it is necessary to perfect the unified social credit evaluation system. The PRC's current social credit system is in the process of construction and has not yet formed a unified social credit evaluation system. Although government departments have a large amount of personal information, citizens' personal information has not been shared uniformly. In the absence of an effective credit scoring system, any voluntary information disclosure without verification could impair investment choices. Therefore, there is a need to extend the coverage of the credit scoring system, and integrate the consequences of personal false information disclosure and default into credit evaluation.

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