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RESEARCH ARTICLE



Strategic co-funding in informal finance market: evidence from China

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ABSTRACT

Information asymmetry in the anonymous informal finance market drives the lenders to screen the borrowers by disclosed information. Using data from a powerful online peer-to-peer lending platform, we study the effects of formal financing records on successful funding and default outcomes in the informal finance market. We find that lenders are more likely to fund borrowers with formal financing records. Borrowers with formal credit are more likely to repay the loans entirely. Co-funding with the formal financial sector is strategic, corresponding to lower default risk. Moreover, without historical success records or with a low-income level, borrowers can use the formal credit signals to mitigate information asymmetry and improve the funding probability. These results are obtained after controlling for loan-level and borrower-level information, city-by-year-month, and day-of-week fixed effects. Several tests show our findings are unlikely to be an unintentional byproduct of the formal financial signals.

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KEYWORDS

Information asymmetry; co-funding; informal finance; peer-to-peer lending

1. Introduction

The information gap between the informed borrowers and uninformed lenders raises the information asymmetry, resulting in adverse selection and credit rationing in the formal and informal finance market (Stiglitz & Weiss, 1981). Formal financing and informal financing are both substitutes and complements in terms of their development (Allen, Qian, & Xie, 2019a). In a classic sense, informal finance is the financing that occurs without a formal financial intermediary, such as through friends or interpersonal borrowing (Galema, 2020). The traditional classification of formal financing (through institutions) and informal financing provides an ambiguous distinction for the recently developed internet technology-based financing forms such as online peer-to-peer lending (Allen, Qian, & Xie, 2019b). The difference between formal and informal finance has become less legible. The funding obtained via an online peer-to-peer lending platform can be defined as informal financing (Galema, 2020), even though the contracts between borrowers and lenders are formal and standardized.

Online peer-to-peer lending, a technology-based informal finance form, attracts many potential borrowers and individual lenders. The Chinese peer-to-peer lending market

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enjoyed rapid growth and became an essential financial industry component during 2008 and 2018 (Jiang, Liao, Wang, & Zhang, 2021). And the total trading volume of online peer-to-peer lending corresponds to about 20% of traditional banks' consumption loans in 2018 in China (Braggion, Manconi, & Zhu, 2018). Moreover, the peer-to-peer lending market accounts for 30% of the U.S. unsecured installment loans in 2016 and supplement traditional banking (Tang, 2019).

The informal lenders have no informational advantages in particular (Lee & Persson, 2016). Therefore the uninformed lenders will screen the borrowers by all available information, even the unverifiable information in the peer-to-peer lending platform (Michels, 2012). When time pressure is more substantial, lenders primarily rely on critical factors, such as interest rates, to invest with fast thinking (Liao, Wang, Xiang, Yan, & Yang, 2020). The formal and informal financial sectors can balance the advantages and disadvantages to each other (Madestam, 2014) and earn higher profits in the co-funding equilibriums (Andersen & Malchow-Møller, 2006). The anonymous attributes between lenders and borrowers in the online peer-to-peer lending market lead to security concerns. Lenders have to make decisions based on the disclosed standard or nonstandard information. The formal financing records as standard information can deliver trustworthy signals, but its effects are still relatively underexplored in informal finance such as the online peer-to-peer lending market. This paper examines the impact of formal financial signals on co-funding and default outcomes in the online peer-to-peer lending market. Specifically, we investigate whether the formal credit records can improve the vulnerable groups' funding probability.

To answer this question, we collect data from an influential Chinese online peer-to-peer lending platform. Our dataset covers all the unsecured credit loans from October 2010 to October 2016, and we trace the repayment records up to February 2020. Our main results rely on the 419,762 loan applications and 28,697 funded loans from all 31 mainland China municipalities and provinces. We control for a rich set of loan-level and borrower-level information, as well as city-by-year-month and day-of-week fixed effects. The granular fixed effects allow us to absorb the confounding local macro-economic shocks, which can help rule out the possibility of alternative competing explanations.

We use the outstanding mortgage records from the formal financial sector to measure the formal financial signals. We document that lenders are more likely to co-fund borrowers who have formal financing records. Among the funded loans, borrowers with formal financing records are more likely to repay the informal loans entirely. Collectively, these findings suggest that co-funding with the formal financial sector is strategic, corresponding to lower default risk. Moreover, borrowers without historical success records or with low income are significantly less likely to be funded by lenders. They can use formal financial signals to alleviate the information gap and improve the funding probability.

This paper directly contributes to the literature on the relationship between formal finance and informal finance. Extant research documents two relationships between formal finance and informal finance. First, informal finance is the intermediary between formal finance and borrowers, playing the role of collecting borrower's nonstandard information, issuing and collecting loans (Bose, 1998; Fuentes, 1996; Varghese, 2005; Warning & Sadoulet, 1998). Second, formal finance and informal finance are horizontal

relationships. Two sectors balance the advantages and disadvantages to each other and co-fund the borrowers for the optimal profits (Andersen & Malchow-Møller, 2006; Degryse, Lu, & Ongena, 2016; Long, 2019; Madestam, 2014). We complement the studies by documenting that the lenders are more likely to co-fund the borrowers with formal financing records in the online peer-to-peer lending market.

In the online peer-to-peer lending domain, the existing literature mainly focuses on the predictable factors, including description (Chen, Huang, & Ye, 2018; Dorfleitner, Priberny, Schuster, Stoiber, Weber, de Castro, & Kammler, 2016; Herzenstein, Sonenshein, & Dholakia, 2011; Larrimore, Jiang, Larrimore, Markowitz, & Gorski, 2011), appearance (Duarte, Siegel, & Young, 2012), social capital (Freedman & Jin, 2017; Lin, Prabhala, & Viswanathan, 2013), gender (Chen, Huang, & Ye, 2020), race (Pope & Sydnor, 2011), credit grade (Emekter, Tu, Jirasakuldech, & Lu, 2015; Han, Chen, Liu, Luo, & Fan, 2018), location (Burtch, Ghose, & Wattal, 2014; Lin & Viswanathan, 2016; Wang, Zhao, & Shen, 2021), education (Chen, Zhang, & Yin, 2018), debt to income ratio (Emekter, Tu, Jirasakuldech, & Lu, 2015; Iyer, Khwaja, Luttmer, & Shue, 2016), etc., on the funding probability and default risk. We add to the literature by investigating formal financial signals' effects on successful funding and default risk in the peer-to-peer lending market. We also find that without historical success records and low-income groups can use the formal financial signals to improve the funding probability.

The remainder of the paper is organized as follows. Section 2 provides the related literature and hypotheses. Section 3 shows our dataset's details, empirical models, and summary statistics of our final sample. Section 4 reports the baseline results, heterogeneity tests, and robustness tests. Finally, Section 5 concludes the paper.

2. Literature review and hypotheses development

2.1. Information asymmetry and decision making

In the formal and informal financial markets, information asymmetry results in adverse selection and credit rationing (Stiglitz & Weiss, 1981). Online peer-to-peer lending is a form of informal financial institution. In the online peer-to-peer lending market, potential lenders and potential borrowers are anonymous and barely meet each other (Chen, Huang, & Ye 2018). Uninformed lenders cannot use the additional data source to screen the borrowers. They should rely on all available information, including verified and unverifiable information, to screen borrowers (Michels, 2012). They also depend on the critical factors to invest with fast thinking under time pressure (Liao, Wang, Xiang, Yan, & Yang 2020). It still has a massive issue of information asymmetry on the anonymous lending market even in the Internet age. Enough standard and nonstandard disclosure can help to mitigate the information asymmetry in the emerging online credit market. A rich strand of literature investigates the effects of standard and nonstandard information on lending decisions.

Loan description, appearance, and social capital are specific nonstandard information, which can alleviate the information asymmetry and affect the lending decisions. Definite descriptions and quantitative words are indicators of trust, which are positively associated with successful funding probability. However, much more humanizing details in the loan description are negatively associated with funding probability (Larrimore, Jiang,

Larrimore, Markowitz, & Gorski, 2011). Trustworthy or successful identities in the narratives are more associated with increased funding than moral and economic identities (Herzenstein, Sonenshein, & Dholakia, 2011). Loans with fewer spelling errors, longer text, and positive emotion in the description are more likely to be funded (Dorfleitner, Priberny, Schuster, Stoiber, Weber, de Castro, & Kammler, 2016) and with more punctuations are less likely to be financed (Chen, Huang, & Ye, 2018). As for appearance and social capital, Duarte, Siegel, & Young, (2012) find trustworthy appearance can increase the successful funding probability and is associated with lower default risk. Online friendships or online social networks can improve funding probability and decrease ex-post default rates (Freedman & Jin, 2017; Lin, Prabhala, & Viswanathan, 2013).

Gender, race, credit grade, location, and debt to income ratio are usually standard information that can affect the funding probability and default risk. Chen, Huang, & Ye, (2020) find that female borrower is not likely to be funded. Loan applications applied by African-Americans are less likely to be supported even though they charged higher interest rates (Pope & Sydnor, 2011). Emekter et al. (2015) find that lower credit grade is associated with higher default risk. As for the geographical location, lenders prefer to lend money to local borrowers (Burtch, Ghose, & Wattal, 2014; Lin & Viswanathan, 2016). Emekter, Tu, Jirasakuldech, & Lu (2015) and Iyer, Khwaja, Luttmer, & Shue (2016) find that high debt to income ratio is associated with higher credit grade and lower default risk. If the lenders can identify the debt-to-income ratio's implication, they will prefer to lend money to the borrowers with a high debt-to-income ratio.

2.2. Co-funding

The relationships between formal finance and informal finance can be divided into two types. First, informal financial organizations are intermediaries between traditional financial institutions and borrowers (Bose, 1998). The informal financial organizations usually collect the borrower characteristics and social capital information, such as social networks, social position, and private information. To some extent, informal financial organizations can screen borrowers and mitigate the information gap by their unique advantage of the data. Therefore, formal financial institutions rely on informal financial intermediaries to issue and collect loans (Fuentes, 1996; Varghese, 2005; Warning & Sadoulet, 1998).

Second, formal finance and informal finance are horizontal relationships. Andersen and Malchow-Møller (2006) find the co-funding equilibriums result in formal and informal sectors earning higher profits. The essential criterion for both sectors to screen borrowers and provide loans is whether they are eligible for co-funding. One sector lends money to the borrowers based on whether they have received loans from the other sector. Madestam (2014) also finds that the co-funding model can simultaneously balance both sectors' advantages and disadvantages, such as the informal financial sector's information advantages and the formal financial sector's cost and scalability advantages. A strand of literature documents that firms with co-funding usually perform better in the future (Degryse, Lu, & Ongena, 2016; Long, 2019). Moreover, firms with mixed relationship lending and transaction lending are more resilient to the crisis (Bolton, Freixas, Gambacorta, & Mistrulli, 2016).

The online peer-to-peer lending platform is an informational intermediary between lenders and borrowers rather than a financial intermediary. It provides small and short-term loans complementing traditional banks (Tang, 2019). Therefore, we assume the online peer-to-peer lending and formal finance is a horizontal relationship. The lenders from the online peer-to-peer lending platform may make investments based on other formal financial sectors' signals. Lenders lending money to borrowers with formal financing records will be recognized as co-funding in the peer-to-peer lending market.

Borrowers can get mortgages from traditional banks if their credit is good enough. Furthermore, they can obtain auto loans from banks, auto finance companies, leasing companies, bonding companies, and internet finance companies. The 2015 China Auto Finance Report from Deloitte China Automotive Service also shows that by the end of 2014, banks issue 54% of auto loans, and non-banks auto loan issuers cover the rest.¹ Therefore, mortgages and auto loans are very different.² Compared with auto loan issuers, mortgage issuers are univocal. It can deliver the single signal of the univocal issuer rather than the mixed signals of multiple formal and informal auto loan issuers. Mortgage can be a clear signal to provide the borrowers' creditworthiness and trustworthiness. In other words, the formal finance sector lends money to the borrowers because they are reliable.

Lenders are smart enough to screen borrowers through many dimensions (Iyer et al., 2016). As noted above, a higher debt-to-income ratio is associated with lower default risk (Emekter, Tu, Jirasakuldech, & Lu, 2015). As income level being equal, borrowers with debt are much trustworthy. Therefore, lenders are more likely to lend money to borrowers with outstanding mortgages. The co-funding behavior is strategic if the borrowers with formal financing records are less likely to default in the scheduled repayments. Otherwise, co-funding behavior is biased. The borrowers funded by traditional banks have better credit quality. They may be less likely to default in the online peer-to-peer lending market. Therefore, co-funding is strategic with lower default risk. We, accordingly, formulate the following two hypotheses:

Hypothesis 1: Lenders are more likely to co-fund borrowers with formal financing records.

Hypothesis 2: Borrowers with loans from the formal financial sectors are less likely to default.

Borrowers with better historical performance can obtain loans with a higher probability and reduce their default risk (Ding, Huang, Li, & Meng, 2019). It indicates that lenders take borrowers' reputation as a critical signal in their lending decisions. The borrower without funding records can not deliver the reputation signal. Wage is a kind of financial information, which can reflect solvency. As the repayment intention being equal, borrowers with higher wages are more likely to repay the loans (Emekter, Tu, Jirasakuldech, & Lu, 2015; Iyer, Khwaja, Luttmer, & Shue, 2016), and they are more likely

¹See 2015 China Auto Finance Report, <https://www2.deloitte.com/content/dam/Deloitte/cn/Documents/manufacturing/deloitte-cn-mfg-auto-finance-en-160129.pdf>.

²We thank an anonymous referee for pointing out the difference.

to be funded. Borrowers without historical funding records and with lower-wage are vulnerable groups. The vulnerable groups are credit rationed groups. They will have a higher funding probability if they can provide additional information to show their creditworthiness. As noted before, the outstanding mortgage can be a signal of trustworthiness. Therefore, vulnerable groups declaring they have formal financing records are more likely to be financed. We assume Hypothesis 3 as following:

Hypothesis 3: Vulnerable groups declaring outstanding formal financing records are more likely to be co-funded.

3. Research design

3.1. Data

Renrendai is a powerful peer-to-peer lending platform in China. As of September 2020, more than 1 million lenders and 4 million borrowers make a deal on *Renrendai*, and the total funded amount is 116 billion CNY. *Renrendai* timely and fairly discloses information, and it has been an important data source to study the Chinese online credit market (Chen, Huang, & Ye, 2020; Jiang, Liu, & Lu, 2020; Li, Deng, & Li, 2020; Liao, Wang, Xiang, Yan, & Yang, 2020; Wang, Zhao, & Shen, 2021; Xu, Hilliard, & Barth, 2020). *Renrendai* provides unsecured, on-site verified, and joint-liability credits. Unsecured credits are more likely to be referred to as online peer-to-peer lending issued by the informational intermediary without on-site verification and joint liability. Moreover, on-site verified and joint-liability loan applications are almost successfully financed and without any default. Therefore, this paper focuses on unsecured credits for investigating co-funding behavior and its economic consequence.

Potential borrower submits a copy of national ID to the platform and fills in individual information, such as age, gender, academic degree, marital status, income, housing, car, mortgage, auto loan, working years, occupation, etc. The amount, interest rate, duration, and loan purpose are also filled in the loan application before posting it online. The lenders lend money to specific loans based on the disclosed information mentioned above. The loan applications will be withdrawn by the platform if they are not fully financed within one week. Otherwise, the borrowers will be funded and should repay the installments on schedule.

The borrowers with lower FICO score are assigned lower credit grade, and lower credit grade is associated with higher default risk (Emekter, Tu, Jirasakuldech, & Lu, 2015). The Chinese online peer-to-peer lending platform gives the borrower a credit score based on their profiles rather than the limited national credit systems. A higher credit score is associated with lower default risk and higher credit grades. The credit grade is highly related to the successful funding probability, and borrowers with lower credit grades are less likely to be funded in the online credit market (Han, Chen, Liu, Luo, & Fan, 2018). *Renrendai* issues seven credit ratings ranging from poor to excellent and updates each borrower's credit rating monthly based on the repayment status of her/his loans (Liao, Wang, Xiang, Yan, & Yang, 2020). One caveat is that the credit ratings we can observe come from a snapshot of

the data retrieval date rather than the dynamic mapping with time. The measurement error in credit ratings does not entirely undermine the predictive power of information in observed credit ratings regarding a borrower's true quality. The cost of omitting credit ratings in the regression exceeds the benefits. Instead of using the entire categories in credit ratings, Liao, Wang, Xiang, Yan, & Yang, (2020) use an indicator variable HR differentiating only high risk and non-high-risk borrowers based on the credit ratings. We follow the same and use the HR indicator as a control variable.

Our loan-level data covers all unsecured credit loans from *Renrendai* between October 2010 and October 2016. Our sample includes a total of 604,072 loan applications. After dropping the observations missing important information, such as academic degree, income level, working years, location, etc., we obtain a final sample of 419,762 loan applications. Among our final observations, 6.8% of the loan applications are successfully financed. Mean and median values of interest rates are 13.63% and 13%, respectively. The last scheduled repayment of our sample is in October 2018. If the loan is not fully repaid by the data retrieval date, February 2020, the loan will be defined as default. Almost 14.4% of the funded loans are not fully repaid the installments.

3.2. Model specifications

Our empirical strategy is based on the linear probability model (LPM), controlling for a rich set of loan-level and borrower-level variables, as well as the city-by-year-month fixed effects and day-of-week fixed effects. These control variables are widely used in *Renrendai*-related research (Chen, Huang, & Ye, 2020; Jiang, Liu, & Lu, 2020; Li, Deng, & Li, 2020; Liao, Wang, Xiang, Yan, & Yang, 2020; Wang, Zhao, & Shen, 2021; Xu, Hilliard, & Barth, 2020). To investigate the effects of the formal financial signals on co-funding behavior, we employ the following linear probability model:

$$\Pr(\text{Funding}_i = 1) = \alpha + \beta FC_i + \gamma \text{Loaninfo}_i + \varphi \text{Borrowerinfo}_i + \mu_{ct} + \text{dow}_t + \varepsilon_i \quad (1)$$

where Funding_i is a dummy variable equaling to 1 if the loan application i is fully funded. FC_i is a dummy variable representing whether the borrower has an outstanding mortgage. We use the mortgage as the proxy of the formal financial signal. Loaninfo_i is a vector of loan details, including logarithm of the loan amount, loan terms, interest rates, consumer loan which is a dummy variable equaling to 1 if the loan is for consumption rather than for business, and logarithm of description length. Borrowerinfo_i is a vector of borrower characteristics, including age, gender, credit rating indicator, historical funding records, verified items, more-educated indicator, marital status, high-income indicator, house owner indicator, car owner indicator, auto loan indicator, more-experienced indicator, and industries. μ_{ct} represents a vector of city-by-year-month fixed effects, aimed to absorb the unobservable, confounding local macro-economic shocks. dow_t is a vector of day-of-week fixed effects. Since the residual term may exhibit autocorrelation between observations within the same industry or the same day, we allow for two-way clustering along the

Table 1. Definition of variables.

Variable	Definition
Funding	Equals 1 if the loan is fully funded and 0 otherwise.
Default	Equals 1 if the loan is not entirely repaid by the data retrieval date and 0 otherwise.
Formal credit	Equals 1 if the borrower has an outstanding mortgage and 0 otherwise.
<i>ln</i> amount (CNY)	The logarithm of the loan amount.
Term (months)	Duration of the loan application.
Interest rate (%)	The interest rate of the loan application.
Consumer loan	Equals 1 if the loan is for consumption and 0 otherwise.
<i>ln</i> text length	The logarithm of the number of words in the loan description.
Age	Borrower's age.
Male	Equals 1 if the borrower is male and 0 otherwise.
HR	Equals 1 if the borrower's credit rating is HR (High Risk) and 0 otherwise.
Historical success	Equals 1 if the borrower has at least one funded loan before the current loan application and 0 otherwise.
More educated	Equals 1 if the borrower obtained a bachelor's degree, master's degree, doctorate, and 0 otherwise.
Married	Equals 1 if the borrower is married and 0 otherwise.
High income	Equals 1 if the self-report monthly income is over the median, and 0 otherwise.
House owner	Equals 1 if the borrower owns a house and 0 otherwise.
Car owner	Equals 1 if the borrower owns a car and 0 otherwise.
Auto loan	Equals 1 if the borrower has an auto loan and 0 otherwise.
More experienced	Equals 1 if the borrower works for more than three years and 0 otherwise.
Industry	A set of dummy variables indicating whether the borrower is employed in the IT, transportation, public services, agriculture, manufacturing, healthcare, construction, real estate, government agencies, education, entertainment, energy, financial services, retail, catering and hotel industries.
Verification	A set of dummy variables indicating whether <i>Renrendai</i> verifies the borrower's credit report, identification, educational qualification, employment, income, house ownership, car ownership, Weibo account, address, marriage certification, phone number, and video interview.

industry and date dimension (Cameron, Gelbach, & Miller, 2011). Table 1 shows a detailed list of variables.

To estimate the effects of the formal financial signals on predicting the default risk in the online peer-to-peer lending market, we use the following linear probability model:

$$\Pr(\text{Default}_i = 1) = \alpha + \beta FC_i + \gamma \text{Loaninfo}_i + \phi \text{Borrowerinfo}_i + \mu_{ct} + \text{dow}_t + \varepsilon_i \quad (2)$$

where Default_i is a dummy variable equaling to 1 if the loan is not fully repaid by the borrowers. The other variables are the same as in the linear probability model 1.

The vulnerable borrowers without historical funding records or with low wages are credit-rationed groups. To investigate the effects of the formal financial signals on improving the vulnerable borrowers' credit availability, we employ the following linear probability model:

$$\Pr(\text{Funding}_i = 1) = \alpha + \beta FC_i \times \text{Var}_i + \gamma FC_i + \phi \text{Var}_i + \tau \text{Control}_i + \mu_{ct} + \text{dow}_t + \varepsilon_i \quad (3)$$

where Var_i represents the weak group-related dummy variable, such as historical funding record or high-income indicator. Control_i is a rich set of control variables, including loan-level and borrower-level characteristics. The rest of the notations are the same as in the linear probability model 1.

Table 2. Summary statistics.

	N	Mean	SD	Min	P25	P50	P75	Max
Funding	419,762	0.068	0.252	0	0	0	0	1
Default	28,679	0.144	0.351	0	0	0	0	1
Formal credit	419,762	0.139	0.346	0	0	0	0	1
Amount	419,762	59,591	94,229	1k	10k	30k	50k	1000k
Term	419,762	15.830	9.284	1	6	12	24	36
Interest rate	419,762	13.634	3.052	3	12	13	15	24.4
Consumer loan	419,762	0.631	0.483	0	0	1	1	1
Text length	419,762	52.322	43.859	1	26	39	62	2391
Age	419,762	29.392	6.371	18	25	28	32	54
Male	419,762	0.859	0.348	0	1	1	1	1
HR	419,762	0.942	0.233	0	1	1	1	1
Historical success	419,762	0.031	0.174	0	0	0	0	1
More educated	419,762	0.223	0.416	0	0	0	0	1
Married	419,762	0.495	0.500	0	0	0	1	1
High income	419,762	0.241	0.428	0	0	0	0	1
House owner	419,762	0.428	0.495	0	0	0	1	1
Car owner	419,762	0.249	0.433	0	0	0	0	1
Auto loan	419,762	0.057	0.232	0	0	0	0	1
More experienced	419,762	0.357	0.479	0	0	0	1	1

This table shows the summary statistics for our final sample. Refer to Appendix [Table A1](#) for the summary statistics of industries, verified items, and year distribution.

3.3. Summary statistics

[Table 2](#) presents the summary statistics for the variables employed in our paper. As for the loan-level information, only 6.8% of the loan applications are fully funded, showing that lenders are cautious because of information asymmetry. The average interest rate is 13.6%. Amount ranges from 1 thousand CNY to 1 million CNY, but the average is only 59,591 CNY, with an even lower median of 30,000 CNY. The average loan term is 15.8 months. More than half (63.1%) are consumer loans. All shows that online credit is primarily micro-loans. Borrower inputs 52 words on average in the loan description. As for the borrower-level information, we find the leading group on the demand side of online credit is young men. Specifically, 85.9% of borrowers are male, and borrower's age is concentrated in the 25–32 age group. And borrowers are more likely to have lower income and without historical funding records before the loan applications. We find that 94.2% of loans are categorized as having a high risk of default (HR), and only 13.9% of borrowers have outstanding mortgages. To some extent, this may explain the low funding rate. Only 22.3% of borrowers are more educated, and 35.7% of borrowers have worked for more than three years. [Table A1](#), shown in the internet appendix, offers summary statistics of industries, verified items, and year distribution of loans.

4. Empirical results

4.1. Baseline results

We first examine the relationship between successful funding and formal financial signal. [Table 3](#) reports the estimates of the linear probability model 1 of successful financing. In Column 1, we only control loan-level information, industry fixed effects, city-by-year-month fixed effects, and day-of-week fixed effects. We add borrower-level information and verification fixed effects in Column 2. In Column 3, we control for both loan-level

Table 3. Effect of the formal financial signal on co-funding.

	(1)	(2)	(3)
		Funding	
Formal credit	0.050*** (0.004)	0.007*** (0.002)	0.010*** (0.002)
<i>In</i> amount	−0.054*** (0.009)		−0.067*** (0.006)
Term	−0.001*** (0.000)		−0.000*** (0.000)
Interest rate	−0.009*** (0.001)		−0.003*** (0.000)
Consumer loan	−0.022*** (0.004)		−0.026*** (0.003)
<i>In</i> text length	0.024*** (0.002)		0.010*** (0.001)
Age		0.000*** (0.000)	0.001*** (0.000)
Male		0.001 (0.001)	−0.002** (0.001)
HR		−0.267*** (0.011)	−0.258*** (0.010)
Historical success		0.316*** (0.013)	0.300*** (0.013)
More educated		0.009*** (0.001)	0.012*** (0.002)
Married		0.003*** (0.001)	0.005*** (0.001)
High income		0.002 (0.004)	0.026*** (0.005)
House owner		−0.003*** (0.001)	−0.005*** (0.001)
Car owner		−0.003** (0.001)	0.003** (0.001)
Auto loan		−0.000 (0.003)	0.003 (0.004)
More experienced		0.010*** (0.002)	0.013*** (0.002)
Verification FE	No	Yes	Yes
Industry FE	Yes	Yes	Yes
City-by-year-month FE	Yes	Yes	Yes
Day-of-week FE	Yes	Yes	Yes
Constant	0.359*** (0.041)	0.256*** (0.009)	0.541*** (0.028)
Observations	419,762	419,762	419,762
Adjusted R-squared	0.169	0.439	0.455

This table shows the formal financial signal's effect on funding probability in the online peer-to-peer lending market, as estimated according to the linear probability model 1. Verification fixed effects are captured by dummy variables indicating whether *Renrendai* verifies the borrower's credit report, identification, educational qualification, employment, income, house ownership, car ownership, Weibo account, address, marriage certification, phone number, and video interview. Industry fixed effects are a rich set of dummy variables corresponding to whether the borrower employed in the IT, transportation, public services, agriculture, manufacturing, healthcare, construction, real estate, government agencies, education, entertainment, energy, financial services, retail, catering and hotel industries. Both regressions include industry, city-by-year-month, and day-of-week fixed effects. Standard errors in parentheses are clustered on date and industry. *** significant at 1%, ** significant at 5%, and * significant at 10%.

and borrower-level characteristics, as well as the fixed effects. The coefficients of *Formal credit*, i.e., the formal financial signal, are significantly positive in Columns 1 to 3, indicating that lenders are more likely to lend money to borrowers with loans from the

formal financial sector. Moreover, after controlling for all the variables in Column 3, the formal financial signal raises the probability of successful funding by a precisely estimated 1.0 percent. Relative to a sample mean of 6.8 percent, this is a 14.7 percent increase.

In Column 3, we can find that loans with an immense amount of money, longer durations, higher interest rates, and consumption are less likely to be fully funded. Loans with longer text in the description are more likely to be supported. Older, married, more educated, and more work-experienced borrowers are also more likely to be funded by lenders. The house owner indicator reduces the probability of successful funding by 0.005, and the verified house ownership raises the likelihood of successful funding by a precisely estimated 0.011 (untabulated). Owning a house is not enough to raise the funding probability. Verified this term or declaring having an outstanding mortgage could help the borrowers increase the funding probability. The borrowers categorized as high risk of default (HR) are less likely to be supported. The HR indicator reduces the successful funding probability by 0.258. Borrowers with historical funding records are more likely to be funded. Having funding records will raise the likelihood of successful funding by 0.300. Furthermore, borrowers with a high-income level are more likely to be supported. It means borrowers with no historical funding records and low-income levels are credit-rationed groups in the anonymous online peer-to-peer lending market.

Table 4 provides the estimates of the linear probability model 2 of default outcome. The coefficients of formal credit indicator are significantly negative at the 1% level in Columns 1 to 3. It shows that the formal financial signal can decrease the default probability in the peer-to-peer lending market. As all else equal in Column 3, the formal financial signal reduces the likelihood of default by a precisely estimated 4.3 percent. It is a 29.9 percent decrease relative to a sample mean of 14.4 percent. It indicates co-funding is strategic and can decrease the loss.

Mortgage can deliver the single signal of the univocal issuer rather than the mixed signals of multiple auto loan issuers. It suggests that the auto loan and outstanding mortgage are very different. Table 4 confirms this point, showing formal-credit indicator and auto-loan indicator have opposite effects on default, consistent with Liao, Wang, Xiang, Yan, & Yang, (2020). Furthermore, funded loans with the immense amount, longer terms, higher interest rates, or longer text are more likely to default. Table 4 also shows that older borrowers are more likely to default. Borrowers categorized as non-HR are trustworthy. More-educated and more-work-experienced indicators can decrease the likelihood of default. The high-income group should have better solvency. To our surprise, borrowers with higher self-report income are less likely to repay the loans entirely. It can be evidence of adverse selection in the anonymous peer-to-peer lending market.

4.2. Heterogeneity

Lenders are more likely to co-fund borrowers with formal financial signals. We have documented that borrowers with no historical funding records and low-income levels are less likely to be funded in the peer-to-peer lending market. One crucial issue is whether they can use the formal financial signal to improve the funding probability? This section

Table 4. Effect of the formal financial signal on default.

	(1)	(2)	(3)
		Default	
Formal credit	−0.060*** (0.008)	−0.045*** (0.009)	−0.043*** (0.008)
<i>ln</i> amount	0.015 (0.009)		0.032*** (0.009)
Term	0.007*** (0.001)		0.007*** (0.001)
Interest rate	0.013*** (0.002)		0.004** (0.002)
Consumer loan	0.001 (0.007)		0.004 (0.006)
<i>ln</i> text length	0.010* (0.005)		0.010** (0.004)
Age		0.005*** (0.001)	0.004*** (0.001)
Male		0.003 (0.010)	0.008 (0.010)
HR		0.255*** (0.017)	0.250*** (0.018)
Historical success		−0.007 (0.010)	0.015 (0.009)
More educated		−0.062*** (0.006)	−0.064*** (0.006)
Married		0.007 (0.007)	0.003 (0.006)
High income		0.043*** (0.013)	0.038*** (0.011)
House owner		−0.017* (0.008)	−0.018** (0.008)
Car owner		−0.032*** (0.010)	−0.025** (0.009)
Auto loan		0.014 (0.009)	0.013 (0.009)
More experienced		−0.014** (0.006)	−0.015** (0.005)
Verification FE	No	Yes	Yes
Industry FE	Yes	Yes	Yes
City-by-year-month FE	Yes	Yes	Yes
Day-of-week FE	Yes	Yes	Yes
Constant	−0.194*** (0.047)	−0.195*** (0.046)	−0.483*** (0.075)
Observations	28,679	28,679	28,679
Adjusted R-squared	0.102	0.193	0.220

This table shows the formal financial signal's effect on predicting default probability in the online peer-to-peer lending market, as estimated according to the linear probability model 2. Both regressions include industry, city-by-year-month, and day-of-week fixed effects. Standard errors in parentheses are clustered on date and industry. *** significant at 1%, ** significant at 5%, and * significant at 10%.

employs the linear probability model 3 to estimate the formal financial signal's effects on co-funding behavior across different groups.

Table 5 reports the formal financial signal's effects on co-funding across historical funding records, as estimated according to the linear probability model 3. The control variables are the same as in Table 3. The results show that the formal financial signals and historical funding records can raise the funding probability, consistent with the baseline results. Different covariates can hardly affect the estimates. The interaction term's coefficients are significantly negative at the 1% level in Columns 1 to 3, indicating that

Table 5. Effect of the formal financial signal on co-funding across historical success.

	(1)	(2)	(3)
		Funding	
Formal credit	0.037*** (0.003)	0.009*** (0.001)	0.013*** (0.002)
Historical success	0.611*** (0.008)	0.328*** (0.013)	0.313*** (0.013)
Formal credit * Historical success	-0.057*** (0.017)	-0.052*** (0.015)	-0.056*** (0.015)
Loan info	Yes	No	Yes
Borrower info	No	Yes	Yes
Verification FE	No	Yes	Yes
Industry FE	Yes	Yes	Yes
City-by-year-month FE	Yes	Yes	Yes
Day-of-week FE	Yes	Yes	Yes
Constant	0.286*** (0.033)	0.256*** (0.009)	0.543*** (0.028)
Observations	419,762	419,762	419,762
Adjusted R-squared	0.309	0.439	0.455

This table shows the effect of the formal financial signal on co-funding across historical financing records, as estimated according to the linear probability model 3. Both regressions include industry, city-by-year-month, and day-of-week fixed effects. Standard errors in parentheses are clustered on date and industry. *** significant at 1%, ** significant at 5%, and * significant at 10%.

Table 6. Effect of the formal financial signal on co-funding across income.

	(1)	(2)	(3)
		Funding	
Formal credit	0.053*** (0.003)	0.009*** (0.002)	0.013*** (0.002)
High income	0.081*** (0.009)	0.004 (0.004)	0.027*** (0.005)
Formal credit * High income	-0.029*** (0.006)	-0.006** (0.003)	-0.007** (0.002)
Loan info	Yes	No	Yes
Borrower info	No	Yes	Yes
Verification FE	No	Yes	Yes
Industry FE	Yes	Yes	Yes
City-by-year-month FE	Yes	Yes	Yes
Day-of-week FE	Yes	Yes	Yes
Constant	0.459*** (0.037)	0.256*** (0.009)	0.541*** (0.028)
Observations	419,762	419,762	419,762
Adjusted R-squared	0.182	0.439	0.455

This table shows the effect of the formal financial signal on co-funding across different income cohorts, as estimated according to the linear probability model 3. Both regressions include industry, city-by-year-month, and day-of-week fixed effects. Standard errors in parentheses are clustered on date and industry. *** significant at 1%, ** significant at 5%, and * significant at 10%.

borrowers without historical funding records can utilize formal financial signals to raise the funding probability.

Table 6 reports the formal financial signal's effect on co-funding across different income cohorts, estimated using a linear probability model 3. The coefficients of formal financial and high-income indicators are positive throughout all specifications, indicating that lenders are more likely to support borrowers with traditional financing or higher wages. The coefficients of the interaction term are negative and highly significant at the 5% level. The high-income borrowers with formal financing records are less likely to be

funded, indicating that the formal financial signal can raise the low-income group's funding probability.

4.3. Robustness

In our final sample, 63.6% of borrowers only request one loan, and others apply more than once. We have documented that the formal financial signal can raise the funding probability. The borrower provides the information on whether he/she has an outstanding mortgage to the platform. It seems that the borrowers could benefit from falsely declaring that they have outstanding mortgages. What prevents them from doing so?

We think a possible reason is that the borrower with a single loan doesn't realize the meaning of formal financial signals. Therefore, they didn't falsely declare the outstanding mortgage. The repeated borrowers learn by doing and may falsely claim the outstanding mortgages in the latter loan request process for higher funding probability. If our conjecture is correct, we will find the baseline results are consistent in the single loan sample. In the last ones of multiple loans, the formal financial signal's effects on co-funding are more potent, and the effects on default outcome are weaker.

Table 7 reports the formal financial signal's effects on co-funding and default outcome, estimated using the single loan and multiple loans sample. Panel A shows the estimates using the single loan sample. The results show that the formal financial signal raises the funding probability by a precisely estimated 0.5 percent, decreases the default probability by a precisely estimated 7.5 percent, and increases the low-income group's funding probability, consistent with our baseline results. Panel B shows the estimates using the last ones of multiple loans sample. The results show that the formal financial signal raises the funding probability by a precisely estimated 1.4 percent which is a 180% increase relative to the single loan estimates. It decreases the default probability by a precisely estimated 1.8 percent, a 76% decrease relative to the single loan estimates.

Renrendai has the verification process where the platform verifies the borrower's credit report, identification, educational qualification, employment, income, house ownership, car ownership, Weibo account, address, marriage certification, phone number, and video interview. As for the verified borrowers, it is more difficult for them to engage in strategic disclosure. We repeat our baseline tests, including only the sample of borrowers who are verified any items (shown in Panel A of Table 8), verified identification (shown in Panel B of Table 8), and verified credit report (shown in Panel C of Table 8). As shown in Table 8, the formal credit indicator can raise the successful funding probability and decreases the default probability throughout all the specifications. The formal financial signal can help no-funding-record and low-income borrowers improve their funding probability, consistent with the baseline results.

The investors quickly snatch high-interest-rate loans without sufficiently examining other information (Liao, Wang, Xiang, Yan, & Yang, 2020). Under time pressure, lenders don't adequately evaluate lots of details in loan contracts. We should give the lenders enough time to examine the loan-level and borrower-level information. In our unsecured credit loan sample, 14% of funded loans are fully fulfilled in 5 minutes, 23% in less than 30 minutes, and 39% less than one day. Lenders need enough time to sufficiently examining the information. We drop the quickly funded loans and re-test the effects of the formal financial signal.

Table 7. Robustness tests: single loan and multiple loans.

Panel A: Single loan			
	(1)	(2)	(3)
	Funding	Default	Funding
Formal credit	0.005***	-0.075***	0.008***
	(0.002)	(0.020)	(0.002)
Formal credit * High income			-0.010*
			(0.005)
Loan info	Yes	Yes	Yes
Borrower info	Yes	Yes	Yes
Verification FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
City-by-year-month FE	Yes	Yes	Yes
Day-of-week FE	Yes	Yes	Yes
Constant	0.721***	-1.122***	0.721***
	(0.036)	(0.204)	(0.036)
Observations	148,498	7,780	148,498
Adjusted R-squared	0.595	0.301	0.595
Panel B: Last one of multiple loans			
	(1)	(2)	(3) (4)
	Funding	Default	Funding Funding
Formal credit	0.014***	-0.018	0.016*** 0.016***
	(0.002)	(0.023)	(0.002) (0.003)
Formal credit * Historical success			-0.055
			(0.032)
Formal credit * High income			-0.005
			(0.004)
Loan info	Yes	Yes	Yes Yes
Borrower info	Yes	Yes	Yes Yes
Verification FE	Yes	Yes	Yes Yes
Industry FE	Yes	Yes	Yes Yes
City-by-year-month FE	Yes	Yes	Yes Yes
Day-of-week FE	Yes	Yes	Yes Yes
Constant	0.586***	-0.416*	0.586*** 0.586***
	(0.033)	(0.222)	(0.033) (0.033)
Observations	84,981	6,067	84,981 84,981
Adjusted R-squared	0.485	0.131	0.485 0.485

This table shows the effect of the formal financial signal on co-funding and default outcome among borrowers with only requested one loan (shown in Panel A) and requested multiple loans (shown in Panel B). There are no related historical success records for the borrowers with only requested one loan. The funding-response heterogeneity with historical success records is not reported in Panel A. Part of borrowers only request one loan in our sample period, and others request more than once. Borrowers with requested multiple loans may gradually learn the benefit of declaring the outstanding mortgage information. They may declare the outstanding mortgage information in the latter loan request process. We use the last observations of borrowers with multiple loans to test the effect of formal financial signals. Both regressions include loan characteristics, demographics, verification, industry, city-by-year-month, and day-of-week fixed effects. Standard errors in parentheses are clustered on date and industry. *** significant at 1%, ** significant at 5%, and * significant at 10%.

Table 9 reports the formal financial signal's effects on co-funding and default outcome, restricted the fulfillment time under reasonable intervals. Panel A shows the estimates limited to the fulfillment time over 5 minutes. The formal financial signal raises the funding probability by 1.0 percent and decreases the default probability by 4.7 percent. With no funding records or low-income levels, the borrowers can declare the outstanding mortgages to improve the funding probability. These results are consistent with the baseline results. Panel B shows the estimates limited to the fulfillment time over 30 minutes. The empirical results show that the formal financial signal can raise the financing likelihood, decrease the default probability, and improve the funding probability of the no-funding-record or low-income borrowers.

Table 8. Robustness tests: sample of verified borrowers.

Panel A: Restricted to borrowers verified any items				
	(1)	(2)	(3)	(4)
	Funding	Default	Funding	Funding
Formal credit	0.016*** (0.003)	−0.043*** (0.008)	0.021*** (0.003)	0.020*** (0.003)
Formal credit * Historical success			−0.064*** (0.016)	
Formal credit * High income				−0.012*** (0.004)
Loan info	Yes	Yes	Yes	Yes
Borrower info	Yes	Yes	Yes	Yes
Verification FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
City-by-year-month FE	Yes	Yes	Yes	Yes
Day-of-week FE	Yes	Yes	Yes	Yes
Constant	0.843*** (0.041)	−0.482*** (0.077)	0.844*** (0.041)	0.842*** (0.041)
Observations	208,929	28,674	208,929	208,929
Adjusted R-squared	0.449	0.220	0.450	0.449
Panel B: Restricted to borrowers verified identification				
	(1)	(2)	(3)	(4)
	Funding	Default	Funding	Funding
Formal credit	0.017*** (0.003)	−0.045*** (0.009)	0.022*** (0.003)	0.021*** (0.003)
Formal credit * Historical success			−0.064*** (0.017)	
Formal credit * High income				−0.012*** (0.004)
Loan info	Yes	Yes	Yes	Yes
Borrower info	Yes	Yes	Yes	Yes
Verification FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
City-by-year-month FE	Yes	Yes	Yes	Yes
Day-of-week FE	Yes	Yes	Yes	Yes
Constant	0.939*** (0.044)	−0.464*** (0.058)	0.940*** (0.044)	0.938*** (0.044)
Observations	201,676	28,419	201,676	201,676
Adjusted R-squared	0.450	0.221	0.451	0.450
Panel C: Restricted to borrowers verified credit report				
	(1)	(2)	(3)	(4)
	Funding	Default	Funding	Funding
Formal credit	0.021*** (0.004)	−0.044*** (0.009)	0.029*** (0.003)	0.024*** (0.004)
Formal credit * Historical success			−0.070*** (0.015)	
Formal credit * High income				−0.008* (0.004)
Loan info	Yes	Yes	Yes	Yes
Borrower info	Yes	Yes	Yes	Yes
Verification FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
City-by-year-month FE	Yes	Yes	Yes	Yes
Day-of-week FE	Yes	Yes	Yes	Yes
Constant	1.141*** (0.058)	−0.414*** (0.077)	1.142*** (0.057)	1.140*** (0.058)
Observations	146,973	26,901	146,973	146,973
Adjusted R-squared	0.458	0.224	0.458	0.458

This table shows the effect of the formal financial signal on co-funding and default outcome among borrowers verified any items (shown in Panel A), verified identification (shown in Panel B), and verified credit report (shown in Panel C). Whether the borrower has an outstanding mortgage is voluntarily provided by the borrower to the platform. For the verified borrowers, it is more difficult to engage in strategic disclosure. We repeat the tests, including only the sample of borrowers who are verified. Both regressions include loan characteristics, demographics, verification, industry, city-by-year-month, and day-of-week fixed effects. Standard errors in parentheses are clustered on date and industry. *** significant at 1%, ** significant at 5%, and * significant at 10%.

Table 9. Robustness tests: reasonable fulfillment time.

Panel A: Restricted to fulfillment time over 5 minutes				
	(1)	(2)	(3)	(4)
	Funding	Default	Funding	Funding
Formal credit	0.010*** (0.002)	−0.047*** (0.010)	0.012*** (0.002)	0.012*** (0.002)
Formal credit * Historical success			−0.056*** (0.017)	
Formal credit * High income				−0.007*** (0.002)
Loan info	Yes	Yes	Yes	Yes
Borrower info	Yes	Yes	Yes	Yes
Verification FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
City-by-year-month FE	Yes	Yes	Yes	Yes
Day-of-week FE	Yes	Yes	Yes	Yes
Constant	0.550*** (0.027)	−0.540*** (0.077)	0.551*** (0.027)	0.550*** (0.027)
Observations	415,011	24,969	415,011	415,011
Adjusted R-squared	0.414	0.212	0.414	0.414
Panel B: Restricted to fulfillment time over 30 minutes				
	(1)	(2)	(3)	(4)
	Funding	Default	Funding	Funding
Formal credit	0.011*** (0.002)	−0.051*** (0.011)	0.012*** (0.002)	0.013*** (0.002)
Formal credit * Historical success			−0.049** (0.018)	
Formal credit * High income				−0.006** (0.002)
Loan info	Yes	Yes	Yes	Yes
Borrower info	Yes	Yes	Yes	Yes
Verification FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
City-by-year-month FE	Yes	Yes	Yes	Yes
Day-of-week FE	Yes	Yes	Yes	Yes
Constant	0.546*** (0.028)	−0.571*** (0.067)	0.546*** (0.028)	0.546*** (0.028)
Observations	411,937	22,354	411,937	411,937
Adjusted R-squared	0.373	0.212	0.373	0.373

This table shows the effect of the formal financial signal on co-funding and default outcome after dropping the quickly fully funded observations. The investors quickly snatch high-interest-rate loans without sufficiently examining other information (Liao, Wang, Xiang, Yan, & Yang, Liao et al., 2020). In our unsecured credit loan sample, 14% of funded loans are fully fulfilled in 5 minutes, 23% in less than 30 minutes, 39% in less than one day. Investors need enough time to sufficiently examining other information. We drop the quickly funded loans and re-test the effects of the formal financial signal. Both regressions include loan characteristics, demographics, verification, industry, city-by-year-month, and day-of-week fixed effects. Standard errors in parentheses are clustered on date and industry. *** significant at 1%, ** significant at 5%, and * significant at 10%.

5. Conclusions

The traditional distinction between formal financing and informal financing has become less legible. It provides an ambiguous recognition for the recently developed peer-to-peer lending form (Allen, Qian, & Xie, 2019b). The loans obtained via an online peer-to-peer lending platform can be defined as informal financing (Galema, 2020), even though the contracts between borrowers and lenders are formal and standardized. Formal finance and informal finance can balance both sectors' advantages and disadvantages for all-win (Madestam, 2014). Co-funding equilibriums in the formal and informal credit market can result in both sectors earning higher profits (Andersen & Malchow-Møller, 2006). Using the data from a powerful online peer-to-peer lending platform in China, we

examine whether the borrowers with formal financial signals are more likely to be co-funded and the economic consequence of co-funding.

The formal financial signal can raise the funding probability by a precisely estimated 1.0 percent, a 14.7 percent increase relative to a sample mean of 6.8 percent. Borrowers with formal financial signals are more likely to repay the loans entirely. Therefore, co-funding is one kind of strategic lending behavior. No-funding-record and low-income borrowers are credit-rationed in the peer-to-peer lending market. Finally, we find declaring the outstanding mortgage information can help the credit-rationed borrowers increase their funding probability. Our results are robust after controlling for a rich set of loan-level and borrower-level variables, city-by-year-month, and day-of-week fixed effects. Several tests show our findings are unlikely to be an unintentional byproduct of the formal financial signals.

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Internet appendix

Table A1. Summary statistics (continued)

	N	Mean	SD	Min	P25	P50	P75	Max
Panel A: Industry								
IT	419762	0.076	0.264	0	0	0	0	1
Transportation	419762	0.041	0.198	0	0	0	0	1
Public services	419762	0.018	0.133	0	0	0	0	1
Agriculture	419762	0.018	0.133	0	0	0	0	1
Manufacturing	419762	0.178	0.383	0	0	0	0	1
Healthcare	419762	0.029	0.169	0	0	0	0	1
Construction	419762	0.053	0.224	0	0	0	0	1
Real estate	419762	0.032	0.175	0	0	0	0	1
Government agencies	419762	0.053	0.225	0	0	0	0	1
Education	419762	0.035	0.183	0	0	0	0	1
Entertainment	419762	0.030	0.172	0	0	0	0	1
Energy	419762	0.035	0.185	0	0	0	0	1
Financial services	419762	0.070	0.255	0	0	0	0	1
Retail	419762	0.146	0.353	0	0	0	0	1
Catering and hotel	419762	0.033	0.179	0	0	0	0	1
Others	419762	0.153	0.360	0	0	0	0	1
Panel B: Verification								
Credit report	419762	0.350	0.477	0	0	0	1	1
Identification	419762	0.480	0.500	0	0	0	1	1
Educational qualification	419762	0.053	0.225	0	0	0	0	1
Employment	419762	0.023	0.150	0	0	0	0	1
Income	419762	0.021	0.144	0	0	0	0	1
House ownership	419762	0.064	0.245	0	0	0	0	1
Car ownership	419762	0.048	0.215	0	0	0	0	1
Weibo account	419762	0.040	0.195	0	0	0	0	1
Address	419762	0.055	0.228	0	0	0	0	1
Marriage certification	419762	0.050	0.217	0	0	0	0	1
Phone number	419762	0.057	0.231	0	0	0	0	1
Video interview	419762	0.029	0.167	0	0	0	0	1
Panel C: Year								
2010	419762	0.002	0.040	0	0	0	0	1
2011	419762	0.047	0.212	0	0	0	0	1
2012	419762	0.066	0.248	0	0	0	0	1
2013	419762	0.120	0.325	0	0	0	0	1
2014	419762	0.341	0.474	0	0	0	1	1
2015	419762	0.418	0.493	0	0	0	1	1
2016	419762	0.005	0.071	0	0	0	0	1

This table shows the summary statistics of industries (shown in Panel A), verified items (shown in Panel B), and year distribution (shown in Panel C) for our final sample.