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Financial literacy and gender difference in loan performance

Jia Chen [a], Jiajun Jiang [b], Yu-jane Liu [a,*]

[a] Guanghua School of Management, Peking University, 5 Yiheyuan Rd., Beijing 100871, China
[b] School of Economics, Fudan University, 600 Guoquan Rd, Shanghai 200433, China

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ABSTRACT

We use data from a major peer-to-peer lending marketplace in China to study whether female and male investors evaluate loan performance differently. Controlling for variables of investor demographics, investor experience, and loan characteristics, we find that loans invested by female investors are more likely to default and have lower loan return in the future than loans invested by male investors. We define abnormal default or abnormal loan return as the part of the loan default or the part of loan return that is not explained by loan characteristics and find that the loans invested by female investors have higher abnormal default and lower abnormal loan return than the loans invested by male investors. Furthermore, female investors perform similarly to male investors in abnormal default or abnormal loan return when investors have high levels of education or income or when investors work in finance or information technology industries.

1. Introduction

The peer-to-peer lending market has grown rapidly across the globe, in particular in China.[1] The rapid growth of this market is driven by pervasive internet and smartphone penetration, which allow more individuals to access financial services, especially in emerging economies. A substantial fraction of the investors in this market are potentially individuals who are not financially literate, and they face the challenge of evaluating performance and risks of peer-to-peer lending products (Duarte et al., 2012; Michels, 2012). We use transaction-level data from a leading online peer-to-peer lending marketplace in China to examine how individual investors evaluate loan performance and risks in this market.

We argue that financial literacy plays an important role when investors evaluate loan performance in China's peer-to-peer lending market. The previous research finds that individuals in the United States and many other countries are not well prepared with financial knowledge (Agarwal et al., 2010; Hastings et al., 2013; Lusardi and Mitchell, 2014), and individuals with low education and low income are the most lacking in financial knowledge (Hastings et al., 2013; Lusardi and Mitchell, 2014). These patterns of financial illiteracy also exist in China (Yin et al., 2014, 2015; Wang et al., 2016).

We examine the implications of financial illiteracy on investors' evaluation of loan performance. Because the peer-to-peer market makes credit available to marginal borrowers who have difficulty obtaining credit from banks, default risk is the most important factor that affects loan performance in this market. We argue that less financially literate investors make more mistakes in the peer-to-peer lending market because it is difficult for them to differentiate between loans with high and low default risk. This argument is supported by the previous literature that finds that investors who are less financially literate make more financial mistakes (Lusardi and Mitchell,

* Corresponding author.
E-mail addresses: jia.chen@gsm.pku.edu.cn (J. Chen), jiangjj@fudan.edu.cn (J. Jiang), yjliu@gsm.pku.edu.cn (Y.-j. Liu).

[1] The outstanding loan balance in China's peer-to-peer market has grown from $0.86 billion in 2012 to $125.6 billion in 2016. This information is from wdzj.com.

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2007, 2008, 2011; Stango and Zinman, 2009; Skimmyhorn, 2016; Christelis et al., 2010; van Rooij et al., 2011; Yoong, 2011; Hastings and Tejeda-Ashton, 2008; Lusardi and Tufano, 2015; Moore, 2003; Brown et al., 2014).

We focus on the gender difference in financial literacy. The previous research finds that males are more financially literate than females around the world (Atkinson and Messy, 2011; Lusardi and Mitchell, 2014; Bucher-Koenen et al., 2017). Xu and Gong (2017) find that a similar gender difference in financial literacy exists in China. The gender difference in financial literacy potentially has significant implications for investor behavior in the peer-to-peer lending market in China, an emerging financial market that is quickly developing. Because female investors are generally less financially literate than male investors, they tend to make more financial mistakes when investing in loans. Therefore, the loans of female investors default more often than loans of male investors do. Because of the higher loan default rates, female investors also experience lower loan returns.

To examine these hypotheses, we observe the time and amount of loan investment transactions and whether and when each loan defaults. We use investor demographics, including gender, education attainment levels, income levels, and age; we consider investors' investing experience and timing, including past default experience and whether investing during working hours; we also include loan characteristics, including loan yields, loan maturity, loan amount, and variables measuring the creditworthiness of the borrower. This data allows us to control for factors that are potentially related to financial literacy (Huston, 2010; Fonseca et al., 2012).

Based on these variables, we match the transactions of male and female investors using propensity score matching, which uses variables of demographic characteristics, investing experience and timing, and loan characteristics. We then use the matched sample to conduct all analyses. This approach allows us to minimize the differences between female and male investors.

Our analysis includes two steps. First, we study the gender difference in loan default rate and loan return. We find that the loans invested by female investors have higher loan default rates and lower loan returns than those invested by male investors. The average default rates of loans invested by females and males are 4.607% and 3.856%, and the gender difference in the default rate is 0.751%. The average returns of loans invested by females and males are 12.533% and 12.575%, the difference of which is −0.041%. Substantial gender differences in loan default rate and loan return are found after controlling for investor demographics, investing experience and timing, and loan characteristics. This result is consistent with the intuition that female investors are less financially literate than male investors; they tend to make more investing mistakes when choosing loans to invest.

Second, we examine what drives the gender difference in loan default and loan return. Female investors invest in loans that have higher default rates and lower loan returns than male investors, because their loans have riskier observable characteristics or because of other reasons. To distinguish between these two channels, we regress an indicator of loan default on loan characteristics and harvest the predicted values and residual values. We name the predicted values the predicted default and name the residual values the abnormal default. Similarly, we define predicted loan return and abnormal loan return as the predicted values and residual values from a regression of loan returns on loan characteristics. The predicted default or loan return is the part of loan performance that investors can evaluate based on observable loan characteristics, and the abnormal default or loan return is the part of loan performance that the investor cannot directly observe.

When regressing abnormal default or abnormal loan returns on the female indicator, we find that female investors invest in loans with higher abnormal default or lower abnormal loan return than male investors do. These results are robust after we control for investor demographics, investing experience and timing, and loan characteristics. On the other hand, when regressing predicted default or predicted loan return on gender indicators, we do not find significant coefficients of the female indicator. Thus, the worse performance of loans invested by female investors relative to those invested by male investors is concentrated in the abnormal component of loan performance. To the extent that the predicted component of loan performance is related to investors' risk preference based on the observable loan characteristics, investment choices of female and male investors are not solely driven by the difference in their risk preferences.

Next, we examine whether the gender differences in loan performance depend on investor demographics. Since the previous literature documents that investors with higher levels of income or education are more financially literate (Hastings et al., 2013; Lusardi and Mitchell, 2014), we expect that the gender difference in financial literacy is reduced when their income and education levels are higher, and females therefore make less financial mistakes relative to males when investing in the peer-to-peer market. Confirming this intuition, we find that the differences in abnormal default or abnormal loan return between female and male investors are not economically or statistically significant among investors with higher levels of income or higher levels of education.

We then consider investors who work in finance or IT industries. If an investor works in the finance industries, he or she may better understand the default risks of loan products because he or she may have better financial knowledge or have better quantitative ability to evaluate loan performance. Although females might have lower quantitative ability than males (Jacobs, 2005), this gender gap in quantitative skills may be lower for people who work in finance or IT industries. For instance, Adams et al. (2017) find that better math education is related to more women working in the finance industry. We, therefore, argue that when choosing loans, investors who work in the finance or IT industries tend to make fewer mistakes than investors working in other industries. We find that the gender differences in abnormal default or abnormal loan return are not economically or statistically significant among investors working in these two industries but significant in the other industries. These findings suggest that with sufficient financial knowledge or quantitative skills, female investors no longer make more mistakes in choosing loans than male investors.

Our study contributes to two strands of literature. First, we contribute to the literature that studies financial literacy, which finds that less financially literate individuals make more financial mistakes (Lusardi and Mitchell, 2014). This literature, however, pays little attention to the relation between financial literacy of investors and the default risks and performance of their investment, especially in debt markets. We add to this literature by examining how differences in financial literacy between female and male investors can be related to different loan performance of their investment in a developing financial market: the peer-to-peer lending market. Furthermore, unlike previous papers that use surveys and experiments, our research uses real transactions in the peer-to-peer market.

We find that loans invested by female investors default more often and have lower loan returns than those invested by male investors. This gender difference is consistent with the intuition that female investors are less financially literate than male investors in China and make more mistakes when investing. We also find that with appropriate levels of education, income, or quantitative ability, female investors can invest as well as male investors do in the peer-to-peer market of China. This result highlights the importance of financial education and literacy in financial investing (Lusardi and Mitchell, 2008, 2011).[2]

Our main results do not contradict with those of the literature that finds women are more risk-averse than men (Croson and Gneezy, 2009). The papers in this literature typically use experiments to isolate the effect of one factor (e.g., risk aversion) controlling for the effects of other factors (e.g., education and quantitative ability). For example, most of these papers conduct experiments using college students, who have similar education levels. Among the few papers that do not use experiments with college students, Beck et al. (2013) study the behavior of loan officers, who have the similar quantitative ability and financial knowledge. Thus, the papers in this literature do not focus on financial literacy. Unlike these papers, our paper focuses on financial literacy and examines the relation between financial literacy of investors and the performance of their loans. Furthermore, we use several methods to try to control for the differences in risk preferences between female and male investors. These methods include (1) propensity score matching, (2) controlling for investor demographics, investing experience and timing, and loan characteristics, and (3) distinguishing between predicted and abnormal components of loan performance. To the extent that the risk preferences of investors are reflected in investor demographics, investing experience and timing, and loan characteristics, the differences in the investment choices of female and male investors are not solely driven by the differences in their risk preferences.

Second, our study is related to research on peer-to-peer payments and online marketplace lending. The previous literature has focused on how characteristics of loan applications impact a project's funding probability and interest rate (Duarte et al., 2012; Freedman and Jin, 2014; Michels, 2012; Lin et al., 2013; Iyer et al., 2015). Contributing to this literature, we show that financial literacy of investors can play an essential role in this market. Recently, researchers have examined whether investors are under time pressure to make decisions in the peer-to-peer marketplace (Wang, 2016) and whether investors' fast thinking is related to the investment behavior in the peer-to-peer market in China (Liao et al., 2017). Our paper contributes to these studies by showing how investor demographics affect the way investors use credit risk information in the peer-to-peer market. Furthermore, the issue of financial literacy can be critical for the healthy development of the peer-to-peer lending market, and our paper is the first to examine the roles that financial literacy plays in the peer-to-peer lending market.

2. Hypothesis development

We know from the previous literature that financial illiteracy is prevalent around the world (Lusardi and Mitchell, 2014). The previous literature finds that people with low education and low income are the most lacking in financial knowledge. Relative to investors who can obtain financial services from banks, investors in the peer-to-peer market of China are individuals who often have low levels of income and education. Hence, financial literacy can be an essential factor in the decision making of investors in the peer-to-peer lending market of China.

The less financially literate individuals tend to make poorer economic and financial decisions. They are less likely to plan for retirement (Lusardi and Mitchell, 2007, 2008, 2011), to accumulate wealth (Stango and Zinman, 2009; Skimmyhorn, 2016), to participate in the stock market (Christelis et al., 2010; van Rooij et al., 2011; Yoong, 2011), and to choose mutual funds with lower fees (Hastings and Tejeda-Ashton, 2008); they are also more likely to use high-cost borrowing (Lusardi and Tufano, 2015; Moore, 2003; Brown et al., 2014). Because males are generally more financially literate than females around the world (Lusardi and Mitchell, 2014; Atkinson and Messy, 2011) and in China in particular (Xu and Gong, 2017), we surmise that females are likely to make more financial mistakes than males in the peer-to-peer lending market.

The most critical risk in the peer-to-peer lending market is default risk. When Renrendai puts a new loan on its webpage, it sets the loan yield by using loan characteristics. Upon observing the loan yield and the loan characteristics of all loans available in Renrendai, investors decide in which loans to invest. When making investment decisions, investors use the loan yield and other loan characteristics to evaluate the default risk of a loan. If female investors make more financial mistakes than male investors in evaluating default risk due to the weaker financial literacy of female investors, the loans invested by female investors will have higher default rates than those invested by male investors. These gender differences can exist even after controlling for loan yield and loan characteristics. Therefore, we hypothesize:

H1a: Everything else equal, loans invested by female investors are more likely to default than loans invested by male investors.

Riskier loans default more often and can have higher loan yields. As a result, although the loans of female investors have higher average rates of default than the loans of male investors, the loans of female investors can have higher or lower average loan return depending on whether the higher default rate is compensated by the higher loan yield. We hypothesize that because female investors have poorer financial knowledge than male investors, and female investors can be stuck with loans with lower returns.

H1b: Everything else equal, loans invested by female investors have lower returns than loans invested by male investors.

There can be two reasons why loans invested by female investors have higher default rates or lower loan returns. First, these loans can have riskier loan characteristics. Second, factors other than observable loan characteristics can lead to higher loan default rates. We further distinguish between these two channels using abnormal default and abnormal loan return. We regress the indicator of default before maturity or loan return on loan yields and loan characteristics. The predicted values of this regression are the predicted default or predicted loan return, and the residuals are the abnormal default or abnormal loan return. The first channel suggests that

[2] We thank an anonymous referee for pointing out this contribution of our paper.

the loans of female investors have higher predicted defaults or lower predicted loan returns. The second channel suggests that, after controlling for observable variables, the loans of female investors have high abnormal default rates and lower abnormal loan returns. When investors are less financially literate, they tend to make poorer investment decisions even after observing the loan characteristics. Hence, we hypothesize:

H2a: Everything else equal, loans invested by female investors have higher abnormal default than loans invested by male investors.

H2b: Everything else equal, loans invested by female investors have lower abnormal loan return than loans invested by male investors.

Previous literature has pointed out that investors who have lower education or income levels also tend to have lower financial literacy, and such investors are more likely to make more financial mistakes than investors with higher levels of education, income and financial literacy (Agarwal et al., 2010; Hastings et al., 2013; Lusardi and Mitchell, 2014). Among that group of investors, it is more likely for female investors to make investment mistakes than for male investors to do so (Bucher-Koenen et al., 2017). Hence, we propose that the positive (negative) relationship between abnormal default (abnormal loan return) and the female indicator is stronger for investors with lower education and lower income levels.

H3a: Everything else equal, the difference in abnormal default between female and male investors is higher among investors with lower educational attainment and lower income.

H3b: Everything else equal, the difference in abnormal loan return between female and male investors is lower among investors with lower educational attainment and lower income.

Investors who work in the finance or IT industries potentially have better financial literacy and potentially have better quantitative ability (Jacobs, 2005). Hence, those investors can better estimate loan performance. We, therefore, hypothesize that the positive difference in abnormal default between female investors and male investors is weaker for investors in those industries. Similarly, the negative difference in abnormal default is weaker for investors in those industries.

H4a: Everything else equal, the difference in abnormal default between female and male investors is lower among investors who work in the finance or IT industries.

H4b: Everything else equal, the difference in abnormal loan return between female and male investors is higher among investors who work in the finance or IT industries.

3. Data description, methodology, and research design

We use a unique dataset on investor behaviors and demographic information from Renrendai, a leading online peer-to-peer lending marketplace in China. Renrendai was established in May 2010 and has grown rapidly since 2012. It is one of the first firms to introduce peer-to-peer lending into China. By the end of August 2017, the total trading volume in the marketplace was over 36 billion Yuan.[3] Renrendai ranks third according to a development index created by the industry rating website WDZJ.com.[4] The marketplace keeps all transaction records and assigns each investor a unique user identification number. This unique data enables us to identify the transactions of each investor and study each investor's trading behavior and performance. Investors can use two methods to invest via Renrendai. First, they can choose in which loans to invest by themselves. Second, they can invest in a loan pool, and Renrendai will then choose for them in which loans to invest. To study individual investor behavior, we limit the data to transactions conducted using the first method.

We obtain detailed demographic information for a subset of investors. The marketplace provides demographic information for potential borrowers who have applied for loans via Renrendai, whether or not the loan application is successfully approved. We identify the investors who applied for loans via Renrendai and obtain demographic information for those investors. We extracted the loan characteristics, borrower's demographic information, bid records, and repayment history of each loan listed on the marketplace's website from May 2010 to September 2016. Because transactions before 2012 are relatively scarce and the recent listings' time-to-maturity is long, we include loan listings from January 2012 to December 2015.

We consider two measures of loan performance. The first measure of loan performance is default before maturity. This variable is one if the loan defaults before the maturity of the loan; otherwise, this variable is zero.[5] This variable measures the loan default outcome that the investor experiences. The second measure is loan return, which we measure with the internal rate of return (IRR).[6] We can estimate the loan return using the amount of the loan principal (*Loan amount*), the time to maturity (T), and the discounted repayment cash flows. The definition of this variable is illustrated in an equation as follows.

$$0 = -Loan\ amount + \sum_{t=1}^{T} \frac{Repayment\ cash\ flow_t}{(1 + Loan\ return)^t}. \tag{1}$$

Borrowers repay both principal and interest each period. If a loan does not default, the borrower will repay the investors the loan principal and the interest in full. The loan will be in default if the borrower misses a payment for more than 30 days. In case of a loan default, the investors will not lose any part of the principal of the loan because Renrendai will pay back the principal using a risk mitigation fund in case of default during our sample period. The investor, however, will lose the remaining interest payment. Therefore, a loan default will decrease the repayment cash flows and reduce loan return. Table 1 provides the definitions of the variables used in the analysis.

[3] Reported by Renrendai at https://www.renrendai.com/pc/home/platform/dataOverview. Last access 9/14/2017.

[4] http://www.wdzj.com/news/yc/905793.html. Last access 9/14/2017.

[5] Renrendai will consider a loan in default if the borrower missed the regular payment day for more than a month. We follow Renrendai's definition.

[6] We construct this measure of internal rate of return in accordance with Liao et al. (2017). We do not compare IRR with a benchmark rate (e.g. the rate for bank deposit) because we use month fixed effects in our analysis, which subsumes the benchmark rate.

Table 1
Variable description.

Variable	Description
Default measures:	
Default before maturity	Dummy variable, 1 if the loan defaulted before maturity
Predicted default	Predicted values from the loan-level regression of default before maturity on all loan characteristics.
Abnormal default	Residual values from the loan-level regression of default before maturity on all loan characteristics.
Loan return	Internal rate of return of loan estimated with equation: $0 = -Loan\ amount + \sum_{t=1}^{T} \frac{Repayment\ cash\ flow_t}{(1+Loan\ return)^t}$.
Predicted loan return	Predicted values from the loan-level regression of loan return on all loan characteristics.
Abnormal loan return	Residual values from the loan-level regression of loan return on all loan characteristics.
Investor demographics:	
Female	Dummy variable, 1 if the investor is female.
Single	Dummy variable, 1 if the investor is single.
High education	Dummy variable, 1 if the investor has graduate or higher degree.
High income	Dummy variable, 1 if the investor's monthly income is higher than RMB 10,000.
High age	Dummy variable, 1 if the investor is older than 30.
House owner	Dummy variable, 1 if the investor owns a house or an apartment.
Finance or IT	Dummy variable, 1 if the investor works in finance or IT industries.
Loan characteristics:	
Loan yield	Annualized loan yield in percentage points.
Log loan amount	Natural logarithm of the loan amount in Renminbi.
Maturity	Maturity at issuance in months.
Credit certificate	Dummy variable, 1 if the borrower has at least one credit certificate.
Past borrowing	Dummy variable, 1 if the borrower has borrowed successfully at least once with Renrendai.
Past delinquency	Dummy variable, 1 if the borrower has had at least one delinquent loan with Renrendai.
Investing experience and timing:	
Past default	Dummy variable, 1 if the investor's default ratio is higher than across-investor average of default ratio in the month. The default ratio is the number of defaulted loans an investor has had divided by the total number of loans that the investor has invested.
Working hours	Dummy variable, 1 if the current transaction happens during working hours. Working hours is between 8:00 and 18:00 Monday to Friday.

We use a method of propensity score matching (PSM) to match the transactions of male and female investors. This matching can help alleviate the concern that male and female investors invest in different loans because their other characteristics differ. We match the transactions of male and female investors by investor demographics, investing experience and timing, and loan characteristics. Specifically, we estimate a Probit regression of the female indicator on investor demographics, investing experience and timing, and loan characteristics and calculate the propensity score using predicted probability. We then find a matched transaction of a male investor for each transaction of a female investor using the nearest propensity score. We allow for replacement and do not use caliper matching. We then use the matched sample to conduct tests.[7] To alleviate the potential influence of extreme observation values, we winsorize all continuous variables in the paper at 1% and 99%.[8]

The matched sample includes 1,720 investors, 24,763 unique loans, and 48,704 transaction records. Panel A of Table 2 reports the summary statistics of the loan performance measures: default before maturity and loan return. In the overall sample, average default before maturity is 4.232%.[9] The average loan default rate of loans invested by female investors is higher than that of the loans invested by male investors. The average of default before maturity is 4.607% across female investors and 3.856% across male investors. The difference in loan default rates between female and male investors is 75.1 basis points and statistically significant. The average loan return in the overall sample is 12.554%. The average loan return of female investors, 12.533%, is lower than that of male investors, 12.575%. The difference in average loan return between female and male investors is −4.1 basis points and statistically significant.

Panel B of Table 2 provides the averages of demographic variables for all investors, females, and males. 50% of all investors are female because we are using a propensity-score matched sample. We find that female investors have lower average income and lower

[7] Rubin (2001) suggests that the samples are sufficiently balanced if Rubin's B is less than 0.5 or if Rubin's R is between 0.5 and 2. In our matched sample, Rubin's B is 0.089, and Rubin's R is 0.95, suggesting that the matching is valid. Robin's B is the ratio of absolute difference in the means of the linear index of the propensity score between the treated and non-treated (matched) group to the standard deviation of the linear index of the two samples combined. Robin's R is the ratio of treated to non-treated (matched) variances of the linear index of propensity score.

[8] Our results are robust to not using winsorization.

[9] The average default rate is based on loans that are originated online as well as loans that are originated offline. The average default rate of loans that are originated online is 12.452%. For a comparison, loans in the sample of Duarte et al. (2012) are originated online, and the average loan default rate is 19.87%.

Table 2
Gender differences in loan performance, investor demographics, loan choice, and investing experience and timing.

Variable	Overall	Female	Male	Diff	*P* value
Panel A: Performance					
Default before maturity (%)	4.232	4.607	3.856	0.751	<0.001
Loan return (%)	12.554	12.533	12.575	−0.041	<0.001
Panel B: Demographics					
Female	0.500				
Single	0.428	0.427	0.430	−0.003	0.498
High education	0.083	0.085	0.082	0.003	0.173
High income	0.142	0.137	0.147	−0.010	0.002
High age	0.676	0.668	0.684	−0.016	<0.001
House owner	0.254	0.253	0.256	−0.003	0.486
Finance or IT	0.152	0.160	0.145	0.015	<0.001
Panel C: Loan characteristics					
Loan yield (%)	12.626	12.611	12.640	−0.028	0.006
Log loan amount	10.931	10.936	10.927	0.009	0.217
Maturity	23.332	23.530	23.133	0.397	<0.001
Credit certificate	0.769	0.770	0.767	0.004	0.356
Past borrowing	0.099	0.096	0.101	−0.005	0.068
Past delinquency	0.044	0.044	0.044	0.000	0.843
Panel D: Investing experience and timing					
Past default	0.443	0.446	0.440	0.006	0.192
Working hours	0.714	0.717	0.711	0.006	0.160
Observations	48,704	24,352	24,352		

This table reports the averages of key variables used in our analysis. We report the means for the overall sample, female and male investors. We report the differences in means between females and males and the *p*-values of *t*-test of the differences. See Table 1 for variable definitions.

average age, and female investors are more likely to be in the Finance and IT industries. The female and male investors do not differ in marital status, education level, and house ownership status.

In Panel C of Table 2, we report summary statistics of loan yield, log loan amount, loan maturity, credit certificates, past borrowing, and past delinquency. These variables of loan characteristics measure the riskiness of the loan. Among the first three variables, the average loan yield, the average log loan amount, and the average maturity are 12.626%, 10.931, and 23.332, respectively. Loan yield is determined by Renrendai at issuance by the marketplace using all borrower and loan characteristics. Female investors choose loans with lower yields than male investors do. The average yield of the loans invested by female investors (12.611%) is 2.8 basis points lower than that of the loans invested by male investors (12.640%). Female investors choose loans with longer maturity than male investors do. The difference in average maturity between female and male investors is 0.397 month. The female and male investors do not differ in loan amount.

The last three variables in Panel C of Table 2 capture the personal risk profile of the borrower. Credit certificate measures the extent to which the borrower submits valid materials about his or her credit risk to Renrendai when applying for loans. These materials include credit bureau reports, diplomas, income statements, and property certificates, among others. We count the unique pieces of materials that the borrower provides, and the credit certificate is a dummy variable that is given a value of one if the borrower provides at least one piece of material and a value of zero otherwise. Past borrowing is a dummy variable that is given a value of one if the borrower has successfully borrowed with Renrendai at least once in the past and a value of zero otherwise. Similarly, we define past delinquency as a dummy variable that is given a value of one if the borrower has been delinquent with Renrendai; otherwise, this variable is zero. The average values of credit certificate, past borrowing, and past delinquency are 0.769, 0.099, and 0.044. The female and male investors choose similar levels of credit certificate, past borrowing, and past delinquency.

We use transaction-level data to construct variables related to investing experience and timing for investors. Because the previous literature suggests that the investing experience of investors affects their investing behavior (Korniotis and Kumar, 2011), we measure the investing experience of an investor using a variable named past default. This variable is a dummy variable that is given a value of one if the default ratio of an investor is higher than the cross-investor average of the default ratio in the month, where the default ratio is the number of loan defaults that the investor has experienced divided by the total number of loans in which the investor has invested. This variable captures whether the investor has experienced more frequent defaults than an average investor after adjusting for trading intensity. Furthermore, because investors can potentially behave differently on Renrendai during different times of the day, we construct a variable called "working hours" to measure whether a trade happens during working hours. This variable is given a value of one if the trade happens between 8 AM and 6 PM on Monday to Friday. We use this variable to capture the potential influence of investing timing on the evaluation of default risk.

In Panel D of Table 2, we report the summary statistics of past defaults and working hours. The mean past default in the overall sample is 0.443. The mean of past default of female investors (0.446) similar to the mean of past default of male investors (0.440). The difference in mean of past default between female and male investors (0.006) is not statistically significant. The mean of working hours in the overall sample is 0.714, which means that 71.4% of trades happen during working hours. 71.7% of trades of female investors happen during working hours, while 71.1% of trades of male investors happen during working hours. The difference in working hours between female and male investors is not statistically significant.

Table 3
Gender differences in loan performance.

Dependent variable	Default before maturity (1)	Default before maturity (2)	Default before maturity (3)	Default before maturity (4)	Loan return (5)	Loan return (6)	Loan return (7)	Loan return (8)
Female	0.621**	0.551*		0.664***	−0.022	−0.021		−0.012**
	(0.266)	(0.281)		(0.243)	(0.021)	(0.020)		(0.005)
High income		−1.625***		−0.684**		0.111*		0.012*
		(0.357)		(0.318)		(0.056)		(0.006)
High education		−0.865		−0.242		0.091**		0.007
		(0.765)		(0.589)		(0.039)		(0.017)
High age		−1.821***		−0.585		0.011		0.010
		(0.412)		(0.388)		(0.032)		(0.008)
Single		−0.041		0.029		−0.176***		0.001
		(0.329)		(0.323)		(0.046)		(0.008)
House owner		−0.002		0.564**		−0.163***		−0.007
		(0.315)		(0.281)		(0.042)		(0.009)
Working hours		2.611***		0.847***		−0.032		−0.021***
		(0.432)		(0.264)		(0.033)		(0.006)
Past default		1.487***		0.208		−0.089*		−0.015*
		(0.419)		(0.306)		(0.046)		(0.008)
Loan yield			0.991***	2.442***			0.921***	0.929***
			(0.056)	(0.359)			(0.003)	(0.013)
Maturity			0.043***	−0.037			0.008***	0.006***
			(0.008)	(0.039)			(0.000)	(0.001)
Credit certificate			−15.285***	−12.378***			0.281***	0.127***
			(0.220)	(1.249)			(0.010)	(0.022)
Past delinquency			11.580***	13.600***			−0.044***	−0.138***
			(0.432)	(1.856)			(0.014)	(0.031)
Past borrowing			4.015***	5.307***			−0.175***	−0.034*
			(0.299)	(1.138)			(0.020)	(0.020)
Log loan amount			−0.733***	−0.355			0.001	−0.009
			(0.102)	(0.310)			(0.005)	(0.009)
Month fixed effects	YES	YES	NO	YES	YES	YES	NO	YES
Observations	48,704	48,704	74,271	48,704	48,704	48,704	74,271	48,704
Adj. R-squared	0.013	0.020	0.125	0.120	0.256	0.265	0.680	0.855

Columns (1), (2), and (4) of this table reports the transaction-level regressions of default before maturity on female dummy and control variables. Column (3) reports loan-level regressions of default before maturity on loan characteristics. Columns (5), (6), and (8) of this table reports the transaction-level regressions of loan return on female dummy and control variables. Column (7) reports loan-level regressions of loan return on loan characteristics. The unit of the dependent variable is percentage point. Standard errors are two-way clustered by loan and month and reported in parentheses. See Table 1 for variable definitions.

* Represent statistical significance at the 10% level.

** Represent statistical significance at the 5% level.

*** Represent statistical significance at the 1% level.

4. Gender difference in loan performance

4.1. Baseline relation between investor gender and loan performance

In this section, we study how and why loan performance differs between male and female investors. In Table 3, we use transaction-level data to estimate regressions of loan return and default before maturity on investor gender and other variables. Default before maturity is the dependent variable in Columns (1) to (4), and loan return is the dependent variable in Columns (5) to (8). Both dependent variables are in percent. We estimate linear probability regressions with standard errors that are two-way clustered by loan and month (Petersen, 2009).[10] In all regressions, we use month fixed effects to control for unobservable time-specific factors.

In Column (1), we regress default before maturity on only the female dummy variable with month fixed effects. The coefficient of the female indicator is 0.621, which means that the default rate of loans of female investors is 62.1 basis points higher than that of loans of male investors after controlling for month fixed effects. The magnitude of this coefficient is 14.67% compared with the average default before maturity in the overall sample (4.232%). In Column (2), after we control for investor demographic information, investors' investing experience and timing, the coefficient of the female indicator is 0.551. This magnitude of the coefficient is similar to that in Column (1). The results in Columns (1) and (2) show that the loans invested by female investors are more likely to default than the loans in which male investors invest.

The estimated coefficients of controlling variables in Column (2) show that investors with higher income levels or older age invest in loans that have a lower probability of default. The coefficient of working hours is positive and significant, meaning that investors tend to make more mistakes investing during working hours than during other time periods. If investors are relatively more occupied by things other than investing with Renrendai (e.g., working) during working hours than other hours, this result is consistent with

[10] Our primary results are robust to using Probit regressions or Logit regressions.

the intuition that the fast thinking of investors can lead to more investing mistakes (Liao et al., 2017). The coefficient of past default is positive, implying that investors with more experience of past defaults make more investing mistakes.[11]

In Column (3), we regress default before maturity on loan yield and loan characteristics at the loan level. In this regression, we use observable loan variables to predict loan defaults. We find that loan yield, loan maturity, past delinquency, and past borrowing are positively related to the probability of default and that the credit certificate and loan amount are negatively related to the probability of default. The signs of those coefficients are consistent with the intuition that loans with riskier characteristics default more often. We use this model to decompose default risks into two parts: predicted default and abnormal default. The predicted default is the fitted values of this regression, and the abnormal default is the residuals of this regression. The predicted default is the part of default risk that investors can measure using observable loan variables, and the abnormal default is unrelated to the observable variables.

In Column (4) of Table 3, we regress default before maturity on both investor demographics and loan characteristics. The coefficient of female indicator implies that loans invested by female investors are 0.664% more likely to default than loans invested by male investors. Compared with the average of default probability of all loans in the sample, 4.232%, this number is 15.69%. This result is consistent with Hypothesis 1a: the loans invested by female investors have higher default rates than the loans invested by male investors. Among the control variables, we find that loan default is positively related to loan yield, maturity, past delinquency, and past borrowing and negatively related to credit certificate and log loan amount. The signs of these coefficients are generally consistent with the intuition that riskier loans have higher probability of default.

We regress loan return on the female indicator, investor demographics, and loan characteristics in Columns (5) to (8). In Column (5), we regress loan return on only female indicator with time fixed effects. The coefficient of the female indicator is −0.022, which means that the average loan return of female investors is 2.2 basis points lower than that of male investors. The magnitude of this coefficient is 0.175% of the average loan return in the overall sample (12.554%) and 1.884% of the standard deviation of loan return in the overall sample (1.168%). The economic magnitude of the coefficient suggests an economically small difference in loan returns between female and male investors, while the gender difference in default rates is economically large. This fact is because Renrendai repays investors the principal loan amount in case of default during our sample period so that the impact of the default on loan performance is relatively small.

In Column (6) of Table 3, we regress loan return on female indicator and investors demographic variables. The coefficient of the female indicator is −0.021, which is similar to the coefficient of the female indicator in Column (5). In Column (7), we regress loan return on loan characteristics variables at the loan level. We find that loan return is positively related to loan yield, maturity, credit certificate, and log loan amount and negatively related to past delinquency and past borrowing. The signs of these coefficients are generally consistent with the intuition that riskier loans have lower loan returns. We use the result of the regression in Column (7) to decompose loan return into two components: predicted loan return and abnormal loan return. The predicted loan return is the fitted values of this regression, and the abnormal loan return is the residuals of this regression. The predicted loan return is the part of loan return that investors can evaluate using observable loan variables, and the abnormal loan return is unrelated to the observable loan variables.

In Column (8), we regress loan return on the female indicator, controlling for both investor demographic variables and loan characteristics variable. The coefficient on female indicator is −0.012. Therefore, the average loan return of female investors is lower than that of male investor after controlling for loan yield, investor income, education level, age, investor experience, and loan characteristics. The magnitude of this coefficient means a 45.45% reduction from the coefficient of the female indicator in Column (5), where the female indicator is the only explanatory variable. This relative small reduction in coefficient suggests that a majority part of the effect of investor gender on loan return is not explained.

4.2. Abnormal loan performance

To further understand the part of default and loan return that is not explained by observable variables, we study how the abnormal default and the abnormal loan return are related to the gender of investors. In Table 4, we present the averages of predicted default, abnormal default, predicted loan return, and abnormal loan return. The unit of these variables is percentage point. The summary statistics show that the average predicted default rate of female investors is similar to that of male investors. The difference is −0.099% with a p-value of 0.121. Compared to the sample average of predicted default, 4.598%, this difference is −2.15%. The average abnormal default rate of female investors is higher than that of male investors. The mean abnormal default rate of female investors is −0.018, and the mean abnormal default rate of male investors is −0.845. The difference in mean abnormal default rate is 0.827% with a p-value less than 0.001. The magnitude of this gender difference is 191.4% of the magnitude of the sample mean of abnormal default (−0.432%). We plot the averages of default before maturity, predicted default, and abnormal default in Fig. 1. This figure shows similar patterns as the data shown in Table 4. The mean default rate of female investors is higher than that of male investors; the mean predicted default of female investors is similar to that of male investors; the mean abnormal default of female investors is higher than that of male investors. Thus, abnormal default drives the difference in default between female and male investors. These results are consistent with our hypotheses 1a and 2a.

The summary statistics of Table 4 show that the average predicted loan return and average abnormal loan return of female investors are both lower than those of male investors. The mean predicted loan return of female investors is 12.472%, and the mean predicted loan return of male investors is 12.495%. The difference between these two means is −2.3 basis points with a p-value

[11] We alternatively calculate default ratio as the weighted average of defaults that the investor has experienced using loan sizes as the weights. We then use this alternative default ratio to construct the indicator variable past default. Our results are robust to using the alternative past default variable.

Table 4
Averages components of loan performance.

Performance	Overall	Female	Male	Diff.	p-value
Predicted default	4.598	4.548	4.647	−0.099	0.121
Abnormal default	−0.432	−0.018	−0.845	0.827	<0.001
Predicted loan return	12.484	12.472	12.495	−0.023	0.016
Abnormal loan return	0.076	0.066	0.085	−0.018	<0.001
Observations	48,704	24,352	24,352		

This table reports the averages of components of default before maturity and loan return. Predicted default is the predicted values from a loan-level regression of default before maturity on loan characteristics. Abnormal default is the residual values from the previous regression. Predicted loan return is the predicted values from a loan-level regression of loan return on loan characteristics. Abnormal loan return is the residual values from the previous regression. See Table 1 for variable definitions.

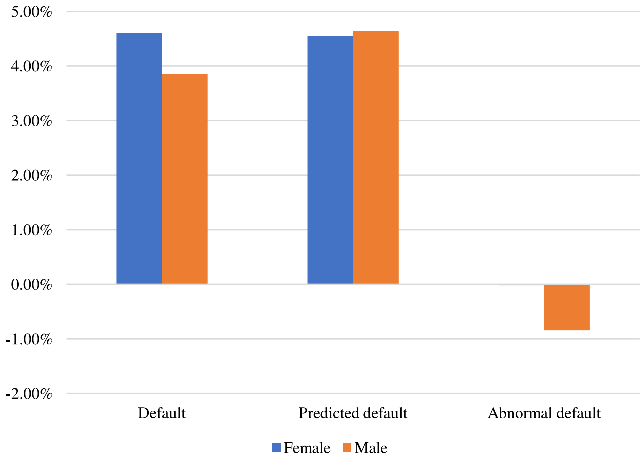


Fig. 1. Average default and components of default for male and female investors. This figure shows the average default measures of male and female investors. The default measures include default before maturity (default), predicted default, and abnormal default. Blue and red bars represent averages for female and male investors, respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

of 0.016. This difference is −0.184% of the mean predicted loan return of the overall sample (12.484%). The mean abnormal loan return of female investors is 0.066%, and the mean abnormal loan return of male investors is 0.085%. The gender difference in mean abnormal loan return is −1.8 basis points with a p-value less than 0.001. The magnitude of this gender difference is −23.7% of the mean abnormal loan return of the overall sample (0.076). These results show that female investors have lower loan return, lower predicted loan return, and lower abnormal loan return than male investors do. We plot the averages of loan return, predicted loan return, and abnormal loan return in Fig. 2. This figure shows similar patterns as the data shown in Table 4. These results are consistent with our Hypotheses 1b and 2b.

To investigate the statistical significance of the gender difference in the components of default and loan return, we regress predicted default, abnormal default, predicted loan return, and abnormal loan return on female indicator and control variables. We study predicted and abnormal default in Table 5. In Column (1) of this table, we estimate a univariate regression of predicted default on female indicator with time fixed effects. In Column (2), we control for investor demographics variables. In Column (3), we control for variables of both investor demographics and loan characteristics. The coefficients of the female indicator in Columns (1), (2), and (3) are −0.015, −0.071, and 0.001 and statistically insignificant. The results suggest that the predicted default is not significantly different between male and female investors. In Column (4), we regress abnormal default on female indicator with time fixed effects, and we further add control variables of investor demographics and loan characteristics in Columns (5) and (6). The results of these three regressions show that the default rate of female investors is higher than that of male investors. The coefficients of the female indicator are 0.616, 0.603, and 0.640 and statistically significant. The magnitudes of the coefficients are economically significant. The average of abnormal default in the overall sample in Table 4 is −0.432. Compared with the magnitude of this average, the magnitudes of the coefficients of the female indicator are 143%, 140%, 148%, respectively. These results suggest that after controlling for other investor demographics and loan characteristics, female investors choose loans with higher abnormal default probability than male investors do. This result is consistent with Hypothesis 2a.

We study predicted and abnormal loan return in Table 6. We arrange regressions in this table in a way similar to the regressions in Table 5. The dependent variable of Columns (1), (2), and (3) is the predicted loan return, and the dependent variable of Columns (4), (5), and (6) is the abnormal loan return. We use female indicator as the only explanatory variable in Columns (1) and (4), and we add variables of investor demographics and variables of loan characteristics in other columns. In Columns (1) to (3), the coefficients of the female indicator are negative, small in magnitude, and statistically insignificant. In Columns (4) to (6), the coefficients of the female indicator are −0.012, −0.013, and −0.011 and statistically significant. These coefficients mean that the mean abnormal

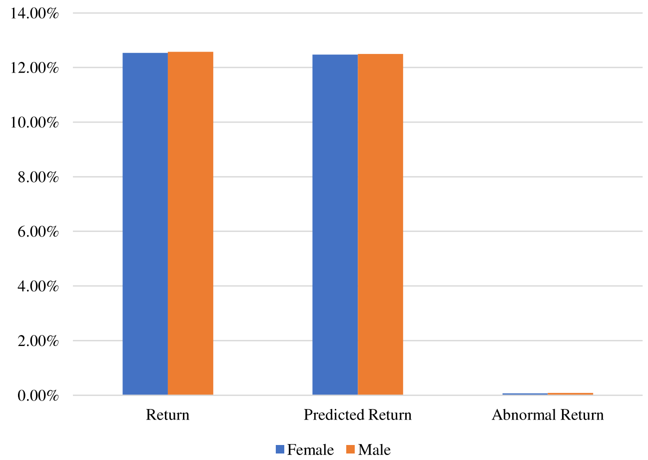


Fig. 2. Average loan return and average components of loan return for male and female investors. This figure shows the average loan return of male and female investors. It also shows the average predicted loan return and abnormal loan return. Blue and red bars represent averages for female and male investors, respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 5
Gender differences in predicted and abnormal default.

Dependent variable	Predicted default (1)	Predicted default (2)	Predicted default (3)	Abnormal default (4)	Abnormal default (5)	Abnormal default (6)
Female	−0.015	−0.071	−0.001	0.616**	0.603**	0.640**
	(0.142)	(0.151)	(0.016)	(0.246)	(0.250)	(0.246)
High income		−1.107***	−0.069***		−0.501	−0.606*
		(0.185)	(0.023)		(0.318)	(0.315)
High education		−0.746***	−0.048*		−0.102	−0.184
		(0.278)	(0.028)		(0.601)	(0.577)
High age		−1.267***	−0.039*		−0.524	−0.521
		(0.182)	(0.022)		(0.382)	(0.385)
Single		0.025	0.020		−0.055	0.021
		(0.201)	(0.021)		(0.318)	(0.314)
House owner		−0.500***	−0.043**		0.498*	0.598**
		(0.147)	(0.020)		(0.272)	(0.277)
Working hours		1.949***	0.089***		0.617**	0.724***
		(0.243)	(0.015)		(0.275)	(0.253)
Past default		1.491***	0.068***		−0.012	0.132
		(0.266)	(0.017)		(0.324)	(0.301)
Loan yield			1.110***			1.226***
			(0.028)			(0.346)
Maturity			0.028***			−0.055
			(0.002)			(0.038)
Credit certificate			−14.523***			1.952
			(0.070)			(1.192)
Past delinquency			6.883***			6.943***
			(0.653)			(2.262)
Past borrowing			4.735***			0.238
			(0.184)			(1.124)
Log loan amount			−0.758***			0.426
			(0.025)			(0.296)
Month fixed effects	YES	YES	YES	YES	YES	YES
Observations	48,704	48,704	48,704	48,704	48,704	48,704
Adj. R-squared	0.217	0.257	0.977	0.019	0.019	0.029

Regressions of predicted and abnormal default on female indicator and control variables. Predicted default is the predicted values from the regression of default before maturity on loan characteristics, and abnormal default is the residual values from the previous regression. Standard errors are two-way clustered by loan and month and reported in parentheses.

* Represent statistical significance at the 10% level.

** Represent statistical significance at the 5% level.

*** Represent statistical significance at the 1% level.

default of female investors is lower than that of male investors. The economic significance of these effects is also large. Compared to the mean abnormal loan return in Table 4 (0.076), the magnitudes of these coefficients are −15.79%, −17.11%, and −14.47%. These results are consistent with Hypothesis 2b.

Table 6
Gender differences in predicted and abnormal loan return.

Dependent variable	Predicted loan return (1)	Predicted loan return (2)	Predicted loan return (3)	Abnormal loan return (4)	Abnormal loan return (5)	Abnormal loan return (6)
Female	−0.010	−0.009	−0.001	−0.012**	−0.013**	−0.011**
	(0.021)	(0.020)	(0.001)	(0.006)	(0.006)	(0.006)
High income		0.115**	0.000		−0.006	0.009
		(0.053)	(0.001)		(0.007)	(0.006)
High education		0.092**	−0.001		−0.002	0.005
		(0.040)	(0.001)		(0.015)	(0.015)
High age		0.017	0.002***		−0.004	0.011
		(0.033)	(0.001)		(0.009)	(0.009)
Single		−0.181***	0.001		−0.001	−0.003
		(0.046)	(0.001)		(0.008)	(0.007)
House owner		−0.154***	0.001		−0.010	−0.006
		(0.042)	(0.001)		(0.007)	(0.007)
Working hours		−0.033	−0.001*		0.004	−0.017***
		(0.033)	(0.001)		(0.006)	(0.005)
Past default		−0.090*	0.001		−0.002	−0.018**
		(0.045)	(0.001)		(0.010)	(0.008)
Loan yield			0.931***			0.021*
			(0.002)			(0.012)
Maturity			0.007***			−0.003***
			(0.000)			(0.001)
Credit certificate			0.276***			−0.135***
			(0.002)			(0.022)
Past delinquency			−0.117***			−0.031
			(0.008)			(0.029)
Past borrowing			−0.055***			0.014
			(0.004)			(0.018)
Log loan amount			−0.005***			−0.006
			(0.002)			(0.007)
Month fixed effects	YES	YES	YES	YES	YES	YES
Observations	48,704	48,704	48,704	48,704	48,704	48,704
Adj. R-squared	0.230	0.240	0.999	0.073	0.073	0.097

Regressions of predicted and abnormal loan return on female indicator and control variables. Predicted loan return is the predicted values from the regression of loan return on loan characteristics, and abnormal loan return is the residual values from the previous regression. Standard errors are two-way clustered by loan and month and reported in parentheses.

* Represent statistical significance at the 10% level.

** Represent statistical significance at the 5% level.

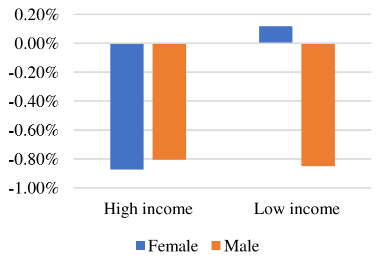
*** Represent statistical significance at the 1 level.

4.3. Investor groups

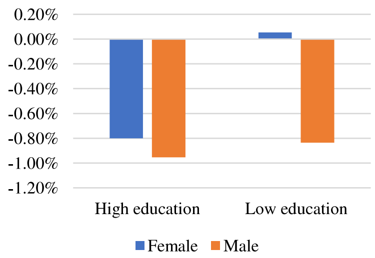
We group the observations by gender and income level, education level, or the industries of investors and study how the gender differences in abnormal loan performance differ between investor groups.[12] We first plot the average abnormal default within each group in Fig. 3. We find that the difference in the abnormal default rate between female and male investors is positive in the low-income group but is close to zero in the high-income group. Similarly, the gender difference in abnormal default rate is positive in the low-education group but is close to zero in the high-education group. We then test the statistical significance of the difference in abnormal default in each of the above groups in Panel A of Table 7. Columns (1) to (4) show that the coefficients of the female indicator are positive and significant for the low-income and low-education groups but are not statistically significant for the high-income and high-education groups. This result is consistent with Hypothesis 3a: gender difference in abnormal defaults is larger for low income and low education groups. These results also show that female investors with high levels of education and income can perform as well as male investors when investing in the peer-to-peer market.

Panel (c) of Fig. 3 shows the average default before maturity for investors grouped by gender and the industry of the investors. We distinguish between investors who work in finance or information technology industries and investors who work in the other industries. The investors working in finance or IT industries tend to have better math and analytical skills than the other investors. As a result, they can potentially better evaluate default risks and loan return. We find in Panel (c) of Fig. 3 that the average abnormal default of female investors is lower than that of male investors when the investors work in finance and IT industries. For investors working in other industries, the pattern is the opposite: the average abnormal default rate of female investors is higher than that of male investors. To study the statistical significance of the above pattern, we regress abnormal default on female indicator and control variables separately for these two groups of investors in Columns (5) and (6) of Table 7. We find that the coefficient of the female

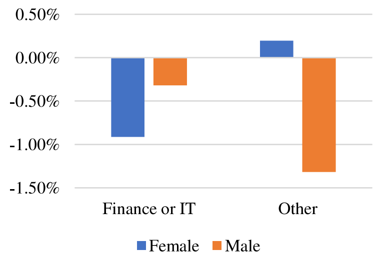
[12] We define high-education group as investors postgraduate or higher degrees. We define high-income group as investors with monthly income higher than RMB 10,000 (approx. $1600).



(a) Abnormal default by gender, income.



(b) Abnormal default by gender, education.



(c) Abnormal default by gender, industry.

Fig. 3. Averages of abnormal default for groups of investors. Panel (a) shows the average abnormal default of subsamples grouped by gender and income levels. Panel (b) shows the average abnormal default of subsample grouped by gender and education levels. Panel (c) shows the average abnormal default of subsamples grouped by gender and Finance or IT industries or other industries. Blue and red bars represent averages for female and male investors, respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 7
Income, education, experience, and gender difference in loan performance.

Group	(1) High income	(2) Low income	(3) High education	(4) Low education	(5) Finance or IT	(6) Other industries
Panel A: Dependent variable is abnormal default						
Female	0.147	0.727**	−0.192	0.695***	−0.684	1.290***
	(0.571)	(0.286)	(0.973)	(0.251)	(0.646)	(0.341)
Investor demographic	YES	YES	YES	YES	YES	YES
Loan Characteristics	YES	YES	YES	YES	YES	YES
Month fixed effect	YES	YES	YES	YES	YES	YES
Observations	6901	41,803	4055	44,649	7413	23,149
Adj. R-squared	0.030	0.030	0.038	0.030	0.035	0.041
Panel B: Dependent variable is abnormal loan return						
Female	−0.010	−0.012*	0.007	−0.012**	0.010	−0.023***
	(0.012)	(0.006)	(0.027)	(0.006)	(0.014)	(0.008)
Investor demographic	YES	YES	YES	YES	YES	YES
Loan characteristics	YES	YES	YES	YES	YES	YES
Month fixed effect	YES	YES	YES	YES	YES	YES
Observations	6901	41,803	4055	44,649	7413	23,149
Adj. R-squared	0.137	0.093	0.123	0.097	0.132	0.110

Regressions of abnormal default and abnormal loan return on female indicator and control variables for investor groups. The investor groups include investors with high or low income levels, investors with high or low education levels, and investors working in Finance or IT industries or working in other industries. Standard errors are two-way clustered by loan and month and reported in parentheses.

* Represent statistical significance at the 10% level.

** Represent statistical significance at the 5% level.

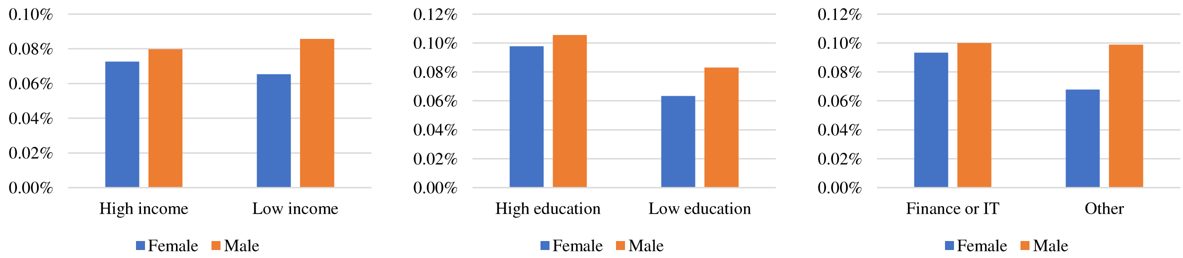
*** Represent statistical significance at the 1% level.

indicator is positive and significant for the Other industries but is not significant for Finance or IT industries. This result is consistent with Hypothesis 4a and suggests that with sufficient financial knowledge or quantitative skills, female investors do not make more financial mistakes than male investors when investing in the peer-to-peer market.

In Fig. 4, we similarly group investors by income, education, or industries and plot the average abnormal loan return of each investor group. We find that the difference in average abnormal loan return between female investors and male investors is lower in the low-income group than the high-income group, lower in the low-education group than in the high-education group, and lower for investors working in finance or IT industries than for the other investors. We then study the statistical significance of these patterns in Panel B of Table 7. We find that the coefficient of the female indicator is negative and significant for the low-income, low-education, and the Other industries and is not significant for the other groups. These patterns are consistent with Hypotheses 3b and 4b. These results mean that female investors with high levels of income or education or with sufficient financial knowledge or quantitative skills can perform equally well as male investors in the peer-to-peer market.

5. Conclusion

We study how default risks and loan performance in peer-to-peer lending market depend on the gender of investors. To do that, we combine information about loan default, trade-level information, and investor demographic data from a large peer-to-peer lending marketplace in China. We find that female investors invest in loans that default more often and have lower loan returns than loans invested by male investors. These results are robust to controlling for the investors' other demographic information, investing experience, and loan characteristics. After documenting the gender differences in default risks and loan return, we then study what



(a) Abnormal loan return by gender, income. (b) Abnormal loan return by gender, education. (c) Abnormal loan return by gender, industry.

Fig. 4. Averages of abnormal loan return for groups of investors. Panel (a) shows the average abnormal loan return of subsamples grouped by gender and income levels. Panel (b) shows the average abnormal loan return of subsamples grouped by gender and education levels. Panel (c) shows the average abnormal loan return of subsamples grouped by gender and Finance or IT industries or other industries. Blue and red bars represent averages for females and males, respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

drives such gender differences. We distinguish between two channels. Female investors invest in loans that have riskier observable characteristics or because of other reasons. To distinguish these two channels, we regress default indicator or loan return on loan yields and loan characteristics. We name the predicted values of this regression the predicted default or predicted loan return and name the residuals of this regression the abnormal default or abnormal loan return. We find that the second channel explains the gender difference in loan default and loan return. The predicted default and predicted loan return of female investors are similar to those of the male investors, but the abnormal default of female investors is higher than that of the male investors, and the abnormal return of female investors is lower than that of the male investors. These results are consistent with the interpretation that female investors have lower financial literacy and lower ability to evaluate default risks than male investors. Furthermore, the gender differences in abnormal default and abnormal loan return are not significant for investors who have higher levels of income or education or for those who work in finance or IT industries. These results suggest that female investors with sufficient education, financial knowledge, or quantitative skills can perform as well as male investors in the peer-to-peer market.

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