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Investing with Fast Thinking*

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Investing with Fast Thinking

Abstract

Using data from a major online peer-to-peer lending market, we document that investors follow a simple rule of thumb under time pressure: they rush to invest in loans with high interest rates without sufficiently examining credit ratings, which are freely available on the trading interface. Our experiments show that making credit rating information more salient "nudges" investors into better decisions. Firsthand experience matters for learning for *non-informational reasons*: An investor responds differently when observing a default of her own loan, relative to observing a default of another investor's loan.

JEL Classification Numbers: G12.

Keywords: Rule of thumb, nudge, firsthand experience, P2P, fast thinking.

I. Introduction

The last four decades have witnessed significant progress in theories of judgment and decision-making. One prominent insight in this literature is the so-called two-system approach. As recently summarized by Daniel Kahneman in *Thinking, Fast and Slow*, System 1 operates automatically and quickly, with little or no effort, while System 2 is slow and deliberate, allocating attention to effortful mental activities. While both systems are thought to be active in decision-making, System 1 typically dominates. System 2, usually in inactive mode, only contributes to the decision process when System 1 runs into difficulty. For convenience, we use "fast thinking" to refer to decision-making with System 1, and "slow thinking" to refer to decision-making with System 2.

While the two-system theory suggests that fast thinking influences most of our everyday decision-making, existing studies have been primarily conducted in experimental settings. The extent to which fast thinking affects decisions in real financial markets is an open question. How do investors make financial decisions using fast thinking? How do they learn from these decisions? Can we modify the environment to influence investors' decision-making at a subconscious level? The greatest challenge in answering these questions is identifying a financial market in which investors must make quick decisions and we can reliably measure the decision time as well as the outcomes of those decisions.

We examine these questions in an online peer-to-peer (P2P) lending market, in which individual investors bid on unsecured microloans listed by individual borrowers. We obtain transaction data from Renrendai, one of the leading P2P lending platforms in China. Three features make this platform ideal for analyzing investments made using fast thinking. First, investors in this market have to make quick decisions. Due to the market environment, which will be explained in detail in Section II, loans on this platform are generally highly appealing and quickly get fully funded. For example, 25% of the loans listed on Renrendai are fulfilled within 42 seconds and 90% are fulfilled in under eight minutes. Second, Renrendai records time stamps for all transactions, allowing us to measure investors' decision time. Third, Renrendai is a sizeable market with several years of detailed investing data. Our main sample contains 10,385 loans and 205,724 transactions. The cumulative principal of the loans during our sample period is over $100 million. Our sample spans two years and four months, which not only allows us to track the performance of the loans, but also enables us to analyze investors' learning in this fast-thinking context.

Our findings are the following. Under pressure to make quick decisions, investors rush to invest in loans with high interest rates, disregarding borrowers' credit ratings, even when the latter are listed on the online trading interface. Specifically, we find that, all else equal, loans with higher interest rates are funded more quickly. Our regression shows that a one-standard-deviation increase in interest rate reduces the fulfillment time (i.e., the time from the moment a loan is listed to the moment it is fully funded) by 36%. In contrast, there is no significant relation between the fulfillment time and credit ratings.

We further show empirically and experimentally that when time pressure is stronger, investors rely more heavily on interest rates. Empirically, our quantile regressions show that fulfillment time for "faster" loans is even more sensitive to interest rate. To examine whether fast thinking causes investors' reliance on interest rates, we conduct a controlled experiment. Subjects in the treatment group face time pressure when making investment decisions, while those in the control group do not. We find that, under time pressure, subjects are more likely to choose loans with higher interest rates, and are consequently more exposed to riskier loans and eventual defaults.

Focusing on interest rate is a sensible strategy for this market, because returns are highly correlated with offered interest rates. Renrendai guarantees to repay investors the outstanding principal of a loan if the borrower fails to make a monthly payment. This principal guarantee mechanism, which was credible at the time, significantly limits investors' exposure to borrowers' credit risk. However, investors still forgo interest payments for roughly two months before receiving the remaining principal from Renrendai. Incorporating credit rating information can thus improve investment returns substantially. We show that by avoiding loans with "High Risk" (HR) ratings, an investor can improve her returns by over 1% per year on average.

Our empirical findings suggest that one might be able to "nudge" investors into making better decisions by making credit rating information more salient. We conduct a controlled experiment. Specifically, we modify the original Renrendai interface by enlarging the font size of the credit rating information, changing its font color, and moving it to a prominent spot for the treatment group, while keeping the original interface for the control group. Our experiments show that, relative to subjects in the control group, those in the treatment group pay more attention to credit ratings, are less likely to choose loans with HR ratings, experience fewer defaults, and have better performance.

Do investors learn from experience to overcome biases in making investment decisions? We show that *firsthand experience* matters for learning. Specifically, after personally experiencing a loan default, an investor tends to increase her decision time, avoids loans with "High Risk" ratings, and consequently obtains higher returns. In contrast, observing *others* experiencing a default has negligible effects on an investor's behavior. That is, investors who experience loan defaults as "participants" appear to learn more from these defaults than do investors who simply witness defaults as "observers."

One potential explanation for the difference in investors' learning is inattention. Investors may pay more attention to defaults on their own loans than defaults on other investors' loans, which they may not even notice. That is, participants may have an informational advantage over observers. However, inattention cannot explain the entire firsthand experience effect because similar results arise in our controlled experiment, where *all* subjects, regardless of whether their selected loan defaults, are informed about the default event.[1] We conjecture that participants and observers *process* the same default information differently. Experiencing a default personally and suffering losses, participants are compelled to reexamine their decision processes and, consequently, improve future decisions. In contrast, investors do not respond to the default on

[1] Other potential explanations include the wealth effect (i.e., participants experience a negative wealth shock from the default, while observers do not) and selection effect (i.e., individuals with low ability might stop investing after experiencing a default). However, these two effects are absent or negligible in our experiments,

fellow investors' loans strongly, perhaps because they do not believe they are subject to the same mistakes in decision making.

Our research contributes to the psychology and economics literature on cognitive biases. Tversky and Kahneman (1974) established the foundation for studies of heuristics and biases. However, studies of decision biases related to fast thinking in a real-world setting have been rare due to the inherent challenges of measuring decision time.[2] To the best of our knowledge, we are the first to investigate the effect of fast thinking on investment decisions. Our study shows that relying on fast thinking leads individual investors to pay excessive attention to salient interest rates and gravitate to loans with higher rates, ignoring their higher default risk. Our paper relates broadly to research on the role of limited attention in financial markets. Given the wealth of available financial information and the scarcity of attention, investors tend to focus on the most salient features (Benartzi and Lehrer, 2015).[3]

Our paper is also related to the literature on nudging (Thaler and Benartzi, 2004). Reutskaja, Nagel, Camerer, and Rangel (2011) show that individuals tend to pay attention to snacks located in a focal region. Milosavljevic, Navalpakkam, Koch, and Rangel (2012) show that a subtle change in visual prominence influences real food choices. In our experiment, by increasing the salience of credit ratings, we can nudge investors to pay more attention to credit risk and improve their investment decisions.

Our paper adds to the literature on learning from experience. One intriguing recent finding is that, rather than forming expectations (e.g., on inflation) based on all historical data, people seem to rely more on personal experiences (Malmendier and Nagel, 2011, 2016). A

[2] It has been demonstrated that, in experimental settings, faster thinking is associated with greater risk-taking (Cella, Dymond, Cooper, and Turnbull, 2007; DeDonno and Demaree, 2008; Candler and Pronin, 2012). We examine fast thinking in a real-world context, using transaction data from the online peer-to-peer (P2P) lending market. In a recent study, Heller, Shah, Guryan, Ludwig, Mullainathan, and Pollack (2017) carry out large-scale randomized controlled trials and find that behavioral intervention and education programs can help young people slow down and reflect on their automatic thoughts and behaviors. Such interventions reduced the rates of arrests and readmission to jail, and improved school engagement and graduation rates.

[3] Barber and Odean (2008) show that individual investors are net buyers of attention-grabbing stocks. Da, Engelberg, and Gao (2011) document that Google search frequency is associated with investor attention and negatively predicts future stock returns. Investors underreact more to earnings surprises when they are distracted, e.g., when earnings announcements are on Fridays (DellaVigna and Pollet, 2009) or when there are multiple announcements on the same day (Hirshleifer, Lim, and Teoh, 2009). Our paper shows that time pressure leads investors to fixate on interest rates and ignore valuable information that is freely available on the trading interface.

growing number of studies have analyzed the effect of experiences on expectation formation and investments in the stock market (Vissing-Jorgensen, 2003; Greenwood and Nagel, 2009; Knupfer, Rantapuska, and Sarvimaki, 2017; Andersen, Hanspal, and Nielsen, 2018) and credit markets (Chernenko, Hanson, and Sunderam, 2016), CEO decisions (Malmendier and Tate, 2005; Malmendier, Tate, and Yan, 2011; Dittmar and Duchin, 2016; Schoar and Zuo, 2017), leverage choice (Koudijs and Voth, 2016), IPO investments (Kaustia and Knupfer, 2008; Chiang, Hirshleifer, Qian, and Sherman, 2011), retirement savings (Choi, Laibson, Madrian, and Metrick, 2009) and policy-making (Malmendier, Nagel, and Yan, 2017). The experience effect has been analyzed theoretically in Ehling, Graniero, and Heyerdahl-Larsen (2018), Malmendier, Pouzo, and Vanasco (2018), and Nagel and Xu (2018). Our results on firsthand experience are closely related to those in Andersen, Hanspal, and Nielsen (2018), which show that investors who lose money on investments in bank stocks during the recent global financial crisis subsequently shy away from risk in their investment portfolios. One key difference is the nature of the experienced loss: we consider smaller, more frequent shocks, while the shocks in Andersen, Hanspal, and Nielsen (2018) are rare and more substantial. More importantly, our paper adds to this experience literature by showing in a controlled experiment that participants and observers respond differently even if they are provided with the *same* information. Thus, we can conclude that firsthand experience effect cannot be fully attributed to inattention.

Our findings also complement the literature, whereby investors form different beliefs based on differential interpretations of the same information (Hong and Stein, 2007). For instance, investors' beliefs are shown to be strongly influenced by their prior portfolio choices (Kuhnen, Rudorf, and Weber, 2017) and political leanings (Meeuwis, Parker, and Vanasco, 2018). Our evidence suggests that first-hand experience can also contribute to differential interpretations of the same information in forming beliefs.

Finally, our paper is part of the growing literature on P2P lending. Since 2006, P2P lending has become an increasingly important method of providing small loans to individual borrowers. Most existing studies focus on Prosper.com. Investigating investor behavior, Zhang and Liu (2012) find evidence of rational herding among investors. Lin and Viswanathan (2015), Pope and Sydnor (2011), Ravina (2018), and Duarte, Siegel, and Young (2012) show the roles of home bias, racial bias, the beauty premium, and trust, respectively, in P2P lending decisions.[4]

The remainder of the paper is organized as follows. Section II describes the institutional background and develops our main hypotheses. Section III analyzes investment decisions made using fast thinking. Sections IV and V examine the roles of time pressure and salience, respectively. Section VI analyzes learning and Section VII concludes.

II. Institutional Background and Hypotheses

A. Institutional background

Our data are collected from Renrendai, a major P2P lending platform in China. Online P2P lending was first introduced in China in 2007 and grew rapidly from 2011 to 2015. Renrendai was founded in 2010 and has an AAA rating, the highest rating for P2P lending platforms, from the Chinese Academy of Social Sciences. We focus on credit loans, which have no collateral and comprise 76% of all loans made on Renrendai during our sample period.

To receive a credit loan, a borrower is required to provide identification information, as well as to submit information on income, employment, and creditworthiness. To provide guidance for investors, Renrendai issues its own credit ratings, ranging from excellent to poor as follows: AA, A, B, C, D, E, and HR (i.e., High Risk). Each rating corresponds to a range of credit scores,[5] and ratings increase with the number of optional documents submitted, including home deed, car title, marriage certificate, diploma, cell phone number, Weibo account (the

[4] Regarding borrowers, Iyer, Khwaja, Luttmer, and Shue (2009) show that lenders effectively use soft and non-standard information to evaluate borrowers' creditworthiness. Lin, Prabhala, and Viswanathan (2013) and Michels (2012) document that friendship networks and voluntary disclosure help reduce information asymmetry in the P2P lending markets.

[5] AA rating: credit score above 210; A rating: credit score in the range [180, 209]; B rating: credit score in the range [150, 179]; C rating: credit score in the range [130, 149]; D rating: credit score in the range [110, 129]; E rating: credit score in the range [100, 109]; and HR rating: credit score below 100.

Chinese version of Twitter), home address, and video interview. Renrendai updates each borrower's credit rating monthly based on the repayment status of her outstanding loans.[6]

Potential borrowers on Renrendai submit loan applications, specifying the requested amount, term, and interest rate. The maximum amount for each loan varies with the borrower's credit quality, ranging from ¥3,000 to ¥500,000 ($1 = ¥6.91 as of March 15, 2017). A borrower is allowed to have multiple loans outstanding as long as the total amount does not exceed a given credit line, determined by her credit rating. There are eight maturities for credit loans available at Renrendai: 3, 6, 9, 12, 15, 18, 24, and 36 months. Borrowers specify the interest rates of their loans, subject to the minimum interest rate requirement determined by Renrendai for each credit rating. In our sample, the minimum interest rate is 10% and the maximum is 24%.

Renrendai denies approximately 95% of loan applications due to poor credit ratings or insufficient verifications. Approved applications are listed on the platform and can be viewed by all potential investors. Each listing includes loan characteristics as well as borrower information such as credit rating, age, education, marital status, monthly income reported as a range, possession of a house (apartment) and/or a car, and the presence of a mortgage or car loan. There are additional verifications that a borrower can provide voluntarily (e.g., credit report, employment record, and home address). Figure 1 depicts a sample loan on the Renrendai website (translated by the authors from Chinese to English).

Renrendai does not charge investors any fees. Investors can choose to lend multiples of ¥50 at a loan's pre-specified interest rate. Once the requested amount is fully funded, or if a loan cannot be fully funded in seven days, the funding process stops. As a result, the borrower receives either 100% funding or no funding. Prepayment is allowed with a penalty of 1% of the outstanding balance.

During the funding process, each investor's commitment is posted online with a time stamp; this information is visible to all investors in real time. This feature enables us to calculate

[6] A borrower's credit rating is updated monthly. The credit score increases by 1 point each month if payments remain current. The credit score is reduced by 3 points if a payment is overdue by 1–30 days, and is set to zero if a payment is overdue by more than 30 days.

the timing of each loan's funding process to the seconds, which is not feasible on other P2P lending platforms, such as Prosper.com.

B. Hypotheses

Renrendai is an ideal context for studying financial decision-making using fast thinking. First, investors are under pressure to make quick decisions. Bank deposit rates in China are highly regulated and kept artificially low (see, for example, Lardy (2008)). Hence, the P2P lending market, if organized properly to limit borrowers' credit risk, is appealing to many households. Indeed, in our sample, more than 90% of loans are fully funded within eight minutes after they are listed on Renrendai. Because loan details are not observable until loans are publicly listed, investors have a short time frame for making decisions.[7]

Second, Renrendai guarantees that it will repay investors the outstanding principal of a loan within 31 days if a borrower fails to make a monthly payment. Hence, investors only forgo roughly two months of interest payments when a default occurs. This guarantee is considered credible because Renrendai not only has an excellent credit rating but also levies an upfront service charge and a monthly management fee for each funded loan. The upfront service charge depends on the borrower's credit rating, and can be as high as 5% of the principal. The monthly management fee is about 0.1–0.35% of the outstanding balance. Principal guarantee significantly limits lenders' exposure to borrowers' credit risk,[8] further modulating the necessity of analyzing

[7] As a comparison, loans listed on Prosper.com, one of the two leading online P2P platforms in the U.S., often take several days to get funded. Moreover, Renrendai differs from Prosper.com on many dimensions. For example, (1) On Renrendai, potential investors observe the bid/investment of each lender in real time, while on Prosper, they only see the fraction of the requested amount that is fulfilled—not the number of lenders or the size of each lender's investment; (2) Renrendai provides the funding start and end time for each completed loan, while Prosper records only the start time of the funding process; (3) On Renrendai, a loan is made only if 100% of its listed amount is raised, while Prosper permits a listed loan to move forward if at least 70% of the listed amount is fulfilled; (4) Renrendai suggests the minimum interest rate based on a borrower's credit rating and the borrower determines the interest rate, while Prosper determines a uniform interest rate for loans made to all borrowers with the same credit rating (as of December 2010); (5) Credit loans listed on Renrendai are much smaller than those listed on Prosper; (6) Renrendai promises to repay the principal if the borrower defaults on the loan, while Prosper does not provide such a guarantee.

[8] Hence, investment returns and interest rates are highly correlated. Indeed, the correlation coefficient between a loan's interest rate and its *ex post* internal rate of return (IRR) is 0.54 in our sample.

credit risk. Based on the insights in Kahneman and Tversky (1979), principal guarantee is especially appealing to investors with loss aversion.

Third, as shown in Figure 1, the interest rate is prominently displayed on the trading interface: it is presented in a large font at the top of the screen, attracting investors' attention. In contrast, credit ratings are displayed in a small font and at a much less prominent location. Hence, we hypothesize that investors' attention gravitates towards interest rates and that they may disregard other information, such as borrowers' credit ratings.

We also examine how investors learn when they make decisions using System 1. One important insight on learning in the recent literature is the so-called experience effect. For example, Malmendier and Nagel (2011, 2016) find that rather than forming expectations based on all historical data, people tend to rely more on their experiences. We attempt to shed light on this insight by distinguishing the effect of experiencing an event as a participant from that of experiencing it as an observer. Specifically, when a borrower defaults on a loan, investors may experience the event in two different ways. If an investor has exposure to the loan, she suffers a loss and feels the pain. We refer to this as "experience as a participant." Alternatively, an investor may observe the default of a loan she has no position in, which we refer to as "experience as an observer." How do these two types of experiences affect investors' behavior? Our dataset allows us to track each investor's experience and subsequent investments to address this question. We also examine the reasons behind the different reactions to default events among observers and participants.

III. Investing with Fast Thinking

A. Data

We extract data from Renrendai on March 10, 2016. Our main sample spans the period from September 1, 2012 to December 31, 2014. We exclude loans originated before September 1, 2012 because Renrendai did not record the start time of the funding process before this date. We exclude loans originated after December 31, 2014 because the repayment status of most of these loans is not yet available at the end of our sample. Our main sample contains 10,385 loans funded by 205,724 investments, corresponding to 25,314 unique investors.

Loan and borrower characteristics are reported in Panel B of Table 1. The mean and median values of the interest rate are 12.70% and 12.00%, respectively. The mean and median loan amounts are ¥25,372 and ¥14,000, respectively. The loan term ranges from 3 to 36 months, with an average of 10.3 months and a median of 9 months.

We find that 71.2% of Renrendai loans are categorized as having a high risk of default (HR), and 87.3% of the loans have male borrowers. The mean and median ages of the borrowers are 32.9 and 32 years, respectively. About one third of borrowers hold a bachelor's degree or higher, and 56.7% have work experience of three or more years. Financially, 41.3% of the borrowers have a monthly income exceeding ¥10,000. While 55.5% of borrowers are homeowners and 40.8% own a car, only 21.7% of borrowers have a current mortgage and 8% have an outstanding car loan.

B. Thinking fast

Due to low bank deposit rates, investors find Renrendai loans appealing and quickly snatch them up once they are listed. Indeed, 25% of loans get fully funded in 42 seconds, 75% of loans get funded in less than three minutes, and 90% in less than eight minutes. For convenience, we refer to the period from the time when a loan is listed to the time when the loan is fully funded as "*FulfillmentTime*." A loan is labeled a "fast loan" if its *FulfillmentTime* is less than 42 seconds, the 25th percentile of *FulfillmentTime* in our sample.

The funding process has accelerated during our sample period; that is, the distribution of *FulfillmentTime* shifts to the left over time. Given how rapidly loan listings disappear from the screen, investors have to make quick decisions. We contrast loan and borrower characteristics for fast loans with those for all other loans and report the results in Panel C of Table 1.

On average, fast loans are smaller (¥13,873 vs. ¥29,299) than other loans and offer higher interest rates (13.71% vs. 12.36%), though they have similar terms (10.57 vs. 10.21 months). Interestingly, although fast loans have higher default rates (19.8% vs. 16.7%), they also have higher IRRs (11.67% vs. 10.53%). Borrowers of fast loans are more likely to be HR-rated (78.7% vs. 68.6%), male (88.2% vs. 86.9%), and younger (average age of 31.31 vs. 33.43 years). Fast-loan borrowers are less likely to be employed for over three years, tend to have lower monthly incomes, and are less likely to own a house or a car. Overall, fast loans appear riskier than other loans.

C. Primacy of interest rate

We posit that investors primarily focus on the interest rates offered and rush to high-interest-rate loans without sufficiently examining other information in loan contracts, such as the borrower's credit risk. As a first step in examining this conjecture, we test whether investors' decision speed depends on interest rate, i.e., whether loans with higher interest rates are funded more quickly. Specifically, we run an OLS regression of *Ln(FulfillmentTime)* on *Interest Rate* and *HR*, where *FulfillmentTime* is the number of seconds it takes for the loan to be fully funded, *Interest Rate* is the interest rate offered in the loan contract, and *HR* is a dummy variable, which equals 1 if the loan is rated "high risk" and 0 otherwise. We cluster standard errors by week, and include 12 verification fixed effects, week fixed effects, day-of-the-week fixed effects, and hour-of-the-day fixed effects to control for time variation in investors' bidding speed. Results are presented in the first column of Table 2.

The coefficient estimate for *Interest Rate* is -0.206, with a *t*-statistic of over 19. Hence, a one-standard-deviation increase in the interest rate (2.20%) reduces *FulfillmentTime* by 36% (=1-exp(-0.206*2.20)). For example, for a loan with the median *FulfillmentTime* (80 seconds), a one-standard-deviation increase in interest rate reduces the *FulfillmentTime* to 51(=80*(1-36%)) seconds. In contrast, the coefficient estimate for *HR* is -0.036 (t=1.28). If investors avoided loans with *HR* ratings, this coefficient would be positive rather than negative.

Some of the control variables are worth mentioning. Naturally, larger loans take longer to fund. To control for potential non-linear effects, we include both *Ln(amount)* and the square of *Ln(amount)* as control variables. The coefficient of *Term* is 0.026 (t=3.57), suggesting that loans with longer maturities take longer to fund. Interestingly, it appears that investors also respond to some borrower characteristics. For example, the coefficient of *MasterOrHigher* is -0.13 (t=3.10), suggesting that if a borrower has a graduate degree, her loans are funded more quickly. Similarly, loans to borrowers who have monthly income between ¥5,000 and 10,000 or own a house are funded more quickly.

D. Loan performance

D.1 Loan return and interest rate

Given the principal guarantee, the performance of a loan should have a strong positive association with its interest rate. Hence, it is sensible for investors to focus on interest rates. To examine this, we measure the performance of a loan using *IRR – CD Rate*, where *IRR* is the realized internal rate of return of the loan and *CD Rate* is the rate of return for a bank deposit with a similar term. *IRR* can be computed as follows:

$$Principal = \sum_{t=1}^{T} \frac{Repayment_t}{(1 + IRR)^t},$$

where *Principal* is the loan amount, *T* is the term, and $Repayment_t$ is the realized cash flow at time t, which may be a scheduled payment, a prepayment from the borrower, or the payment from Renrendai when the borrower defaults.

To test these hypotheses, we regress *IRR – CD Rate* on *Interest Rate*, *HR*, and other loan and borrower characteristics. The results are reported in Table 3. In both specifications, we include week fixed effects, day-of-week fixed effects, and hour-of-day fixed effects to account for potential time trends in loan performance, market conditions, or investor preferences. As shown in column (1), the coefficient of *Interest Rate* is 0.804 (t=31.78). That is, a 1% increase in the interest rate leads to an 80-basis-point increase in *IRR – CD Rate*.

This evidence confirms our hypothesis: Renrendai investors' reliance on interest rates is a sensible response to the pressure to make quick decisions. However, do investors miss other information that is relevant for loan performance? We analyze this question next.

D.2 Loan returns, credit ratings, and other characteristics

Consistent with the hypothesis that investors pay insufficient attention to credit ratings, we find that after controlling for interest rate, *HR* is negatively related to performance. In column (1) of Table 3, for example, the coefficient of *HR* is -1.109 (*t*=19.34). That is, all else equal, the average return is 1.109% lower for loans with *HR* ratings than for other loans, on average. This is somewhat surprising – one might have expected that *HR* loans would offer higher average returns since they are riskier. However, it appears that investors do not realize that these high-interest-rate *HR* loans are more likely to default. With two months of interest forgone upon default (and remaining principal paid off by Renrendai), the average returns of HR loans are lower *ex post*.

Loan performance appears correlated with other variables that are easily observable. For example, *IRR – CD Rate* is strongly negatively correlated with the loan term. As shown in column (1), the coefficient of *Term* is -0.106 (*t*=21.05). Since there is no secondary market for investors to resell their loans, one might assume that loans with longer maturities are less liquid investments and should command higher average returns. In our sample, however, loans with longer maturities have lower average returns. *IRR – CD Rate* is also strongly negatively correlated with the loan amount. For example, in column (4), the coefficient of *Ln(Amount)* is -0.297 (*t*=8.08) after controlling for the interest rate, loan characteristics, the borrower's credit rating, and other borrower characteristics. *IRR – CD Rate* is also strongly correlated with borrower characteristics, even after controlling for the interest rate and the borrower's credit rating. We find that loans to female borrowers, younger borrowers, and borrowers with college degrees perform better. We add verification fixed effects in column (2) and obtain results very similar to those in column (1).

D.3 Loan default

We now examine whether a borrower's credit rating predicts loan default after controlling for interest rate. Specifically, we create a dummy variable $Default_{it}$, which equals 1 if a loan *i* defaults on day *t*, and run a Cox proportional hazards model with the same independent variables as those in Table 3. As shown in column (1) of Table 4, the coefficient of interest rate is 0.109 (*t*=6.71). That is, loans with higher interest rates are more likely to default. However, even after controlling for interest rate, an *HR* rating still predicts a higher likelihood of default. As shown in row 2, the coefficient of *HR* is 2.011 (t=8.26). This implies that, for loans with a given interest rate, investors can reduce their exposure to default by avoiding *HR* loans.

Consistent with the results reported in Table 3, we find that larger loans and loans with longer maturities are more likely to default. In addition, loans to male borrowers, older borrowers, and borrowers without college degrees are more likely to default. Adding verification fixed effects yields similar results; see column (2).

These results are consistent with the interpretation that investors fail to fully appreciate the information provided by borrower characteristics. Interestingly, it appears that Renrendai also fails to fully incorporate the information in borrower characteristics into their credit ratings. That is, these borrower characteristics predict the likelihood of default even after controlling for credit rating.

D.4 **Portfolio-based evidence**

The above evidence suggests that many observables, such as credit ratings and other loan and borrower characteristics, are not incorporated into loan prices (i.e., interest rates). To further examine this idea, we estimate the gains an investor can achieve by paying more attention to these characteristics. Our analysis below focuses on credit rating.

For each week, we calculate the principal-amount-weighted averages of *IRR – CD Rate* for *HR* loans and non-*HR* loans. We then calculate the time series averages of *IRR – CD Rate* for *HR* and non-*HR* loans, and the difference in these averages. The results are reported in Table 5. As shown in the first row, *HR* loans underperform non-*HR* loans by 1.121% (*t*=5.26). The magnitude is comparable to the *HR* coefficient estimate in Table 3. Our interpretation is that investors pay insufficient attention to credit rating and the corresponding default risk, because they only lose two months of interest payments when default occurs due to the principal guarantee.

For HR loans, the higher probability of default and greater loss in interest payments upon default dominate the effect of higher interest payments when default does not occur. The higher the interest rate, the bigger the consequences from neglecting the information in credit ratings. Thus, the potential performance improvement from paying attention to credit ratings should increase with interest rates. To test this prediction, for each week, we sort loans into quintiles by interest rate. Then, for each quintile, we calculate the value-weighted averages of (*IRR – CD Rate*) for *HR* loans and non-*HR* loans. Finally, we calculate, for each quintile, the time series averages of *IRR – CD Rate* for *HR* and non-*HR* loans, and their differences. The results are reported in rows 2 through 6 in Table 5. The underperformance of *HR* loans is highly significant for all quintiles, and, consistent with our prediction, the magnitude of underperformance increases almost monotonically with interest rate, growing from 0.669% to 1.301%.

IV. Time Pressure

The previous evidence is consistent with the interpretation that time pressure leads investors to follow a simple rule of thumb: relying on interest rates to make quick decisions. This interpretation also implies that, when time pressure is stronger, investors should rely more on interest rates. In Section IV.A, we show that *FulfillmentTime* is indeed more sensitive to interest rate for faster loans. While this is consistent with our hypothesis, it does not necessarily establish a causal relation between time pressure and reliance on interest rate. Hence, in Section IV.B, we conduct a controlled experiment, which shows that time pressure causes subjects to choose loans with higher interest rates, exposing themselves to higher default risk.

A. Empirical evidence

Our hypothesis implies that for fast loans, *FulfillmentTime* should be even more sensitive to interest rate. To test this implication, we run quantile regressions of *Ln(FulfillmentTime)* on *Interest Rate*.

The main difference between an OLS regression and a quantile regression is that the former provides the conditional expected value of the dependent variable, while the latter provides the conditional quantile-τ value of the dependent variable for a quantile-τ regression, for $\tau \in (0,1)$.[9] This implies that the coefficient of *Interest Rate* should be more negative for small values of τ (i.e., for faster loans). In other words, for faster loans, investors must rely more on their rule of thumb and are thus more responsive to interest rate.

We run quantile regressions for $\tau = 10\%$, 25%, 75%, and 90%. The results are reported in columns (2) through (4) of Table 2. Consistent with our interpretation, the coefficient estimate for *Interest Rate* is negative and significant at the 1% level for all quantile regressions. Moreover, the absolute value of the coefficient estimate for *Interest Rate* decreases monotonically in τ. The coefficient estimate for *Interest Rate* is -0.220 for the 10th quantile, -0.199 for the 25th quantile, -0.173 for the 75th quantile, and -0.157 for the 90th quantile. In other words, when investors make decisions more quickly, as they do in the low quantiles of *Ln(FulfillmentTime)*, they appear more responsive to interest rates.

We plot the coefficient estimate for *Interest Rate* against quantile-τ in Figure 2. The horizontal axis is quantile τ. The vertical axis is the coefficient estimate for *Interest Rate* from the quantile-τ regression of *Ln(FulfillmentTime)* on *Interest Rate* as in Table 2. The solid green line represents the estimate of the coefficient for *Interest Rate* from quantile regressions, and the grey region is the 95% confidence interval for the coefficient estimate. The figure shows that the coefficient estimate for *Interest Rate* increases gradually (becoming less negative) as *Ln(FulfillmentTime)* moves from the 5th to the 95th percentiles. This is consistent with the interpretation that when investors make decisions more quickly, they focus more on, and are hence more responsive to, interest rates.

In contrast, for the other variables that *Ln(FulfillmentTime)* is sensitive to in the OLS regression (e.g., term, income, education, and homeownership), the coefficients in quantile regressions do *not* imply that *Ln(FulfillmentTime)* is more sensitive to those variables for smaller

[9] For more details on quantile regressions, see, for example, Koenker (2005).

τ. Moreover, as in the OLS regression, the coefficient of *HR* is insignificant for all quintile regressions.

B. Experimental evidence

To complement the above evidence and establish a causal relation between time pressure and investors' fixation on interest rates, we conducted the following experiment on January 15, 2017. We recruited 60 subjects from a first-year graduate class at the People's Bank of China School of Finance (PBCSF), Tsinghua University and tasked them with selecting a loan to invest in from a pool of five loans. The five loans were chosen from the 16 loans listed on the Renrendai platform on November 4, 2013, an arbitrary day in the middle of our sample period. Among those loans, 10 had the *HR* rating; 2 ended up in default. We randomly chose two non-*HR* loans that were fully repaid. We then randomly chose three HR loans, one of which ultimately defaulted. The fraction of *HR* loans and the default rate of these five loans are comparable to those of our full sample. Details of these five loans are reported in Panel A of Table 6.

Before making their loan choices, all 60 subjects went through the same training session. Specifically, they were provided with Renrendai's institutional background and the experiment procedure, as well as loan characteristics, borrower characteristics, and the eventual outcomes for 50 loans listed from October 4, 2013 to November 3, 2013, the 30-day period prior to the date on which the five loans in experiment are chosen. Those 50 loans were randomly selected from the 194 loans listed on Renrendai in that 30-day window. There were two screenshots of each loan. The first provided basic details about the loan and the borrower, and the second gave the loan's repayment status. All subjects were given 30 minutes to study these 50 loans. They were encouraged to summarize the relationship between the loan details and repayment status. Participants were asked to think about what types of loans deliver higher returns and what types of loans are likely to default. Communication among subjects was prohibited.

After the training session, subjects were randomly divided into two groups of 30. Those in the treatment group were asked to make their choices within 42 seconds (the 25th percentile of the *FulfillmentTime* in our sample). Those in the control group were asked to take a minimum of

180 seconds to make their decisions. To avoid interference, the two groups made investment decisions in different rooms.

Facing time pressure, participants in the treatment group were more likely to resort to choosing loans based primarily on interest rates. Indeed, as shown in Panel B of Table 6, the average interest rate of the loans chosen by the treatment group was 16.27%, while the control group's average interest rate was 15.07%. The difference is 1.20%, with a *t*-statistic of 3.02. Since loans with high interest rates tend to be those with *HR* ratings, participants in the treatment group were more likely to choose *HR* loans. In fact, 27% of the loans chosen by the treatment group had an *HR* rating. In contrast, only 7% of the loans chosen by the control group were *HR* loans. The *t*-statistic for the difference between the two values is 2.12. Naturally, the treatment group participants were more likely to experience a default: 23% of the loans chosen by the treatment group defaulted. In contrast, there were zero defaults among the loans chosen by the participants in the control group in this experiment. As a result, the treatment group underperformed the control group by 44 basis points (t=2.17). As a comparison, the last two rows report the results on term and loan size, and show that time pressure has *no* significant effect on investors' preference for term and loan size.

V. The Role of Salience

When making quick decisions, people are more likely to rely on salient information and underreact to relevant but less salient information. In Section V.A, we first analyze the role of salience empirically, utilizing the introduction of a mobile app that changed the relative salience of the information on the Renrendai interface. To establish a causal relationship and analyze the potential for nudging investors to make better decisions, we conduct experiments in Section V.B.

A. Empirical evidence: Mobile app

On July 30, 2014, Renrendai launched its mobile app, which enabled individuals to invest through mobile phones. The screen of a mobile phone is smaller than that of a computer and contains less information. As shown in Figure 3, the most salient aspect of a listed loan on the mobile app is its interest rate: not only it is located near the top and in the middle of the screen (easy-middle bias; see Reutskaja, et al., 2011, and Milosavljevic, et al., 2012), but it is also shown in orange (the only information not presented in black). Additionally, the constantly updated funding status shown on the screen (e.g., "99% Funded") could pressure investors to make quick decisions. Interestingly, the credit rating of the borrower is not shown at all. Hence, one has to make extra effort to obtain the rating information.

The introduction of the mobile app can be considered a shock to investors' information environment. How does this shock affect investors' decisions? Note that when investors make quick decisions, they tend to rely on a rule of thumb and focus on information that is prominent and easy to access. Hence, one hypothesis is that, by suppressing information such as borrowers' credit ratings, the mobile interface further encourages investors to make quick decisions based on interest rates. The hypothesis translates into two predictions. First, mobile-based investors should make decisions more quickly than computer-based investors. Second, loans with higher interest rates should attract a larger fraction of mobile-based investors.

To test the first prediction, we run a panel regression of $Ln(DecisionTime_{ij})$ on $Mobile_{ij}$, where $DecisionTime_{ij}$ is investor *i*'s decision time for investing in loan *j* (from the time the loan *j* is listed to the time of investor *i*'s bid), and $Mobile_{ij}$ is a dummy variable, which equals 1 if investor *i*'s bid for loan *j* is made through the mobile app, and 0 otherwise. As shown in column (1) of Panel A of Table 7, where the specification includes loan fixed effects, the coefficient of $Mobile_{ij}$ is -0.146 (t=29.79). That is, mobile bidders are about 13.5% (=1-exp(-0.146)) faster than PC bidders on average.

While this result is consistent with the hypothesis that the mobile interface makes investors bid more quickly, it can also be the result of selection: investors who tend to bid more quickly might have a higher likelihood of adopting the mobile app. To address this selection issue, we include investor fixed effects in the regression. As shown in the second column, the coefficient of $Mobile_{ij}$ is -0.101 (t=13.24). That is, even the same investor tends to bid 9.61% (=1-exp(-0.101)) more quickly when using the mobile app. Moreover, we repeat this analysis on a restricted sample consisting only of investors who used both the mobile and PC interfaces during our sample period. As shown in columns (3) and (4), in both specifications, the mobile app is associated with faster decisions. These results alleviate some concerns about the selection issue, but cannot completely rule it out.[10] Hence, in Section V.B, we conduct a controlled experiment to examine the causal effect of salience on investors' decisions.

To test the second prediction, we construct the variable $MobileProportion_i$ for each loan, which is the fraction of the investment in loan i made through the mobile app. We then regress it on *Interest Rate*, *HR*, and control variables. As shown in Panel B, the coefficient of *Interest Rate* is 0.675 (t=3.28). This is consistent with our interpretation that mobile investors pay more attention to interest rates.[11] In contrast, the coefficient of *HR* is statistically insignificant.

B. Experimental evidence: Nudging

Our evidence in Table 3 shows that ignoring the information provided by credit ratings is costly to investors. A natural question is: can we nudge investors to improve their decisions? One potential nudge involves making credit rating information more prominent on the interface, so that investors might pay more attention to it and adjust their decisions accordingly. This is motivated by the evidence in the previous section that mobile app investors, who use an interface where interest rates are shown more prominently, are even more fixated on this variable. In this section, we conduct controlled experiments to examine whether the redesigned interface nudges investors to pay more attention to credit ratings.

The experiment was conducted in two trials to obtain a sufficient sample size. We recruited 105 graduate students from PBCSF for the first trial on January 10, 2018 and 77

[10] The specification with investor fixed effects addresses the concern that quick decision-makers may be more likely to adopt the mobile app, but does not address the concern of time variation of preference, i.e., the concern that an individual's preference for speed may change over time, and he/she prefers to use a PC (the mobile app) when he/she makes slow (quick) decisions.

[11] Since the mobile app was introduced in July 2014, towards the end of our main sample period (Sept. 2012 to Dec. 2014), we extend the sample period to March 2016 in this regression. We can utilize the 2015–2016 data because this regression does not require information on payments and defaults. Finally, we also repeat the regression for our main sample; the coefficient estimate of *Interest Rate* is also positive and statistically significant at the 10% level.

graduate students from the School of Management and Engineering, Nanjing University for the second trial on March 19, 2018. The procedures for the two trials were the same.

For each trial, subjects were divided randomly into three groups. The training session was the same as in Section IV.B, except that the screenshot of the loan information was presented differently across the three groups. For Group 1, the screenshot was the original PC interface, as in Figure 4. For Group 2, we modified the original interface by reducing the font size of the interest rate and moving it to a less prominent location, as shown in Figure 5. For Group 3, we modified the original interface by enlarging the font size of the credit rating, changing its color to orange, moving it to the top of the screen, and placing it to the immediate left of the interest rate, as shown in Figure 6.

After the training session, subjects were asked to choose one of the same five loans that were shown in the experiment in Section IV.B. For all subjects, the interface for those five loans matched what they saw during their training session. To measure subjects' thinking processes, we asked the following question at the end of the experiment:

Which of the following factors do you value most when you make investment decisions?

A. Interest Rate; B. Term; C. Amount; D. Credit Rating; E. Others.

We hypothesize that, relative to the control group (i.e., Group 1), Group 2 subjects would pay less attention to interest rate and Group 3 subjects would pay more attention to credit rating. Moreover, both Groups 2 and 3 should make decisions more slowly, since the modified interfaces prompt subjects to be less fixated on interest rate and take other characteristics into account.

Indeed, as shown in Panel A of Table 8, 39% of subjects in Group 1 chose interest rate as the most valued variable in their investment decisions. When interest rate was presented less prominently (for Group 2 subjects), only 20% of respondents indicated it as the most important variable in their decisions. The difference between these results is 19%, with a *t*-statistic of 2.29. In contrast, the differences in attention to other variables (*HR*, *Amount*, and *Term*) across the two groups are statistically insignificant. The difference in opinions across Groups 1 and 2 is somewhat reflected in their loan selections. As shown in Panel B, the average interest rate among the loans chosen by Group 1 subjects was 17.32%, while the rate among the loans chosen by Group 2 subjects was 16.86%, although the difference between the two is statistically insignificant.

The effects of salience on Group 3 subjects are much stronger. For example, as shown in Panel A, 23% of the subjects in Group 1 chose credit rating as the most important variable in their decisions. In contrast, when credit rating was highlighted prominently on the interface, 48% of the subjects stated that it was the most important variable in their decisions. The difference is 25%, with a *t*-statistic of 2.96. This difference is clearly reflected in subjects' loan choices and loan performance. As shown in Panel B, 63% of the loans chosen by Group 1 subjects had the *HR* rating, but only 48% of the loans chosen by Group 3 subjects had the *HR* rating. The *t*-statistic for the difference is 1.76. To avoid loans with *HR* ratings, Group 3 subjects chose loans with slightly lower interest rates. The average interest rate was 17.32% for Group 1 and 16.53% for Group 3. The difference is 0.80% (*t*=2.27). Moreover, the default rate for the loans chosen by Group 3 subjects was much lower. While 31% of the loans chosen by Group 1 defaulted, only 10% of the loans chosen by Group 3 did. The difference is 21% (*t*=2.98). As a result, Group 3 subjects achieved higher returns than their counterparts in Group 1. The difference in IRR is 0.67% (*t*=2.13). That is, simply by highlighting credit ratings on the interface, we can nudge subjects to pay more attention to this variable, reducing their exposure to default risk and increasing their returns.

Finally, the average decision time increases from 117.11 seconds for Group 1 to 148.54 seconds for Group 2, and further climbs to 152.35 seconds for Group 3. This evidence is consistent with our hypothesis that when relevant information is more visible, investors slow down their decision process and try to incorporate the additional information into their decisions.

VI. Firsthand Experience Effect

In an environment where fast thinking prevails, do investors learn from experience and improve their decisions? Moreover, do investors with different kinds of experience learn differently when they observe the same data? The latter question is partly motivated by the intriguing findings in Malmendier and Nagel (2011, 2016), who show that people rely primarily on their personal experiences, rather than all historical data, in forming expectations. Hence, two people born in different cohorts may respond to the same data differently based on their experiences.

In contrast, we examine whether a "participant" and an "observer" learn differently when they are presented with the same data, where the difference between a participant and an observer is whether they have "skin in the game." Specifically, after observing the default of a loan, a participant (who has a position in the loan) may behave differently from an observer (who does not). In Section VI.A, we examine empirically whether investors learn more from firsthand experience and show that this is the case. To assess potential explanations for the empirical results, we conduct experiments in Section VI.B.

A. **Empirical evidence**

We construct a proxy for an investor's experience, $CumBid_{it}$, which is the total number of bids investor i has made through the end of day t. As shown in Panel A of Table 9, the mean and median of *CumBid* are 50 and 11, respectively. To distinguish between observers and participants, we construct the dummy variable $Default3M_{it}$, which equals 1 if investor i has invested in a loan that defaulted in the previous 3 months, and 0 otherwise. As shown in Panel A, this variable has a mean of 0.252. $DecisionTime_{it}$ is the duration between the time when a loan is listed and the time when investor i invests in the loan on day t. Panel A shows that the mean and median of *DecisionTime* are 635 seconds and 93 seconds, respectively. The table also reports the summary statistics of the characteristics of the loans funded by investor i on day t, such as *Interest Rate*, *HR*, and *IRR – CD rate*.

To analyze the effect of learning on decisions, we first regress *DecisionTime* on *CumBid*. As shown in column (1), the coefficient of *CumBid* is 1.08 (t=2.45), suggesting that experience slows down investors' decision making. However, the magnitude of this effect is relatively small. On average, the experience of investing in an additional loan slows down an investor by 1.08 seconds. Do investors learn differently from defaults on their own loans than from defaults on others' loans? To test this, we include *Default3M* in the regression. As shown in the second column, its coefficient is 79.216 (*t*=2.21). That is, after experiencing a loan default, an investor takes almost 80 seconds longer to make investment decisions.[12]

Somewhat surprisingly, the third column shows that the coefficient of *CumBid* is 0.001 (*t*=2.80), suggesting that investors with more experience tend to choose loans with slightly higher interest rates. However, by the end of our sample period, a representative investor has invested in three loans, and would thus select loans with interest rates that are just 0.3 basis points higher than those chosen by a new investor.[13] On the other hand, experiencing a recent default has a stronger effect on an investor's choices. Column (4) shows that the coefficient of *Default3M* is 0.035 (t=2.18). That is, the average interest rate of the loans chosen by investors who have experienced a default in the last 3 months is 3.5 basis points higher that of other loans.

In the regression of *HR* on experience, shown in column (5), the coefficient of *CumBid* is insignificant. That is, on average, prior lending experience has a negligible effect on an investor's willingness to invest in a high-risk loan. In contrast, experiencing a default firsthand has a much stronger effect. As shown in column (6), the coefficient of *Default3M* is -0.031 (*t*=6.30). In other words, investors who have experienced a recent default are 3.1% less likely to invest in *HR* loans.

Finally, to examine the effect of experience on an investor's performance, we regress the *IRR-CD rate* of the loan chosen by an investor on the investor's experience measures. As shown in column (7), the coefficient of *CumBid* is insignificant. That is, on average, experience has a negligible effect on the investor's performance. However, in the last column, the coefficient of *Default3M* is 0.280 (*t*=6.42), suggesting that experiencing a recent default firsthand increases an investor's return by 28 basis points per year.

In summary, our evidence suggests that participants and observers appear to learn differently. After a firsthand experience of default, investors tend to significantly increase their

[12] At least one loan defaulted in all rolling windows of 90 days over our sample period; that is, investors can always observe defaults of other investors' loans over the previous three months.

[13] For all investors who have appeared in our sample, we calculate their *CumBid* on December 31, 2014, the last day of our sample. The mean and median of this sample of *CumBid* is 15 and 3, respectively.

decision time, choose loans with slightly higher interest rates while avoiding HR ratings, and receive higher returns. In contrast, for investors whose loans have not defaulted recently, the experience effects are significantly smaller or negligible.

Why do participants learn differently from observers? One potential reason is the wealth effect. A participant suffers a loss from a default, while an observer does not. Hence, the two may have different responses to defaults. However, this effect is unlikely to be significant because the loss from a default is usually small. The mean and median bid sizes are ¥979 and ¥500, respectively. Moreover, with the principal guarantee, investors only lose two interest payments, which are an order of magnitude smaller than the loan principals.

Second, the results might be due to a selection effect. After suffering a loan default, an investor with low ability may choose to stop investing in future loans. As a result, the set of investors who choose to stay in the market after suffering a default should have a higher average ability.[14] In principle, this selection effect may have contributed to our results. However, we expect its magnitude to be small: due to the principal guarantee, investors can still make a profit as long as borrowers make one payment, and so have little incentive to exit the market. Moreover, our experiment in the next section shows a significant difference between participants' and observers' learning where this selection effect is absent.

Third, one might attribute the results to inattention. If a defaulting loan is not in an investor's portfolio, it is likely that the investor would pay little attention to the default. Consequently, participants should respond more strongly than observers. While this interpretation is feasible, it is unlikely to explain the entire phenomenon. This is because, as shown in the next section, a similar participant vs. observer difference arises in our experiments, where all subjects are confronted with the outcomes of all loans, including the default event.

B. Experimental evidence

We recruited 68 undergraduate students from various departments and majors at Tsinghua University on June 23, 2018. All subjects went through a training session, which was the same as

[14] See Seru, Shumway, and Stoffman (2010) for a recent study on this selection issue.

that employed in previous experiments. Subjects were then randomly divided into two groups of 34.

The subjects in the treatment group participated in two rounds of investments. In each round, subjects were asked to select one of five loans offered. The five loans for the first round were chosen from loans issued in the two-week-period after November 4, 2013, and include three *HR* loans, one of which ultimately defaulted. The five loans for the second round were the same as those used in the previous experiments. After subjects made their first-round choices, the outcomes of all five loans (i.e., their realized cash flows) were announced. Then, subjects were asked to choose one of the five loans in second round. After the second round of investment, we surveyed all subjects in the treatment group by asking the following questions:

1. *Which of the following factors do you value most when you make investment decisions?*

   A. Interest Rate; B. Term; C. Amount; D. Credit Rating; E. Others.

2. *Please rate the extent to which you rely on intuition in making lending decisions on a scale of 1 to 7, where 1 indicates the lowest possible reliance on intuition and 7 indicates the highest possible reliance on intuition.*

While the first question tries to elicit where investors direct their attention, the second question aims to estimate the extent to which subjects make decisions based on System 1, i.e., rely on their intuition.

Our first test examines how experience affects the way investors make decisions. Specifically, we test whether investors focus on different variables across the two rounds of investments. Our surveys of the subjects in the treatment group were conducted after they observed the first-round investment outcomes and made their choices for the second round. If we had also surveyed them after the first round of investment decisions but *before* they learned the outcomes of the five loans, we would be able to measure the effect of experience on investors' beliefs by comparing the results from the two surveys. However, we choose not to directly survey the subjects in our treatment group, since the survey itself might influence subjects' behavior in the second round. Instead, we let the subjects of the control group go through the same investment decisions for the first round. We survey them after they make investment decisions but before they learn the outcomes of the loans. Since subjects are randomly assigned to the treatment and control groups, this survey is also representative of the beliefs of the treatment-group subjects before they learn the outcome of their first round of investments. Hence, the difference between the results of our two surveys reflects the effect of the investment experience. To avoid interference, experiments were conducted separately for the treatment group and the control group.

Panel A of Table 10 compares the survey results between the two groups. As shown in the first row, the percentage of subjects who select interest rate as the most important factor in their investment decisions is substantially lower for the treatment group than for the control group (23.53% vs. 50.00%). The difference between the two is 26.47%, with a *t*-statistic of 2.32. On the other hand, the percentage of subjects who select credit rating as the most important factor is substantially higher for the treatment group than for the control group (44.12% vs. 20.59%). The *t*-statistic for the difference between these two percentages is 2.11.

Moreover, after observing loan performance, subjects appear to rely less on intuition for their second round investment choices. The average score is 3.41/7 for the treatment group and 4.41/7 for the control group. The *t*-stat for the difference between the two average scores is 2.85. In contrast, as shown in the last three rows, the treatment and control groups have similar opinions about loan term, loan amount, and other variables. In summary, consistent with our interpretation, subjects pay more attention to credit ratings and less attention to interest rates after they gain more investment experience.

Our empirical evidence in the previous section shows that participants and observers learn differently. That is, an investor who experiences a recent default tends to choose loans with better credit ratings relative to investors who observe *others* experiencing defaults. Our experiment complements this evidence in two ways. First, it allows us to analyze what investors *think* through surveys. Second, it helps to narrow down potential interpretations of our empirical results.

In particular, we run cross-sectional regressions based on survey data from the subjects in the treatment group. In the specification in column (1) of Panel B, the dependent variable is *Intuition Score* and the independent variable is $Default_i$, which equals 1 if the loan chosen by investor *i* in the previous round defaults and 0 otherwise. The coefficient of *Default* is -1.164 (*t*=2.41), suggesting that, relative to the investors who did *not* experience a default in the first round, those whose loan defaulted rely less on their intuition when making investments in the second round. In column (2), the dependent variable is $Credit\ Rating_{it}$, which is a dummy variable that equals 1 if investor *i* chooses credit rating as the most important factor for his decision and 0 otherwise. The coefficient of *Default* is 0.458 (*t*=2.52), suggesting that, relative to the investors who did *not* experience a default in the first round, those who did are 45.8% more likely to choose credit rating as the most important factor in the second round. We run a similar regression for interest rate. As shown in column (3), the coefficient of *Default* is -0.320 (*t*=2.00), suggesting that the subjects who experienced a default in the first round are 32% less likely to choose interest rate as the most important factor for the second round investment. Finally, the last two columns show that default experience does not significantly affect subjects' views on loan term and amount.

Panel C shows that the subjects' investment choices appear consistent with the survey evidence in Panel B. Specifically, we run cross-sectional regressions based on the loan choices of the subjects in the treatment group. The first column shows that, relative to the investors who did not experience a default in the first round, those who did spend an extra 44.35 seconds (*t*=3.64) making decisions in the second round. Similarly, column (2) shows that subjects who experienced a default in the first round are 44% less likely to choose loans with an *HR* rating. Since non-*HR* loans have lower interest rates, as shown in column (3), the average interest rate of the loans chosen by subjects who experienced a default in the first round is 1.80% lower than that of loans chosen by subjects who did not experience a default. Column (4) shows that the effect of experiencing a default on IRR is positive, but statistically insignificant. Finally, the last two columns show that the effect is insignificant for loan term and amount.

These results not only corroborate our empirical evidence, but also shed light on its potential interpretations. In particular, our experimental evidence suggests that inattention, a likely contributor, cannot explain the entire firsthand experience effect. In our experiments, all subjects are informed about the performance of all loans, including the default event. We conjecture that participants and observers process the default information differently. Facing a default on one's own loans, participants are more likely to reexamine their decision processes and, consequently, improve their future decisions.

This finding adds to the literature on how experience affects belief formation along two dimensions. First, we show that firsthand experience plays a special role in affecting an investor's decisions. This is consistent with the findings in Andersen, Hanspal, and Nielsen (2018), which show that investors who suffered losses from investments in banks that defaulted following the 2008 financial crisis are more likely to shy away from risk. One key difference between our studies is the nature of the firsthand experience. The experience in Andersen et al. (2018) is based on shocks that are rare but can cause substantial losses. In response, investors who experienced the shock later completely avoided risk. In our study, however, the negative experience comprises more frequent but smaller shocks. Instead of avoiding risk altogether, investors in our study pay more attention to it and hence improve their future investments. More importantly, our experiment suggests that the firsthand experience effect cannot be attributed entirely to inattention. An investor is less responsive to other investors' losses not because she is not aware of such losses but, perhaps, because she is less likely to learn from others' mistakes when planning her investments.

VII. Conclusion

This paper analyzes how investment decisions are made in a real financial market when fast thinking prevails. Under time pressure, investors in an online P2P lending market appear to focus mostly on interest rates without sufficiently examining other information such as credit ratings. This simple rule of thumb is sensible, since interest rates and loan performance are highly correlated in this market. Consistent with this interpretation, our empirical and experimental evidence suggests that investors are more reliant on this rule of thumb when they experience more time pressure.

Moreover, considering borrowers' credit ratings, which are freely available on the trading interface, can significantly improve investment decisions. Through experiments, we show that by making credit rating information more salient, we can "nudge" investors into paying more attention to credit ratings and hence substantially improve their investment returns.

Finally, *firsthand experience* matters for learning: After experiencing a loan default personally, investors tend to increase their decision times and avoid loans with "High Risk" ratings, obtaining higher future returns. In contrast, after observing *others* experiencing a default, the effects are significantly smaller or negligible. Our empirical and experimental evidence suggests that this result cannot be fully explained by inattention. Our conjecture is that the psychological responses to firsthand experience are stronger than responses to other experiences.

In an increasingly digitized world, many financial decisions, including equity investments and portfolio choices for retirement, are made with a few swipes of a thumb. The sheer amount and speed of information may overwhelm investors, leading them to ignore details that are important for decision-making. Our research sheds light on investors' behavioral biases in a context of limited time and attention. It can help investors avoid the trap of fast thinking and improve their investment decisions.

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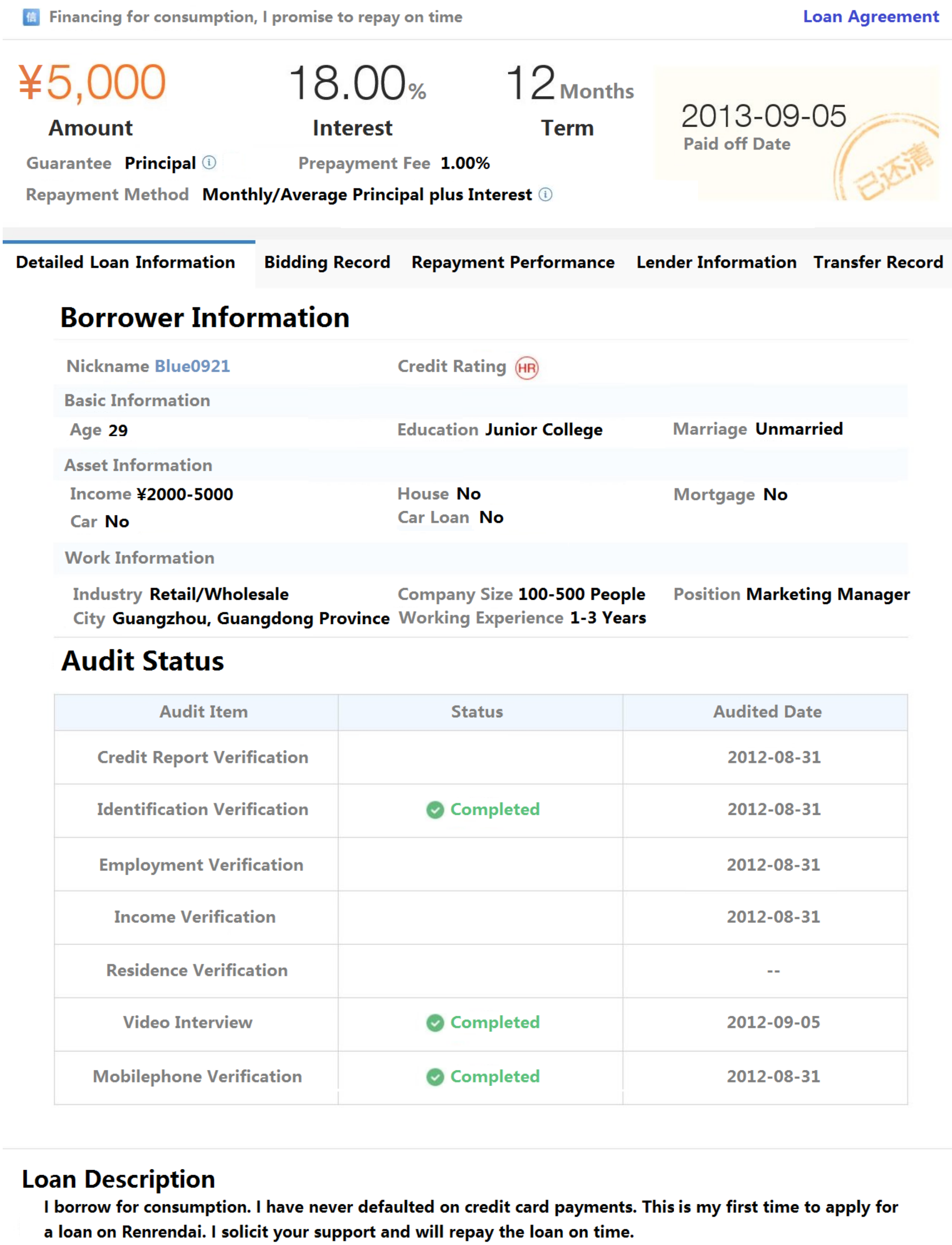
Figure 1. Computer screenshot of a sample loan



Financing for consumption, I promise to repay on time

Loan Agreement

¥5,000 Amount

18.00% Interest

12 Months Term

2013-09-05 Paid off Date

已还清

Guarantee Principal

Prepayment Fee 1.00%

Repayment Method Monthly/Average Principal plus Interest

Detailed Loan Information | Bidding Record | Repayment Performance | Lender Information | Transfer Record

Borrower Information

Nickname Blue0921

Credit Rating HR

Basic Information

Age 29

Education Junior College

Marriage Unmarried

Asset Information

Income ¥2000-5000

House No

Mortgage No

Car No

Car Loan No

Work Information

Industry Retail/Wholesale

Company Size 100-500 People

Position Marketing Manager

City Guangzhou, Guangdong Province

Working Experience 1-3 Years

Audit Status

Audit Item	Status	Audited Date
Credit Report Verification		2012-08-31
Identification Verification	Completed	2012-08-31
Employment Verification		2012-08-31
Income Verification		2012-08-31
Residence Verification		--
Video Interview	Completed	2012-09-05
Mobilephone Verification	Completed	2012-08-31

Loan Description

I borrow for consumption. I have never defaulted on credit card payments. This is my first time to apply for a loan on Renrendai. I solicit your support and will repay the loan on time.

Figure 2. Marginal effect of interest rate on fulfillment time at different quantiles

The horizontal axis is the quantile of *Ln(FulfillmentTime)* from 0.05 to 0.95. The vertical axis is the coefficient estimate for *Interest Rate* from the quantile regression of *Ln(FulfillmentTime)* on *Interest Rate* and a list of control variables, as in Table 2. The solid green line is the coefficient estimate for *Interest Rate* from quantile regressions and the grey region is the 95% confidence interval for the coefficient estimate for *Interest Rate*.

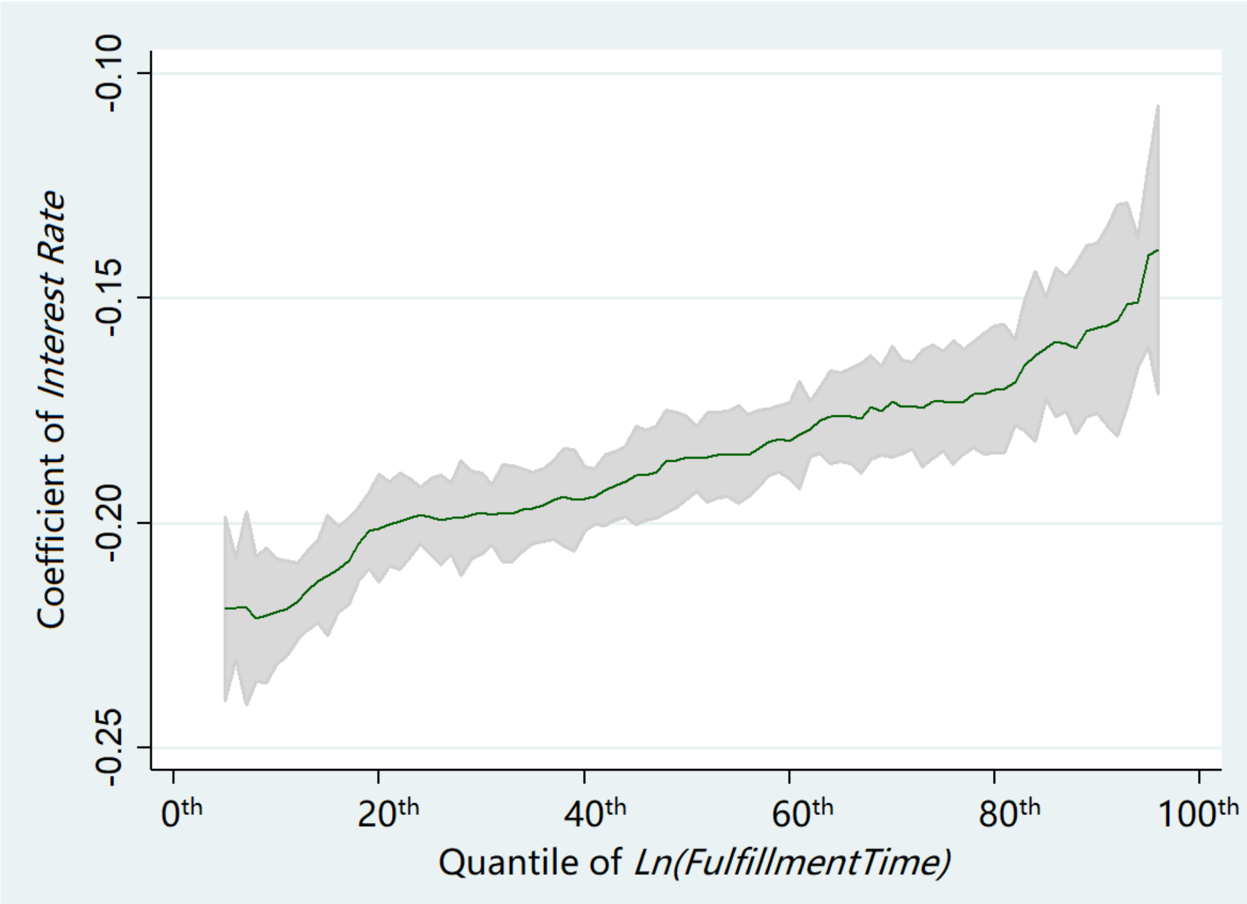


Figure 3. Mobile App screenshot of a sample loan

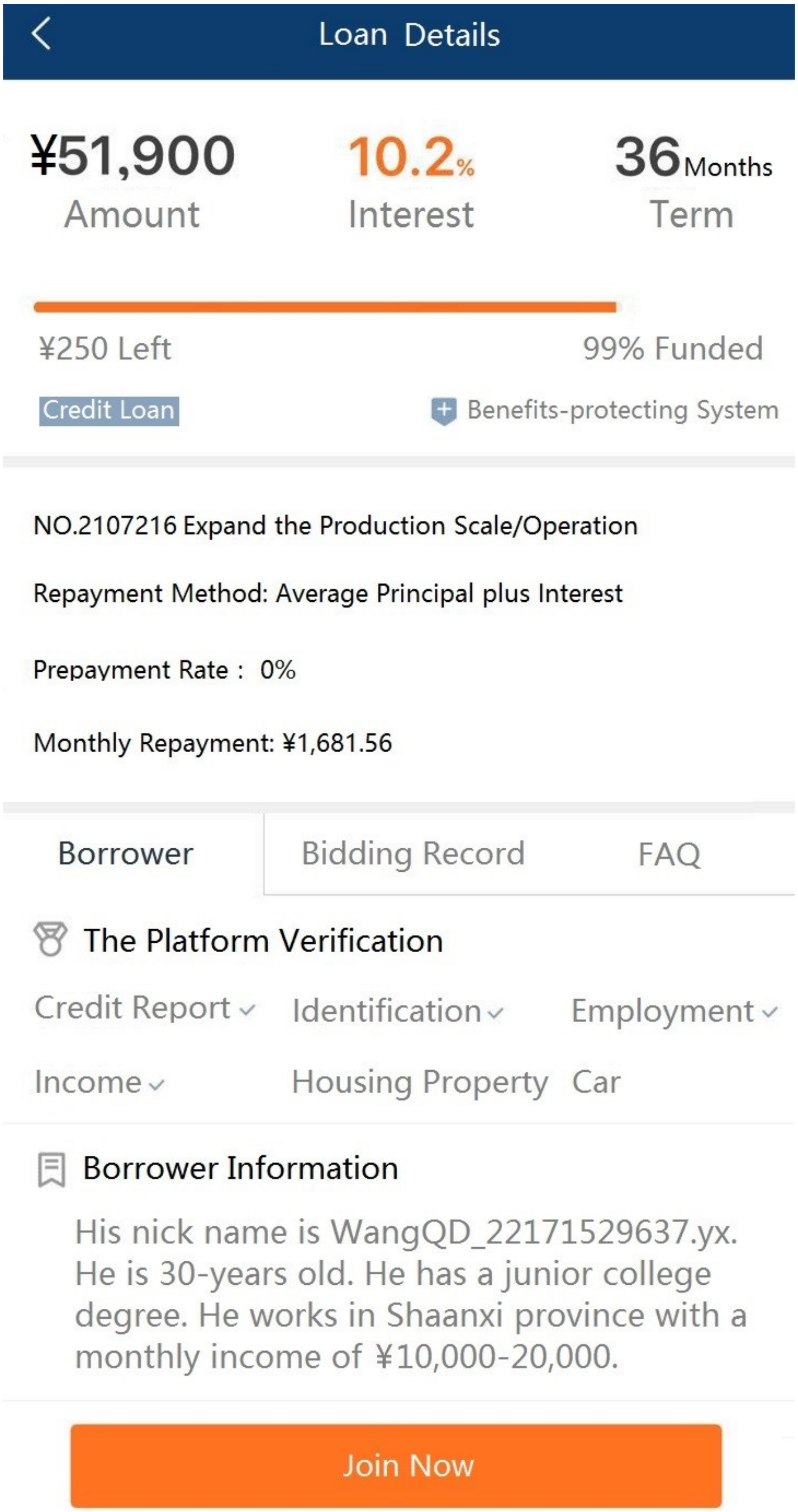
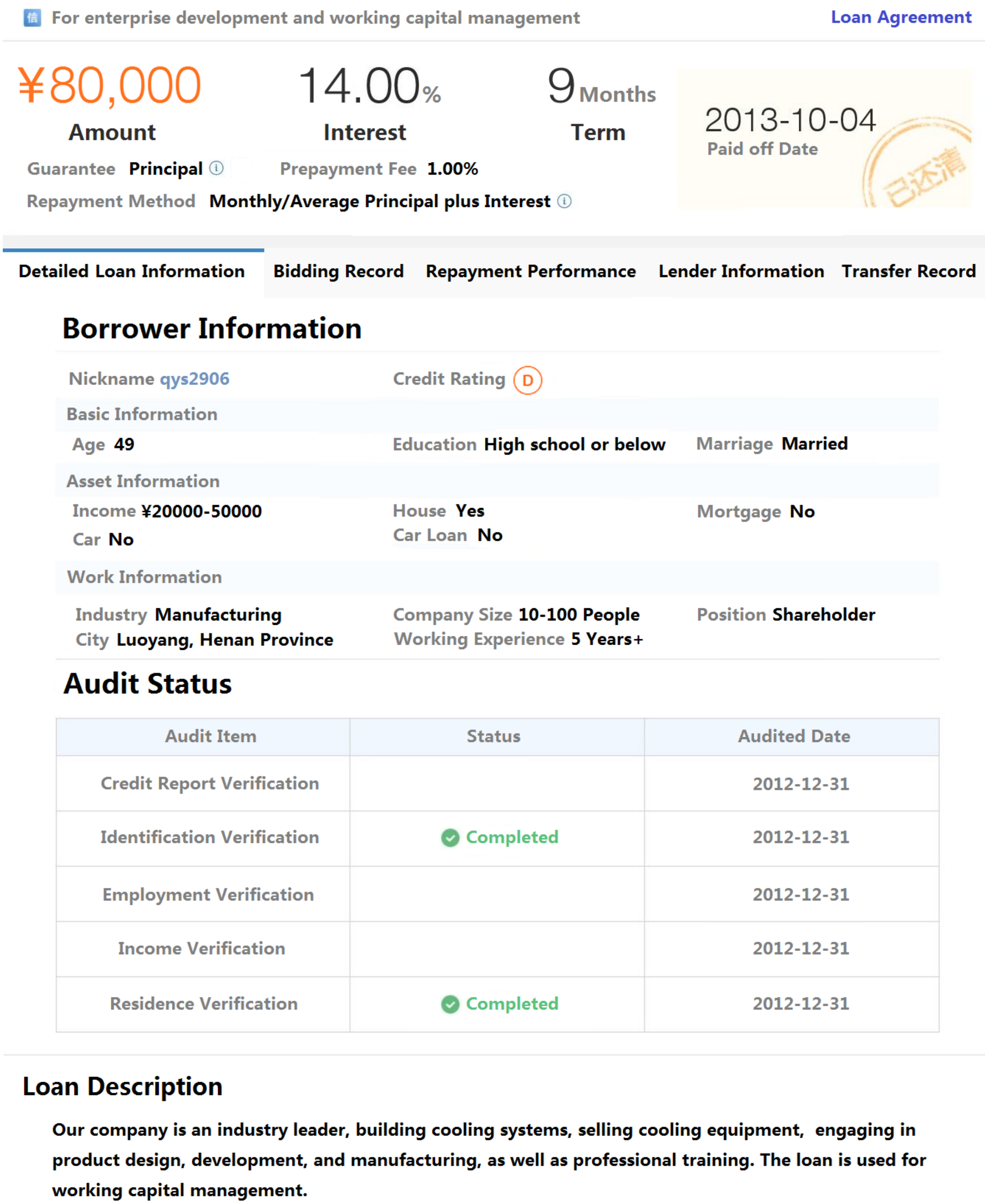


Figure 4. Computer screenshot of a sample loan for Group 1 (original)



For enterprise development and working capital management

Loan Agreement

¥80,000 Amount

14.00% Interest

9 Months Term

2013-10-04 Paid off Date

已还清

Guarantee **Principal**

Prepayment Fee **1.00%**

Repayment Method **Monthly/Average Principal plus Interest**

Detailed Loan Information | Bidding Record | Repayment Performance | Lender Information | Transfer Record

Borrower Information

Nickname qys2906

Credit Rating D

Basic Information

Age **49**

Education **High school or below**

Marriage **Married**

Asset Information

Income **¥20000-50000**

House **Yes**

Mortgage **No**

Car **No**

Car Loan **No**

Work Information

Industry **Manufacturing**

Company Size **10-100 People**

Position **Shareholder**

City **Luoyang, Henan Province**

Working Experience **5 Years+**

Audit Status

Audit Item	Status	Audited Date
Credit Report Verification		2012-12-31
Identification Verification	Completed	2012-12-31
Employment Verification		2012-12-31
Income Verification		2012-12-31
Residence Verification	Completed	2012-12-31

Loan Description

Our company is an industry leader, building cooling systems, selling cooling equipment, engaging in product design, development, and manufacturing, as well as professional training. The loan is used for working capital management.

Figure 5. Computer screenshot of a sample loan for Group 2 (interest rate in a smaller font)

For enterprise development and working capital management | Loan Agreement

¥80,000 — Amount | 9 Months — Term | 2013-10-04 Paid off Date 已还清

Guarantee **Principal** | Prepayment Fee **1.00%** | Interest **14.00%**

Repayment Method **Monthly/Average Principal plus Interest**

Detailed Loan Information | Bidding Record | Repayment Performance | Lender Information | Transfer Record

Borrower Information

Nickname qys2906 | Credit Rating D

Basic Information

Age **49** | Education **High school or below** | Marriage **Married**

Asset Information

Income **¥20000-50000** | House **Yes** | Mortgage **No**

Car **No** | Car Loan **No**

Work Information

Industry **Manufacturing** | Company Size **10-100 People** | Position **Shareholder**

City **Luoyang, Henan Province** | Working Experience **5 Years+**

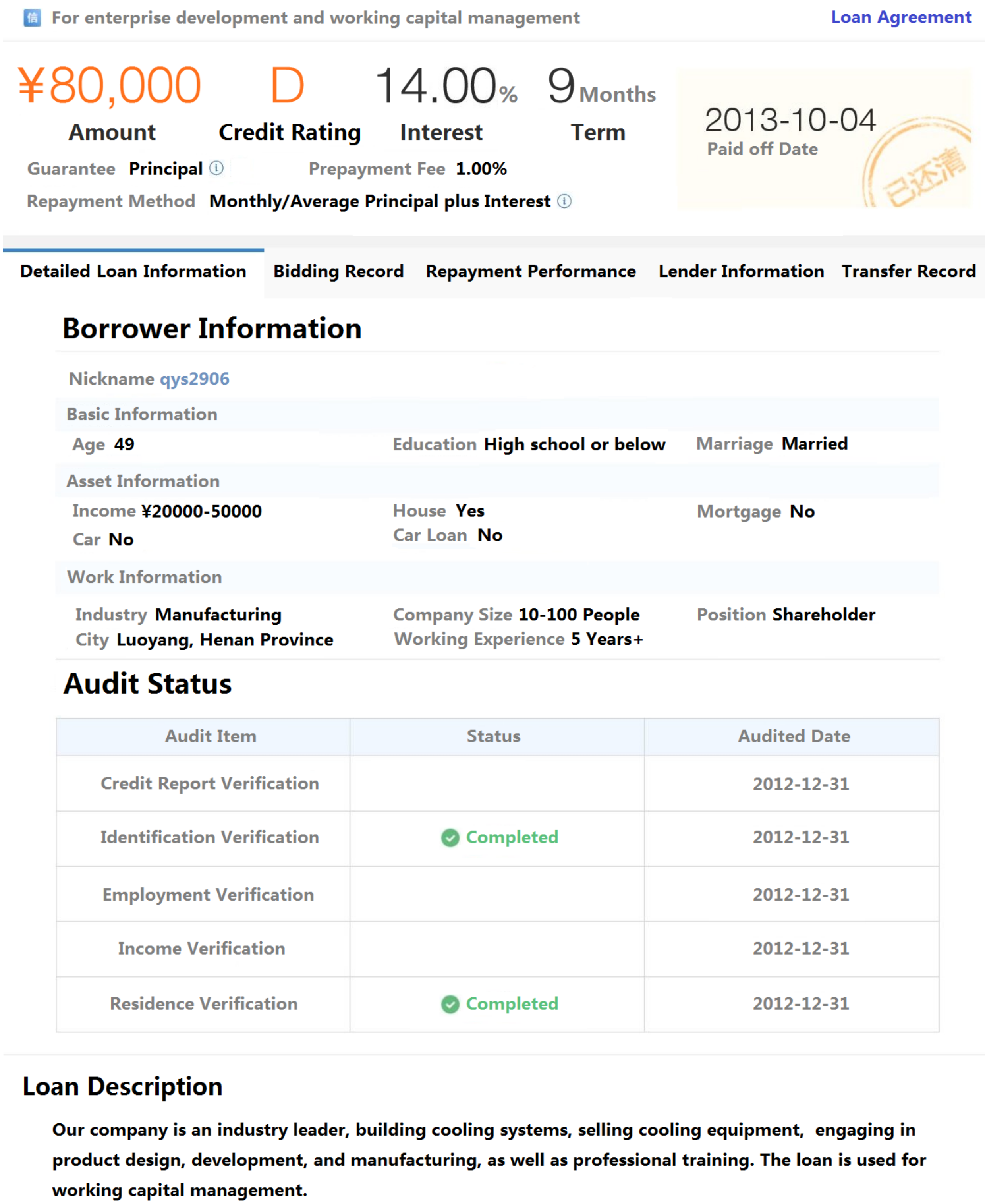
Audit Status

Audit Item	Status	Audited Date
Credit Report Verification		2012-12-31
Identification Verification	Completed	2012-12-31
Employment Verification		2012-12-31
Income Verification		2012-12-31
Residence Verification	Completed	2012-12-31

Loan Description

Our company is an industry leader, building cooling systems, selling cooling equipment, engaging in product design, development, and manufacturing, as well as professional training. The loan is used for working capital management.

Figure 6. Computer screenshot of a sample loan for Group 3 (credit rating in a larger font)



For enterprise development and working capital management

Loan Agreement

¥80,000 Amount

D Credit Rating

14.00% Interest

9 Months Term

2013-10-04 Paid off Date

已还清

Guarantee Principal

Prepayment Fee 1.00%

Repayment Method Monthly/Average Principal plus Interest

Detailed Loan Information | Bidding Record | Repayment Performance | Lender Information | Transfer Record

Borrower Information

Nickname qys2906

Basic Information

Age 49

Education High school or below

Marriage Married

Asset Information

Income ¥20000-50000

Car No

House Yes

Car Loan No

Mortgage No

Work Information

Industry Manufacturing

City Luoyang, Henan Province

Company Size 10-100 People

Working Experience 5 Years+

Position Shareholder

Audit Status

Audit Item	Status	Audited Date
Credit Report Verification		2012-12-31
Identification Verification	Completed	2012-12-31
Employment Verification		2012-12-31
Income Verification		2012-12-31
Residence Verification	Completed	2012-12-31

Loan Description

Our company is an industry leader, building cooling systems, selling cooling equipment, engaging in product design, development, and manufacturing, as well as professional training. The loan is used for working capital management.

Table 1. Data description

Panel A lists the definitions of our main variables. Panel B reports their summary statistics, and Panel C compares the characteristics of fast loans and other loans.

Panel A. Definitions

Variable	Definition
Interest Rate (%)	The interest rate of the loan.
Ln(Amount) (¥)	The natural log of the loan amount.
Term (months)	The term of the loan. At Renrendai, a borrower can choose from eight terms: 3 months, 6 months, 9 months, 12 months, 15 months, 18 months, 24 months, or 36 months.
FulfillmentTime (seconds)	The time interval between the beginning and ending times of a loan's funding process.
IRR (%)	The internal rate of return (IRR) for the loan.
Default	equals 1 if the loan defaults and 0 otherwise. Both overdue loans and advanced loans are classified as defaulted. Overdue loans are loans that have been overdue for less than 30 days; advanced loans are loans that have been overdue for more than 30 days, which Renrendai has repaid to the borrowers.
Rm	The rate of return in the A-share market in China over the past 20 trading days.
Rf (%)	The annualized rate of return of time deposits with the same term as the loan.
HR	Takes a value of 1 if the borrower's credit rating is HR (High Risk) and 0 otherwise.
Male	equals 1 if the borrower is male and 0 otherwise.
Age (in years)	Age of the borrower.
Bachelor	equals 1 if the borrower's highest degree is a bachelor's degree and 0 otherwise.
MasterOrHigher	equals 1 if the borrower's highest degree is a master's degree or higher and 0 otherwise.
Employ(3–5yrs)	equals 1 if the borrower has work experience of 3 to 5 years and 0 otherwise.
Employ(5yrs+)	equals 1 if the borrower has work experience of more than 5 years and 0 otherwise.
Income(¥5,000–10,000)	equals 1 if the borrower's monthly income is between ¥5,000 and 10,000 and 0 otherwise.
Income(¥10,000–20,000)	equals 1 if the borrower's monthly income is between ¥10,000 and 20,000 and 0 otherwise.
Income(¥20,000–50,000)	equals 1 if the borrower's monthly income is between ¥20,000 and 50,000 and 0 otherwise.
Income(¥50,000+)	equals 1 if the borrower's monthly income is above ¥50,000 and 0 otherwise.
House	equals 1 if the borrower owns a house and 0 otherwise.
Mortgage	equals 1 if the borrower has an unpaid mortgage and 0 otherwise.
Car	equals 1 if the borrower owns a car and 0 otherwise.
CarLoan	equals 1 if the borrower has an unpaid car loan and 0 otherwise.
Bid_t	equals 1 if the investor invests in month t and 0 otherwise.
$Ln(FulfillmentTime)_t$ *(seconds)*	The average of the natural log of one plus the time interval between the beginning and ending time of a loan's funding process in month t.
$ProportionFastBids_t$ *(%)*	The proportion of fast loans among all loans made by an investor in month *t*.
$CumBid_{it}$	The cumulative number of loans made by an investor i up to day *t*.

Panel B. Summary statistics (N=10,385)

Variable	Mean	S.D.	*p*1	*p*10	*p*25	*p*50	*p*75	*p*90	*p*99
Loan characteristics:									
Interest Rate (%)	12.70	2.20	10	10	11	12	13	15	20
Amount (¥'000)	25.37	39.67	3.00	5.00	8.00	14.00	27.00	50.00	200.00
Ln(Amount) (¥)	9.63	0.92	8.01	8.52	8.99	9.55	10.20	10.82	12.21
Term (months)	10.30	7.08	3	3	6	9	12	18	36
FulfillmentTime (seconds)	291	1,581	4	23	42	80	180	480	2,972
Ln(FulfillmentTime)	4.54	1.27	1.61	3.18	3.76	4.39	5.20	6.18	8.00
IRR (%)	10.82	3.80	0	6.43	8.02	10.77	13.00	15.15	21.97
IRR – CD Rate (%)	7.89	3.81	-2.80	3.68	5.07	7.77	10.20	12.20	19.16
Default	0.18	0.38	0	0	0	0	0	1	1
Market Conditions:									
Rm	0.037	0.068	-0.117	-0.039	-0.004	0.025	0.063	0.137	0.247
Rf (%)	2.924	0.355	2.55	2.6	2.75	2.8	3	3	4.25
Borrower characteristics:									
HR	0.712	0.453	0	0	0	1	1	1	1
Male	0.873	0.333	0	0	1	1	1	1	1
Age	32.889	7.024	23	25	28	32	37	43	52
Bachelor	0.298	0.457	0	0	0	0	1	1	1
MasterOrHigher	0.023	0.151	0	0	0	0	0	0	1
Employ(3–5yrs)	0.220	0.414	0	0	0	0	0	1	1
Employ(5yrs+)	0.347	0.476	0	0	0	0	1	1	1
Income(¥5,000–10,000)	0.267	0.442	0	0	0	0	1	1	1
Income(¥10,000–20,000)	0.140	0.348	0	0	0	0	0	1	1
Income(¥20,000–50,000)	0.143	0.350	0	0	0	0	0	1	1
Income(¥50,000+)	0.130	0.336	0	0	0	0	0	1	1
House	0.555	0.497	0	0	0	1	1	1	1
Mortgage	0.217	0.412	0	0	0	0	0	1	1
Car	0.408	0.492	0	0	0	0	1	1	1
CarLoan	0.080	0.272	0	0	0	0	0	0	1

Panel C. Average characteristics of fast loans vs. other loans

Variable:	Fast (*N* =2,644)	Other (*N* =7,741)	Fast minus Other Diff	Fast minus Other t-stat
Loan characteristics:				
Interest Rate (%)	13.71	12.36	1.351	28.24***
Amount (¥)	13,873	29,299	-15,427	-17.52***
Ln(Amount) (¥)	9.276	9.752	-0.476	-23.57***
Term (months)	10.57	10.21	0.359	2.25**
FulfillmentTime (seconds)	25.71	381.52	-355.81	-10.04***
Ln(FulfillmentTime)	3.127	5.025	-1.897	-87.87***
IRR(%)	11.67	10.53	1.141	13.44***
IRR – CD Rate (%)	8.718	7.609	1.108	13.01***
Default	0.198	0.167	0.031	3.55***
Borrower characteristics:				
HR	0.787	0.686	0.101	10.03***
Male	0.882	0.869	0.013	1.75*
Age (years)	31.31	33.43	-2.11	13.48***
Bachelor	0.291	0.301	-0.01	0.96
MasterOrHigher	0.022	0.024	-0.002	0.69
Employ(3–5yrs)	0.208	0.224	-0.016	1.69*
Employ(5yrs+)	0.304	0.361	-0.057	5.28***
Income(¥5,000–10,000)	0.31	0.253	0.057	5.75***
Income(¥10,000–20,000)	0.127	0.145	-0.018	2.23**
Income(¥20,000–50,000)	0.095	0.16	-0.065	8.27***
Income(¥50,000+)	0.061	0.153	-0.092	12.33***
House	0.476	0.582	-0.106	9.50***
Mortgage	0.205	0.221	-0.016	1.66*
Car	0.292	0.448	-0.156	14.25***
CarLoan	0.056	0.089	-0.033	5.27***

Table 2. Fulfillment Time vs. Interest Rate and HR: OLS and Quantile Regressions

This table reports the results of the OLS regression (column (1)) and quantile regressions (columns (2) through (5) for the 10^{th}, 25^{th}, 75^{th}, and 90^{th} percentiles, respectively). The dependent variable is *Ln(FulfillmentTime).* All independent variables are defined in Table 1. Verifications fixed effects are captured by dummy variables indicating whether Renrendai verified the borrower's credit report, ID, employment, income, home deed, car title, marriage certificate, education diploma, mobile phone, Weibo account, address, and video interview. All specifications include week fixed effects, day-of-week fixed effects, and hour-of-day fixed effects. All continuous variables are winsorized at the 1^{st} and 99^{th} percentiles in the OLS regression. T-statistics are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	OLS	10th Quantile	25th Quantile	75th Quantile	90th Quantile
Interest Rate	-0.206***	-0.220***	-0.199***	-0.173***	-0.157***
	(-19.55)	(-22.40)	(-40.56)	(-30.08)	(-17.46)
Ln(Amount)	-1.357***	-0.105	-0.829***	-1.772***	-2.115***
	(-7.86)	(-0.32)	(-5.09)	(-9.27)	(-7.09)
Ln(Amount)Squared	0.097***	0.028*	0.065***	0.117***	0.135***
	(10.64)	(1.72)	(7.85)	(12.07)	(8.90)
Term	0.026***	0.029**	0.022***	0.021***	0.026**
	(3.57)	(2.47)	(3.72)	(2.98)	(2.34)
Rm	0.066	-0.057	-0.172	0.075	0.295
	(0.03)	(-0.05)	(-0.30)	(0.11)	(0.28)
Rf	-0.118	-0.211	-0.051	-0.085	-0.118
	(-0.85)	(-0.90)	(-0.44)	(-0.62)	(-0.55)
HR	-0.036	-0.038	0.037	-0.015	-0.072
	(-1.28)	(-0.70)	(1.37)	(-0.49)	(-1.47)
Male	-0.003	0.003	0.011	0.028	-0.036
	(-0.13)	(0.06)	(0.42)	(0.89)	(-0.72)
Age	-0.000	-0.001	0.002	-0.001	-0.001
	(-0.10)	(-0.36)	(1.00)	(-0.64)	(-0.24)
Bachelor	-0.031	-0.054	-0.024	-0.025	-0.036
	(-1.58)	(-1.28)	(-1.14)	(-1.00)	(-0.93)
MasterOrHigher	-0.130***	-0.032	-0.069	-0.155**	-0.219**
	(-3.10)	(-0.27)	(-1.14)	(-2.18)	(-1.97)
Employ(3–5yrs)	-0.023	0.012	0.000	-0.025	-0.071
	(-1.10)	(0.25)	(0.01)	(-0.89)	(-1.61)
Employ(5yrs+)	-0.001	0.030	-0.009	0.020	-0.016
	(-0.03)	(0.64)	(-0.40)	(0.75)	(-0.36)
Income(¥5,000–10,000)	-0.045**	-0.020	-0.048**	-0.024	0.004
	(-2.16)	(-0.40)	(-1.99)	(-0.85)	(0.09)
Income(¥10,000–20,000)	-0.009	-0.008	-0.028	0.043	0.108*
	(-0.27)	(-0.13)	(-0.92)	(1.18)	(1.91)
Income(¥20,000–50,000)	-0.021	-0.043	-0.015	0.017	0.022
	(-0.57)	(-0.64)	(-0.45)	(0.43)	(0.35)
Income(¥50,000+)	-0.040	-0.027	-0.021	0.027	0.036
	(-0.91)	(-0.35)	(-0.54)	(0.61)	(0.51)
House	-0.062***	-0.059	-0.044*	-0.057**	-0.060
	(-2.78)	(-1.23)	(-1.83)	(-2.03)	(-1.36)
Mortgage	-0.024	-0.012	0.000	-0.006	-0.049
	(-1.02)	(-0.23)	(0.01)	(-0.20)	(-1.05)
Car	-0.003	-0.046	0.003	0.012	-0.010
	(-0.10)	(-0.86)	(0.10)	(0.38)	(-0.20)
CarLoan	0.026	0.083	0.058	0.029	0.030
	(0.78)	(1.16)	(1.63)	(0.69)	(0.46)
Constant	14.064***	7.893***	10.851***	16.271***	18.411***
	(15.08)	(4.44)	(12.21)	(15.60)	(11.31)
Verification Fixed Effects	YES	YES	YES	YES	YES
Week Fixed Effects	YES	YES	YES	YES	YES
Day-of-week Fixed Effects	YES	YES	YES	YES	YES
Hour-of-Day Fixed Effects	YES	YES	YES	YES	YES
No. of Obs.	10,385	10,385	10,385	10,385	10,385
Adjusted/Pseudo- R^2	0.575	0.328	0.352	0.423	0.454

Table 3. Loan Performance

This table reports the estimates of regressions of IRR_i – *CD Rate* on *Interest Rate*, *HR*, and control variables, where IRR_i is the internal rate of return of loan *i* and *CD Rate* is the bank deposit rate in the same month as the loan and with the same term. Verifications fixed effects are described in Table 2. All specifications include week fixed effects, day-of-week fixed effects, and hour-of-day fixed effects. All continuous variables are winsorized at the 1st and 99th percentiles. Standard errors are clustered by week. T-statistics are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	*IRR – CD Rate (%)*	
	(1)	(2)
Interest Rate	0.804***	0.809***
	(31.78)	(32.13)
HR	-1.109***	-1.076***
	(-19.34)	(-15.74)
Ln(Amount)	-0.297***	-0.303***
	(-8.08)	(-8.21)
Term	-0.106***	-0.105***
	(-21.05)	(-20.71)
Rm	-0.960	-1.052
	(-0.75)	(-0.82)
Male	-0.166**	-0.151**
	(-2.59)	(-2.36)
Age	-0.016***	-0.015***
	(-3.93)	(-3.61)
Bachelor	0.347***	0.343***
	(6.97)	(6.99)
MasterOrHigher	0.762***	0.784***
	(5.09)	(5.30)
Employ(3–5yrs)	0.089	0.089
	(1.42)	(1.44)
Employ(5yrs+)	0.101	0.115
	(1.40)	(1.55)
Income(¥5,000–10,000)	-0.112*	-0.106*
	(-1.74)	(-1.67)
Income(¥10,000–20,000)	-0.057	-0.054
	(-0.76)	(-0.72)
Income(¥20,000–50,000)	0.016	-0.006
	(0.20)	(-0.07)
Income(¥50,000+)	-0.015	-0.032
	(-0.17)	(-0.35)
House	-0.099	-0.067
	(-1.52)	(-0.99)
Mortgage	0.311***	0.332***
	(4.02)	(4.26)
Car	0.165***	0.192***
	(2.78)	(2.63)
CarLoan	-0.056	-0.049
	(-0.54)	(-0.47)
Constant	5.025***	5.223***
	(5.85)	(5.98)
Verification Fixed Effects	NO	YES
Week Fixed Effects	YES	YES
Day-of-week Fixed Effects	YES	YES
Hour-of-day Fixed Effects	YES	YES
No. of Obs.	10,385	10,385
R-squared	0.599	0.602

Table 4. Loan Default

This table reports the estimates of a Cox proportional hazards model, where the survival time is the time elapsed from the moment when the loan gets funded to the moment when the loan defaults or gets repaid. The dependent variable is $Default_{it}$, which is a dummy variable that equals 1 if loan *i* defaults in month *t* and zero otherwise. Verifications fixed effects are described in Table 2. All specifications include week fixed effects, day-of-week fixed effects, and hour-of-day fixed effects. All continuous variables are winsorized at the 1st and 99th percentiles. Standard errors are clustered by week. T-statistics are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	*Default*	
	(1)	(2)
Interest Rate	0.109***	0.108***
	(6.71)	(6.60)
HR	2.011***	2.012***
	(8.26)	(9.03)
Ln(Amount)	0.139***	0.170***
	(2.90)	(3.54)
Term	0.048***	0.047***
	(16.15)	(14.98)
Rm	3.306**	3.512**
	(2.11)	(2.24)
Male	0.213**	0.195**
	(2.42)	(2.25)
Age	0.024***	0.020***
	(5.28)	(4.68)
Bachelor	-0.585***	-0.532***
	(-10.00)	(-9.08)
MasterOrHigher	-1.199***	-1.090***
	(-4.28)	(-4.01)
Employ(3–5yrs)	-0.042	-0.079
	(-0.68)	(-1.25)
Employ(5yrs+)	-0.158**	-0.190***
	(-2.41)	(-2.83)
Income(¥5,000–10,000)	0.179***	0.178***
	(3.14)	(3.03)
Income(¥10,000–20,000)	0.233***	0.244***
	(2.77)	(2.91)
Income(¥20,000–50,000)	0.492***	0.538***
	(4.92)	(5.49)
Income(¥50,000+)	0.618***	0.645***
	(5.62)	(5.92)
House	0.108*	0.111*
	(1.70)	(1.74)
Mortgage	-0.436***	-0.429***
	(-6.16)	(-5.83)
Car	-0.234***	-0.303***
	(-3.30)	(-3.37)
CarLoan	0.106	0.091
	(0.91)	(0.81)
Verification Fixed Effects	NO	YES
Week Fixed Effects	YES	YES
Day-of-week Fixed Effects	YES	YES
Hour-of-day Fixed Effects	YES	YES
No. of Obs.	10,385	10,385
Wald chi2	3.04e11	8.64e8
Prob > chi2	0.000	0.000

Table 5. Performance of *HR* vs. *non-HR* Loans

This table reports the performance of *HR* and non-*HR* loans. For each week, we sort loans into five quintiles based on their interest rates. Then, we calculate the principal-value-weighted average of *IRR – CD Rate* for *HR* and non-*HR* loans, both for each quintile and for the overall sample. The first row reports the time-series average of these weekly averages for the overall sample, and rows two through six report the results for quintiles one through five, respectively. The last row reports the difference in differences. T-statistics, reported in parentheses, are based on standard errors that are Newey-West adjusted with 24 lags. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Variable:	*IRR – CD Rate (%)*		
	HR Loans (1)	Non-*HR* loans (2)	Diff (2) - (1)
Full Sample	8.219	9.340	1.121***
			(5.26)
Quintile 1 (high)	9.672	10.983	1.301***
			(7.29)
Quintile 2	8.165	9.526	1.399***
			(4.09)
Quintile 3	7.882	9.190	1.258***
			(3.92)
Quintile 4	7.994	8.766	0.769***
			(4.26)
Quintile 5 (low)	7.507	8.183	0.669***
			(4.80)
Diff-in-diff (1)-(5)			0.632***
			(3.43)

Table 6. Time pressure experiment

The experiment was conducted on January 15, 2017. We recruited 60 subjects from a first-year graduate class at the People's Bank of China School of Finance (PBCSF), Tsinghua University. All subjects went through the training session described in Section IV.B. They were then instructed to select one of five offered loans to invest in. Subjects were randomly divided into two groups of 30. The subjects in the treatment group were asked to select a loan within 42 seconds, while those in the control group were asked to take a minimum of 180 seconds to make their selection. Panel A reports the details of the five loans from which the subjects chose. Panel B records the average characteristics of the selected loans for the treatment and control groups. T-statistics are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Details of the five loans

Variable	Mean	Loan 1	Loan 2	Loan 3	Loan 4	Loan 5
Borrower characteristics:						
Interest Rate (%)	16.8	20	15	16	15	18
Amount (¥ '000)	12.4	10	10	12	5	25
Term (Months)	15	12	24	12	3	24
IRR(%)	15.40	12.99	15	16	15	18
Default	0.2	1	0	0	0	0
Borrower characteristics:						
HR	0.6	1	0	1	0	1
Age (in years)	32	35	36	32	29	28
Bachelor	0.8	0	1	1	1	1
MasterOrHigher	0	0	0	0	0	0
Employ(3-5yrs)	0.4	0	0	0	1	1
Employ(5yrs+)	0.2	0	1	0	0	0
Income(¥5,000-10,000)	0	0	0	0	0	0
Income(¥10,000-20,000)	0	0	0	0	0	0
Income(¥20,000-50,000)	0	0	0	0	0	0
Income(¥50,000+)	0	0	0	0	0	0
House	0	0	0	0	0	0
Mortgage	0	0	0	0	0	0
Car	0.2	0	0	0	1	0
CarLoan	0	0	0	0	0	0

Panel B. Characteristics of loans selected by the treatment and control groups

Variable:	Treatment group (*N*=30)	Control group (*N*=30)	Diff (Treatment - control)
Interest rate (%)	16.27	15.07	1.20***
			(3.02)
HR	0.27	0.07	0.20**
			(2.12)
Default	0.23	0.00	0.23***
			(2.97)
IRR (%)	14.63	15.07	-0.44**
			(2.17)
Term (months)	14.90	14.10	0.80
			(0.32)
Amount (¥)	9,000	7,700	1,300
			(1.57)

Table 7. Introduction of Mobile App

Panel A reports the estimate of a panel regression of $Ln(DecisionTime_{ij})$ on $Mobile_{ij}$, where $DecisionTime_{ij}$ is investor *i*'s decision time for investing in loan *j* and $Mobile_{ij}$ is a dummy variable, which equals 1 if investor *i*'s bid for loan *j* is made through the mobile app and 0 if it is made using a computer. The first two columns report the estimates based on the overall sample; the last two columns are based on the subsample of investors who used both the mobile app and a PC in their bidding during our sample period. Panel B reports the estimates of a regression of $MobileProportion_i$, which is the fraction of the investment in loan *i* that comes from the mobile app, on *Interest Rate* and control variables. This regression is based on an extended sample period from Sept. 2012 to March 2016. All continuous variables are winsorized at the 1st and 99th percentiles. Standard errors are clustered by week. T-statistics are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Mobile bidders are faster

Dependent variable:	*Ln(DecisionTime)*			
	Overall sample		Subsample (users of both mobile and PC)	
	(1)	(2)	(3)	(4)
Mobile	-0.146***	-0.101***	-0.130***	-0.111***
	(-29.79)	(-13.24)	(-16.07)	(-11.40)
Constant	4.437***	4.404***	4.201***	4.201***
	(2,620.56)	（3.43）	(1,088.55)	（3.45）
No. of Obs.	204,872	196,165	69,358	68,408
R-squared	0.797	0.832	0.780	0.815
Investor Fixed Effects		Yes		Yes
Loan Fixed Effects	Yes	Yes	Yes	Yes

Panel B: Fractions of bids from the mobile app

	MobileProportion
Interest Rate	0.675***
	(3.28)
Ln(Amount)	-1.383***
	(-4.42)
Term	0.188*
	(1.85)
Rm	-6.488
	(-0.93)
Rf	-1.579
	(-0.91)
HR	0.411
	(1.42)
Age	-0.026
	(-1.28)
Bachelor	0.562***
	(2.66)
MasterOrHigher	0.511
	(0.94)
Employ(3–5yrs)	0.011
	(0.04)
Employ(5yrs+)	-0.034
	(-0.15)
Income(¥5,000–10,000)	0.416
	(1.33)
Income(¥10,000–20,000)	0.644
	(1.30)
Income(¥20,000–50,000)	0.891*
	(1.98)
Income(¥50,000+)	2.297***
	(4.48)
House	0.044
	(0.14)
Mortgage	-0.724***
	(-2.90)
Car	-0.300
	(-0.95)
CarLoan	-0.080
	(-0.21)
Constant	14.164
	(1.23)
Verification Fixed Effects	YES
Week Fixed Effects	YES
Day-of-Week Fixed Effects	YES
Hour-of-Day Fixed Effects	YES
No. of Obs.	16,533
R-squared	0.875

Table 8. Experiment on the effect of salience

The experiment was conducted in two rounds. We recruited 105 graduate students from PBCSF for the first round on January 10, 2018 and 77 graduate students from the School of Management and Engineering, Nanjing University for the second round on March 19, 2018. The procedures for the two rounds of experiments were the same. For each round, subjects were divided randomly into three groups. The training session was the same as in Section IV.B, except that the screenshot of the loan information is presented differently across the three groups. For Group 1, the screenshot was the original PC interface, as in Figure 4. For Group 2, we modified the original interface by reducing the font size of the interest rate and moving it to a less prominent location, as shown in Figure 5. For Group 3, we modified the original interface by enlarging the font size of the credit rating, changing its color to orange, and moving it to the top of the screen, as shown in Figure 6. After the training session, subjects were asked to choose one out of same five loans that were shown in the experiment in Table 6. For all subjects, the format of the interface for those five loans matched what they saw during the training session. We asked the following question at the end of the experiment:

Which of the following factors do you value most when you make investment decisions?

A. Interest Rate; B. Term; C. Amount; D. Credit Rating; E. Others.

Panel A compares the most valued variables across the three groups. It reports the fraction of subjects who choose each variable as the most important factor in their decisions. Panel B reports the average value of each variable among the loans chosen by each group. T-statistics are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Comparison of the most valued variables in the survey

Variable:	Group 1 (*N*=65)	Group 2 (*N*=56)	Group 3 (*N*=61)	Diff (1)-(2)	Diff (1)-(3)
Interface	Original	Smaller interest rate	Larger credit rating		
Interest Rate	0.39	0.20	0.26	0.19**	0.12
				(2.29)	(1.47)
HR	0.23	0.36	0.48	-0.13	-0.25***
				(-1.53)	(-2.96)
Amount	0.14	0.09	0.07	0.05	0.07
				(0.84)	(1.34）
Term	0.11	0.18	0.03	-0.07	0.07
				(1.12)	(1.64)

Panel B. Comparison of loan choices

Variable:	Group 1 (*N*=65)	Group 2 (*N*=56)	Group 3 (*N*=61)	Diff (1)-(2)	Diff (1)-(3)
Interface	Original	Smaller interest	Larger credit		
Interest Rate (%)	17.32	16.86	16.53	0.47	0.80**
				(1.21)	(2.27)
HR	0.63	0.54	0.48	0.10	0.16*
				(1.06)	(1.76)
Default	0.31	0.25	0.10	0.06	0.21***
				(0.70)	(2.98)
IRR (%)	15.17	15.11	15.84	0.06	-0.67**
				(0.19)	(-2.13)
Amount	12,492	11,857	13, 541	635	-1,049
				(0.51)	(-0.75)
Term	14.35	16.13	16.03	-1.77	-1.68
				(-1.20)	(-1.07)
DecisionTime (seconds)	117.11	148.54	152.35	-31.43*	-35.25**
				(-1.74)	(-2.22)

Table 9. Experience and investment choices

Panel A reports the summary statistics of the main variables. $CumBid_{it}$ is the total number of bids investor i has made through the end of day t. $Default3M_{it}$ is a dummy variable, which equals 1 if investor i has invested in a loan that defaulted in the previous 3 months, and 0 otherwise. $DecisionTime_{it}$ is the duration between the time when a loan is listed and the time when investor i bids to invest in the loan during week t. If an investor bids on multiple loans during week t, we use the principal-weighted average as the decision time. Panel B reports the results of regressions of various dependent variables on *CumBid* and *DecisionTime*. All continuous variables are winsorized at the 1st and 99th percentiles. Standard errors are clustered by week. T-statistics are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Summary statistics

Variable:	No. of Obs.	Mean	S.D.	*p*1	*p*10	*p*25	*p*50	*p*75	*p*90	*p*99
CumBid	114,975	50.34	106.56	1	1	3	11	43	141	629
Default3M	114,975	0.252	0.434	0	0	0	0	1	1	1
DecisionTime (seconds)	114,975	635	2,771	9	21	38	93	300	1,055	12,451
InterestRate (%)	114,975	12.703	1.542	10	11	11.98	13	13	15	18
HR	114,975	0.524	0.462	0	0	0	0.6	1	1	1
IRR-CD rate (%)	114,975	8.647	3.211	-0.46	4.56	7.91	9.18	10.20	11.57	15.20

Panel B. Firsthand experience in default and loan choices

Dependent variable:	*Decision Time*	*Decision Time*	*Interest Rate*	*Interest Rate*	*HR*	*HR*	*IRR-CD rate*	*IRR-CD rate*
CumBid	1.080**	0.900**	0.001***	0.001**	-0.000	0.000	0.001	-0.000
	(2.45)	(2.26)	(2.80)	(2.60)	(-0.96)	(0.08)	(1.00)	(-0.20)
Default3M		79.216**		0.035**		-0.031***		0.280***
		(2.21)		(2.18)		(-6.30)		(6.42)
Constant	984.354***	982.488***	13.288***	13.287***	0.271***	0.272***	10.138***	10.132***
	(10.10)	(10.05)	(603.02)	(604.41)	(36.81)	(36.78)	(315.68)	(302.36)
No. of Obs.	114,975	114,975	114,975	114,975	114,975	114,975	114,975	114,975
R-squared	0.435	0.435	0.497	0.497	0.391	0.391	0.451	0.452
Investor fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 10. Experiment on learning

We recruited 68 undergraduate students from various departments and majors at Tsinghua University on June 23, 2018. They were randomly divided into two groups of 34. All subjects went through the same training session, described in Section IV.B, and participated in two rounds of investment decisions. During each round, all subjects were shown the same five loans and asked to select one. After the first-round choices, the outcomes of all five loans (i.e., their realized cash flows) were announced to the subjects in the treatment group, but not those in the control group. Then, all subjects were shown another five loans and asked to select one. After the second round of selections, we surveyed the subjects in the treatment group by asking the following questions:

1. Which of the following factors do you value most when you make investment decisions?

A. Interest Rate; B. Term; C. Amount; D. Credit Rating; E. Others.

2. Please rate the extent to which you rely on intuition in making lending decisions on a scale of 1 to 7, where 1 indicates the lowest possible reliance on intuition and 7 indicates the highest possible reliance on intuition.

In the control group, we asked participants the same questions after they made the first round of selections and before their second round of selections. Panel A contrasts the survey results across the treatment and control groups. Panel B reports the estimates of the regressions of the treatment group's survey results on *Default*, which equals one if the loan selected by a subject in the first round defaults and zero otherwise. In column (1), the dependent variable is the intuition score. In columns (2), the dependent variable is a dummy variable, which equals one if a subject chooses credit rating as the most valued factor and zero otherwise. The dependent variables in columns (3) though (5) are also dummy variables and are similarly defined. Panel C reports the estimates of the regressions of the treatment group's loan choices on *Default*. The dependent variables are labeled at the top of each column. T-statistics are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Comparison of the survey results across the treatment and control groups

Variable:	Treatment group (*N*=34)	Control group (*N*=34)	Diff (Treatment - control)
Interest Rate (%)	23.53	50.00	-26.47**
			(2.32)
Credit Rating (%)	44.12	20.59	23.53**
			(2.11)
Intuition Score	3.41	4.41	-1.00***
			(2.85)
Term (%)	8.82	17.65	-8.82
			(1.07)
Amount (%)	20.59	11.76	8.82
			(0.98)
Others (%)	2.94	2.94	0
			(0.00)

Table 10 Panel B. Survey results and default experience for the treatment group

Dependent variable:	*Intuition Score* (1)	*Credit Rating* (2)	*Interest Rate* (3)	*Term* (4)	*Amount* (5)
Default	-1.164**	0.458**	-0.320*	0.031	-0.129
	(2.41)	(2.52)	(2.00)	(0.27)	(0.80)
Constant	3.720***	0.320***	0.320***	0.080	0.240***
	(14.991)	(3.422)	(3.881)	(1.370)	(2.908)
No. of Obs.	34	34	34	34	34
R-squared	0.154	0.165	0.111	0.002	0.020

Panel C. Loan choices and default experience for the treatment group

Dependent variable:	*Decision Time* (1)	*HR* (2)	*Interest Rate* (3)	*IRR* (4)	*Term* (5)	*Amount* (6)
Default	44.35***	-0.44**	-1.80**	0.16	5.24	-1,546.67
	(3.64)	(-2.58)	(-2.37)	(0.32)	(-1.47)	(-0.72)
Constant	87.320***	0.440***	16.800***	14.837***	11.760***	9,880.000***
	(13.95)	(5.01)	(43.02)	(56.27)	(6.40)	(8.93)
No. of Obs.	34	34	34	34	34	34
R-squared	0.293	0.172	0.149	0.003	0.063	0.016