Investment under Fast-Thinking*

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This Draft: June 15, 2018

* We would like to thank Nick Barberis, Yunling Chen, Phil Dybvig, Kewei Hou, HyunJoong Im, Daniel Kim, Mingfeng Lin, Lin Peng, Alessandro Previtero, Noah Stoffman, Baolian Wang, Chunyang Wang, and Bin Zhao, conference participants at the CFRC, and the Finance Research and Practice Forum at Guanghua; the WFA-CFAR and JFI Conference (2017); and seminar participants at Indiana University, Peking University HSBC Business School, Peking University Guanghua School of Management, Southwest University of Finance and Economics, and Tsinghua University, SEM for helpful comments and discussions. We thank Hannah Bolte and Katerina Manoff for their editorial help. Please send all correspondences to Jun Yang, 1309 E 10th Street, Bloomington, IN 47405, tel: 812-855-3395.

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Abstract

Using data from a major online peer-to-peer (P2P) lending market, we document that investors appear to follow a simple rule of thumb: they rush to loans with high interest rates without sufficiently examining other information (e.g., borrower's credit rating), which is freely available on the interface. For example, on average, loans with a "High Risk" rating underperform other loans by over 1% per year. Through experiments, we show that by making credit rating information more salient, we can "nudge" investors into paying more attention to ratings and hence improve their investment returns. Finally, *first-hand experience* matters for learning: After a recent default of his own loan, an investor tends to increase his decision time, avoid loans with "High Risk" ratings, and hence obtain higher returns. In contrast, after observing *others* experiencing a default, the effects are significantly smaller or negligible.

JEL Classification Numbers: G12.

Keywords: Rule of thumb, nudge, first-hand experience, P2P, fast-thinking.

I. Introduction

The last four decades have witnessed significant progress in the theory of judgement and decision making. One prominent insight in this literature is the so called two-system approach to judgement and choice. 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, deliberate and allocates attention to the effortful mental activities. Under this view, both systems are active whenever we are awake but our decisions are mostly influenced by System 1. System 2, usually in the inactive mode, only starts to contribute to the decision process when System 1 runs into difficulty. For convenience, we use "fast-thinking" to refer to decision making under System 1, and "slow-thinking" to refer to decision making under System 2.

While this view suggests that fast-thinking influences most of our everyday decision making, existing studies have been primarily conducted based on experiments. It is an open question how much fast-thinking determines decisions in real financial markets. How do investors make financial decisions under fast-thinking? Can we modify the environment to influence investors' decisions under fast-thinking? How do investors learn when they primarily rely on fast-thinking? The greatest challenge for answering these questions is identifying a financial market, where investors must make quick decisions, and we can reliably measure the decision time and 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. The following three features make this market an ideal setup for analyzing investments under 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, the loans on this platform were generally highly appealing and were usually sold out quickly. For example, 25% of the loans listed on Renrendai are fulfilled within 42 seconds and 90% are fulfilled in under eight minutes. Second, Renrendai keeps the time stamps of the transactions, allowing us to measure investors'

decision time. Third, this is a sizeable market with a long sample period. Our main sample contains 10,385 loans and 205,724 transactions, and the cumulative amount of loans in our sample is over $100 million. Our sample spans two years and four months, which not only allows us to track the ex post performances of the loans, but also enables us to analyze investors' learning under this fast-thinking environment. Our findings are the following.

First, our evidence suggests that, under pressure to make quick decisions, investors rush to loans with high interest rates, but appear not responsive to borrower's credit rating, which is listed close to interest rate on the interface. Specifically, we find that, all else being 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 (the time from a loan being listed to being fully funded) by 57%. In contrast, there is no significant relation between the fulfillment time and credit ratings.

Second, although focusing on interest rate is a sensible strategy for this market, incorporating the information in credit ratings can significantly improve investment returns. As will be discussed in detail in Section II, Renrendai guarantees to repay investors the outstanding principal of a loan if the borrower fails to make a monthly payment. This principal guarantee, which is widely considered credible, significantly limits investors' exposure to borrowers' credit risk. Hence, from investors' perspective, their investment returns and the offered interest rates are highly correlated. In the presence of time pressure, it is sensible to primarily focus on interest rate. Nevertheless, we find that credit rating can help improve investment returns. For example, on average, loans with a "High Risk" (HR) rating underperform other loans by over 1% per year.

Third, our interpretation of the above two results is that due to time pressure, a sensible response is to rely on interest rate, which is salient, and highly relevant for performance because of the principal guarantee mechanism. This interpretation implies that when time pressure is stronger, investors would rely more on interest rate. We test this prediction empirically, as well as experimentally. Empirically, our quantile regressions show that for "faster" loans, their fulfillment time is even more sensitive to interest rate. That is, when time pressure is stronger, investors would rely on interest rate even more heavily. To further examine the *causal* relation

between fast-thinking and the reliance on interest rate, we conduct a controlled experiment, where the subjects of the treatment group face time pressure when making their investment choices. We find that, relative to the subjects in the control group who face no time pressure, those in the treatment group are more likely to choose loans with higher interest rates, and hence are more exposed to riskier loans and have more defaults.

Fourth, our interpretation also implies that one might be able to "nudge" investors into better decisions by making credit rating information more salient. Specifically, we modify the original interface at Renrendai by enlarging the fonts and changing the color of the credit rating information for the treatment group. Our experiments show that, relative to the subjects in the control group who face the original interface, those in the treatment group pay more attention to credit ratings, and are less likely to choose loans with HR ratings and have fewer defaults.

Fifth, *first-hand experience* matters for learning. Specifically, after a recent default of his own loan, an investor tends to increase his decision time and avoid selecting those with HR ratings, and hence obtains higher future returns. In contrast, after observing *others* experiencing a default, the effects are significantly smaller or negligible. That is, "participants" appear to learn more from loan defaults than do "observers."

Why do participants and observers learn differently? Potential explanations include wealth effect (i.e., participants, not observers, experience a negative wealth shock from the default), selection effect (i.e., individuals with low ability might stop investing after suffering a default), and inattention (i.e., investors may pay more attention to the default of their own loans). However, we show that similar results arise in our controlled experiment, where these three effects are absent or negligible. Hence, we conjecture that there might be different psychological reactions between participants and observers. Confronted with a default of one of their loans, participants are more responsive in reexamining their decision processes, and consequently improve their future decisions. After witnessing a default of others' loans, however, investors are less eager to reexamine their decision processes and hence are less responsive. That is, first-hand experience matters!

Our research contributes to the psychology and economics literature on cognitive biases. Kahneman and Tversky (1974) established the foundation for studies of heuristics and biases. However, studies of decision biases under fast-thinking in a real-world setting have been rare due to the inherent challenges of measuring decision time.[1] To our knowledge, we are the first to investigate the effect of fast-thinking on financial investment decisions.

Our paper also adds to the literature of learning from experience. One intriguing recent finding is that rather than forming expectations based on all available data, people seem to rely more on the data they "experienced" during their life time (Malmendier and Nagel, 2011, 2016).[2] Our paper adds to this insight by showing that participants and observers respond differently even if they observe the same data. That is, first-hand experience matters!

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 certain details—usually those that are most salient (Benartzi and Lehrer, 2015). For example, 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 predicts future stock returns. Investors underreact more to earnings surprises when they are distracted, e.g., when the 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 due to the time pressure, investors fixate on interest rate and ignore valuable information that is freely available on the interface.

Our paper adds to the literature based on the idea of nudging, which is studied in Thaler and Benartzi (2004) and popularized in (Thaler and Sunstein, 2008). Reutskaja, Nagel, Camerer,

[1] In a recent study, Heller, Shah, Guryan, Ludwig, Mullainathan, and Pollack (2017) carried 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. This reduced the rates of arrests and readmission to jail, and improved school engagement and graduation rates.

[2] A growing number of studies have analyzed the effect of experience on the expectations on and investments in technology stocks (e.g., VissingJorgensen (2003), Greenwood and Nagel (2009)), CEO decisions, (e.,g., Malmendier and Tate (2005), Malmendier, Tate, and Yan (2011)), IPO investments (Kaustia and Knupfer (2008) and Chiang, Hirshleifer, Qian, and Sherman (2011)) and policy making (Malmendier, Nagel, and Yan, (2017)). The experience effect has been analyzed theoretically in Ehling, Graniero, and Heyerdahl-Larsen (2018) and Malmendier, Pouzo and Vanasco (2018).

and Rangel (2011) show that individuals tend to pay attention to subjects (snacks) located in certain areas of the screen (the top left one in a two by two arrangement, and the middle one in a three by three arrangement). Milosavljevic, Navalpakkam, Koch, and Rangel (2012) show that a subtle change in visual prominence of an item can have a big impact on the choice. In our context, by increasing the salience of the credit rating information, one can nudge investors to pay more attention to credit risk and improve their decisions.

Finally, our paper belongs to 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. For example, 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. Zhang and Liu (2012) show rational herding among Prosper investors. Investigating the behavioral biases of P2P investors, Lin and Viswanathan (2015) find evidence of home biases that cannot be fully explained by rational models. Pope and Sydnor (2011), Revina (2008), and Duarte, Siegel, and Young (2012) show the roles of racial bias, the beauty premium, and trust in P2P lending decisions.

In an increasingly digitized world, many financial decisions, including equity investments and portfolio choices for retirement, are made with a few swipes of the thumb. The sheer amount and speed of information may overwhelm investors, leading them to ignore details that are important for decision-making. Our study shows that relying on System 1, individual investors pay excessive attention to salient interest rates, rushing to loans with higher rates and ignoring their higher default risks. It sheds light on investors' behavioral biases in a context of limited time and attention. Our results can help investors avoid the trap of fast-thinking and improve the quality of their investment decisions.

The remainder of the paper is organized as follows. Section II describes the institutional background and develops our main hypotheses. Section III analyzes the investment decisions

under fast-thinking. Section IV and V examine the role of time pressure and salience, respectively. Learning is analyzed in Section VI and Section VII concludes.

II. Institutional Background and Hypotheses

A. Institutional background

Our main data are 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 from the Chinese Academy of Social Sciences, the highest rating for P2P lending platforms. We focus on credit loans, which have no collateral, and comprise 76% of all loans made on Renrendai during our sample period. The cumulative amount of credit loans on Renrendai as of September 2016 was over $100 million.

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,[3] and ratings increase with the number of optional documents submitted, including home deed, car title, marriage certificate, diploma, cellphone number, Weibo account (the 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.[4]

Potential borrowers on Renrendai submit loan applications, specifying the requested amount, maturity (time to maturity), 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

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

[4] 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.

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 its platform, and can be viewed by all potentially investors. Each listing includes its 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 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 the timing of each loan's funding process to the seconds, which is not feasible at other P2P lending platforms, such as Prosper.com.

B. Hypothesis

Renrendai is an ideal setup for studying financial decision making under fast-thinking. First, investors are under pressure to make quick decisions. This is because that bank deposit rates in China are highly regulated and are kept artificially low (see, e.g., Lardy (2008)). Hence, the P2P leaning market, if organized properly to reduce borrowers' credit risk, is quite appealing to many

households. Indeed, in our sample, more than 90% of the loans are fully funded within eight minutes after they are listed on Renrendai. Moreover, loans are not observable until they are publically listed. Hence, investors have a short time window to make decisions.[5]

Second, Renrendai guarantees to repay investors the outstanding principal of a loan within 31 days of the due date if a borrower fails to make a monthly payment. This guarantee is considered credible because Renrendai not only has a top 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.

Due to these two features, investors are likely to rely on System 1 in their decision making. The principal guarantee significantly limits lenders' exposure to borrowers' credit risk, making elaborate analysis less important. Combined with time pressure, this implies that investors may follow a simple rule of thumb, rather than going through thorough analysis, when making decisions.

Given the time pressure for decisions, which variable would investors focus on? A natural conjecture is perhaps interest rate. Due to the principal guarantee, investment returns and the interest rates are expected to be 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. Moreover, as shown in Figure 1, the display of interest rate on the interface is quite prominent: at the top of the screen, in large fonts. This may further attract investors' attention.

[5] 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 the credit rating of a borrower and the borrower determines the interest rate, while Prosper determines the interest rate for loans from the borrowers with the same credit rating (starting from 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.

On the other hand, we conjecture that investors may pay insufficient attention to other variables in the loan contracts, such as credit rating. There are two reasons. First, due to the principal guarantee, investors are not subject to the loss of principal. Given the insight in Kahneman and Tversky (1979), this feature is especially appealing to investors with loss aversion, making analyzing credit risk less important. Second, this hypothesis is also motivated by the fact that, as shown in Figure 1, credit rating is displayed in small fonts at a much less prominent place on the interface. In summary, our hypothesis is that given the pressure to make decisions quickly, investors may follow a simple rule of thumb rather than conducting comprehensive analysis: their attention gravitates towards interest rate and they may pay insufficient attention to other variables such as borrowers' credit ratings.

Another issue that we can analyze is learning when decisions are mostly based on System 1. How do investors learn in this environment? One important insight 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 available data, people seem to rely more on the data they "experienced" during their life time. Our dataset allows us to shed new light on this insight by distinguishing experience into two types: "experience as observers" vs. "experience as participants."

More specifically, when a borrower defaults on a loan, investors may have two different types of experiences. The first is the experience by participating. These investors have invested in the loan, and so suffer a loss from this default. We refer to this as "first-hand experience." The second type is the experience by observing. These investors observe the default but have no position in this loan. Do these two types of experiences affect investors' behavior differently? Our dataset makes it possible to track each investor's experience and subsequent investments to address this question.

III. Investment Decisions Under fast-thinking

A. Data

We extract data from Renrendai on March 10, 2016. Our main sample is from September 1, 2012 to December 31, 2014. We exclude loans originated before September 1, 2012 in our main sample, since 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 investors, 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. Loan Maturity 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 the 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 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

As expected, due to the low bank deposit rates, investors find these 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 as a "fast loan" if its *FulfillmentTime* is less than 42 seconds, the 25th percentile of the *FulfillmentTime* in our sample.

The funding process has accelerated during our sample period; that is, the distribution of the *FulfillmentTime* shifts to the right 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 all other loans and report the results in Panel B of Table 1.

On average, fast loans offer higher interest rates (13.71% vs. 12.36%), are smaller (13,873 vs. 29,299RMB), and have similar Maturity (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 (31.31 vs. 33.43 years). Fast loan borrowers are less likely to be employed for more than three years. Their monthly income tends to be lower on average. Fast loan borrowers are also less likely to own a house or a car. Overall, fast loans appear riskier than other loans.

C. Gravitation towards interest rate

Our conjecture is that investors primarily focus on the interest rates offered in the loan contracts and rush to high-interest-rate loans without sufficiently examining other information, such as the borrower's credit risk. As the first step to examine this conjecture, we test if 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*, where *FulfillmentTime* is the number of seconds it takes for the loan to be fully funded and *Interest Rate* is the interest rate offered in the loan contract. We cluster standard errors by week, and include 12 verification fixed effects, week fixed effects, day-of-the-week, 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 of *Interest Rate* is -0.206, with a *t*-statistic of over 19. Hence, a one-standard-deviation increase in the interest rate reduces the *FulfillmentTime* by 57%. For example, a loan with a median *FulfillmentTime* (80 seconds), a one standard deviation increase in interest rate reduces the *FulfillmentTime* to 34 seconds. In contrast, the coefficient estimate of

HR is -0.036 (t=1.28). That is, the coefficient is insignificantly different from zero. Moreover, if investors' response to credit rating is to avoid loans with *HR* ratings, this coefficient should be positive, rather negative.

Some of the control variables are worth mentioning. Naturally, loans with a larger amount take longer to fund. To control for potential non-linear effect, we include both *Ln(amount)* and the square of *Ln(amount)* as control variables. The coefficient of *Maturity* is 0.026 (t=3.57), suggesting that loans with longer maturities take longer to be funded. Interestingly, it appears that investors also respond to some borrower's characteristics. For example, the coefficient of *MasterOrHigher* is -0.13 (t=3.10), suggesting that if a borrower has a master or higher degree, her loans are funded more quickly. Similarly, loans from borrowers who have higher income 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 bond should be strongly positively related to the interest rate. Hence, it is sensible that investors' attention gravitates towards interest rate. To examine this, we measure the performance of a loan by *IRR – CD Rate*, where *IRR* is the realized internal rate of return of the loan and *CD Rate* is the rate of return for bank deposit with a maturity that is the closest to the loan maturity. *IRR* can be computed from

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

where *Principal* is the loan amount, *T* the time to maturity and $Repayment_t$ the realized cash flow at time *t*, which may be scheduled payment, 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, a credit rating dummy *HR*, which is 1 if the loan is rated as "high risk" and 0 otherwise, as well as 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 points increase in *IRR – CD Rate*.

This evidence suggests that when under pressure to make quick decisions, it is sensible for investors to follow a simple rule of thumb and heavily rely on interest rate. However, do investors miss important information that is relevant for performance? We analyze this in the next section.

D.2 Loan return, credit rating, and other characteristics

Consistent with the hypothesis that investors pay insufficient attention to the credit rating, we find that after controlling for interest rate, *HR* is negatively related with 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 returns of loans with *HR* rating are lower by 1.109% on average. This is surprising since one might have expected that *HR* loans are riskier and should offer higher average returns. However, this is consistent with the interpretation that investors do not pay enough attention to the information in rating, i.e., they simply pick up loans with high interest rate, which tend to have *HR* ratings, and do not realize that *HR* loans are risker than they think, and have lower *ex post* average returns.

Somewhat surprisingly, loan performances appear correlated with some other variables that are easily observable. For example, *IRR – CD Rate* is strongly negatively correlated with the loan maturity. As shown in column (1), the coefficient of *Maturity* is -0.106 (t=21.05). Note that since there is no secondary market for investors to resell their loans. One would have thought that the investment in loans with longer maturity is less liquid and should command higher average returns. Instead, loans with longer maturities have lower average returns in our sample. *IRR – CD Rate* is strongly negatively correlated with the loan amount. For example, in column (4), the coefficient of *Ln(Amount)* is -0.297 (t=8.08). This evidence is surprising since it is after controlling for interest rate, loan characteristics and borrower's credit rating and other

characteristics. *IRR – CD Rate* is also strongly correlated with borrowers' characteristics, even after controlling for both interest rate and borrower's credit rating. We find that loans to female borrowers, younger borrowers, and borrowers with college degrees perform better. Loans to borrowers with higher monthly income, home mortgage, and loans to car owners tend to perform better. We also include verification fixed effects in column (2), and the results remain very similar to those in column (1).

D.3 Loan default

We now examine if credit rating indeed predicts future default even after controlling for interest rate. Specifically, we create a $Default_{it}$ dummy variable, which is 1 if a loan *i* defaults on day *t* and run a Cox proportional hazards model where independent variables are the same as those in Table 3. As shown 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, *HR* rating still predicts higher default likelihood. 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, for example, avoiding *HR* loans.

Consistent with the results reported in Table 3, we find that larger loans and loans with longer maturity are more likely to default. In addition, loans to male borrowers, older borrowers, and borrowers without college degrees are more likely to default. Loans to borrowers with shorter than five years employment and higher self-reported income are more likely to default. Finally, loans to borrowers with a house but without mortgage, and loans to borrowers without a car are more likely to default. We also include verification fixed effects in column (2), and the results remain very similar to those in column (1).

These results are consistent with the interpretation that investors fail to fully appreciate the information contained in borrower characteristics. Interestingly, it appears that Renrendai also fails to fully incorporate the information in borrower characteristics into their rating. That is, these borrowers' 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 rating and other loan and borrower characteristics are not incorporated into the prices of the loans (i.e., the interest rates). To further examine this, we estimate the gains an investor can achieve if he pays more attention to those variables. Our analysis below focuses on credit rating.

Specifically, for each week, we calculate the principal-amount-weighted average of *IRR – CD Rate* for HR loans and non-HR loans. We then calculate the time series average of *IRR – CD Rate* for HR and non-HR loans, and their difference. 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 estimate of the coefficient of *HR* in Table 3. Our interpretation is that investors pay insufficient attention to the credit rating, and are surprised by the higher than anticipated default rate. In other words, had investors paid attention to credit ratings, they could have increased their investment returns.

Our interpretation that investors paid insufficient attention to credit ratings also implies that the performance difference between *HR* and non-*HR* loans should be larger for loans with higher interest rates. This is because that, in the event of default, investors only lose the interest payment due to the principal guarantee. Hence, the higher the interest rate, the bigger the consequences is from neglecting the information in credit ratings. Therefore, the performance difference between *HR* and non-*HR* loans is larger when the interest rate of the loan is higher.

To test this prediction, for each week, we sort loans by interest rate into 5 quintiles. Then, for each quintile, we calculate the value-weighted average of (*IRR – CD Rate*) for *HR* loans and non-*HR* loans. Finally, we calculate, for each quintile, the time series average of *IRR – CD Rate* for *HR* and non-*HR* loans, and their differences. The results are reported in rows 2 through 6 in Table 4. The underperformance of *HR* loans is highly significant for all quintiles, and the magnitude of underperformance increases almost monotonically with interest rate, ranging from 0.669% to 1.301%.

IV. Time Pressure

The previous evidence is consistent with the interpretation that due to time pressure, investors follow a simple rule of thumb to rely on interest rate to make quick decisions. This interpretation also implies that when time pressure is stronger, investors would rely more on interest rate. In Section IV.A, we show that, indeed, for faster loans, their *FulfillmentTime* is more sensitive to interest rate. 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 due to time pressure, subjects choose loans with higher interest rate, and also expose themselves to higher default risk.

A. Empirical evidence

Our hypothesis implies that for fast loans, their *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 we obtain the conditional expected value of the dependent variable from an OLS regression, but obtain the conditional quantile-τ value of the dependent variable for a quantile-τ regression, for $\tau \in (0,1)$.[6] Our interpretation 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 have to rely more on a rule of thumb and are thus more responsive to interest rate. Hence, the *FulfillmentTime* is more sensitive to interest rate for faster loans.

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 of *Interest Rate* is negative and significant at the 1% level for all quantile regressions. Moreover, the absolute value of the coefficient estimate of *Interest Rate* decreases monotonically in τ. The coefficient estimate of *Interest Rate* is -0.220 for the 10th quantile, -0.199 for the 25th quantile, -

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

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 of *Interest Rate* against quantile-τ in Figure 2. The horizontal axis is quantile τ. The vertical axis is the coefficient estimate of *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 of *Interest Rate* from quantile regressions, and the grey region is the 95% confidence interval for the coefficient estimate. It shows that the coefficient estimate of *Interest Rate* increases gradually (becoming less negative) as *Ln(FulfillmentTime)* moves from 5th to 95th percentiles. This is consistent with the interpretation that when investors make decisions more quickly, they focus even 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., maturity, income, education, and homeownership), their coefficients in quantile regressions do *not* imply that *Ln(FulfillmentTime)* is more sensitive to those variables for smaller 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 effect of time pressure on investors' focus on interest rate, we conduct the following experiment on January 15, 2017. We recruit 60 subjects from a first-year graduate class at the People's Bank of China School of Finance (PBCSF), Tsinghua University. Their task is to select one out of five loans to invest. Those five loans are chosen from the loans listed on November 4, 2013, an arbitrary day in the middle of our sample period. There were 16 loans listed on November 4, 2013. Among those loans, 10 have the *HR* rating, two of which ended up in default. We randomly chose three HR loans, one of which ended up in default. We then randomly chose two non-*HR* loans that were fully repaid. That is, three out of the five loans have the *HR* rating, and one out of the five

defaults. Both statistics are comparable to those for our sample. Details of these five loans are reported in Panel A of Table 6.

Before making their choices, all 60 subjects went through the same training session. Specifically, they were provided with the institutional background of Renrendai and 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 are randomly selected from the 194 loans listed on Renrendai in that 30-day window. There were two screenshots of each loan, the first one was the basic information of the loan and the borrower, and the second one was the repayment information of the loan. All subjects were given 30 minutes to study these 50 loans. They were encouraged to summarize the relationship between the loan information and repayment information. 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.

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 make investment decisions in different rooms.

Facing the time pressure, participants in the treatment group are more likely to resort to a simple rule of thumb. Given the principal guarantee, participants in the treatment group are more likely to focus on interest rate. Indeed, as shown in Panel B of Table 6, the average interest rate of the loans chosen by the treatment group is 16.27%, while that for the control group is 15.07%. The difference is 1.20%, with a t-statistics of 3.02. Since loans with high interest rates tend to be those with *HR* ratings, participants in the treatment are more likely choosing *HR* loans. In fact, 27% of the loans chosen by the treatment group have an *HR* rating. In contrast, only 7% of the loans chosen by the control group are *HR* loans. The t-statistic for the difference between the two values is 2.12. Naturally, the treatment group participants are more likely to incur default: 23.3%

of the loans chosen by the treatment group default. In contrast, there is no default for the loans chosen by the participants in the control group in this experiment. As a comparison, the last two rows report the results on maturity and loan size, and show that time pressure has no significant effect on investors' preference for maturity and loan size.

That is, when investors are under time pressure to make decisions, they are more likely to focus on interest rate. They choose loans with higher interest rate, and so expose themselves to higher default risk.

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 the mobile app that changed the relative salience of the information on the interface. To establish the causal relation and analyze the potential to nudge investors to making better decisions, we conduct experiments in Section V.B.

A. Empirical evidence: Mobile apps

On July 30, 2014, Renrendai launched its mobile app, which enabled people 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 updated funding status of "99% Funded" shown on the screen could press investors to act fast. Interestingly, the credit rating of the borrower is not shown at all, making credit rating invisible.

The introduction of the mobile app can be considered a shock to investors' information environment. How would this 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 borrowers' information such as credit rating, the mobile interface would further encourage investors to make quick decisions based on interest rate. The hypothesis has two predictions. First, mobile-based investors would make decisions more quickly than computer-based investors. Second, loans with higher interest rates would 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 the decision time for investing in loan j (from the time the loan is listed to the time of the investor's bid), $Mobile_{ij}$ is a dummy variable, which is 1 if investor i's bid to loan j is through a 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 14.6% 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 due to selection: investors who tend to bid more quickly might have a higher likelihood to adopt the mobile app. To partially address this selection issue, we include bidder 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 for the same investor, he or she tends to bid 10.1% more quickly when using the mobile app. Moreover, we repeat this analysis on the restricted sample where all investors have bid through both the mobile and PC interfaces during our sample period. As shown in columns three and four, in both specifications, mobile app is associated with faster decisions. These results alleviate some concerns about the selection issue, but cannot completely rule it out.[7] Hence, Section V.B, we conduct a controlled experiment to examine the casual effect of salience on investors' decisions.

To test the second prediction, for each loan, we construct a variable $MobileProportion_i$, which is the fraction of the investment in loan i that is from the mobile app. We then regress it on interest rate, *HR*, as well as the control variables. As shown in Panel B, the coefficient of interest

[7] The specification with bidder fixed effects addresses the concern that fast-decision investors 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 prefers to use PC (the mobile app) if he/she makes slow (quick) decisions.

rate is 0.680 (t=3.31). This is consistent with our interpretation that, mobile investors pay more attention to interest rates.[8] In contrast, the coefficient of *HR* is statistically insignificant.

B. Experimental evidence: Nudging

Our evidence in Tables 3 shows that ignoring the information in credit rating is quite costly. A natural question is: can we nudge investors to improve their decisions? One potential answer is to make credit rating information more prominent on the interface, such that investors might pay more attention to it and adjust their decisions accordingly. This is motivated by the evidence in the previous section, which is consistent with the interpretation that mobile investors, facing an interface where interest rate is shown more prominently, are even more fixated to interest rate. In this section, we conduct controlled experiments to examine whether the interface can indeed nudge investors to pay more attention to credit ratings.

In order to obtain a sufficient sample size, 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 on March 19, 2018. The procedures for the two rounds of experiments are kept the same.

For each round of experiment, subjects were divided randomly into three groups. The training session is the same as in Section IV.B, except that the screen shot for the loan information is presented differently across the 3 groups. For Group 1, the screenshot is original PC interface, as in Figure 4. For Group 2, we modified the original interface by reducing the font size of interest rate and moving it to a less prominent place, as shown in Figure 5. Finally, for Group 3, we modified the original interface by enlarging the font size of credit rating and 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 the same five loans as in the experiment in Section IV.B. For all subjects, the format of the interface of those five loans

[8] Since the mobile app was introduced in July 2014, towards the end of our main sample (Sept. 2012 to Dec. 2014), we extend the sample period to March 2016 in this regression. We can utilize the data during 2015–2016 because this regression does not need information on payment and default. 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.

matches to what they saw during the training session. That is, group-1 subjects face the original interface; interest rate is presented in a reduced font size at a less prominent position for group-2 subjects; and group-3 subjects face the interface with a credit rating in a larger font size in orange at a prominent position. To measure subjects' thinking process, we conduct the following survey at the end of the experiment.

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

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

Our hypothesis is that, relative to the control group (i.e., Group 1), Groups-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 interfaces prompt subjects to be less fixated on interest rate, and take into account of other variables.

Indeed, as shown in Panel A of Table 8, 39% of subjects in group 1 choose interest rate as the most important variable that they rely on for their decisions. Once interest rate is presented less prominently for Group-2 subjects, only 20% of them choose it as the most important variable for their decisions. The difference is 19%, with a t-statistic of 2.29. In contrast, the differences in attention to other variables (*HR*, *Amount* and *Maturity*) 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 is 17.32% while that by Group-2 subjects is 16.53%, although the difference between the two is statistically insignificant.

The effects on Group-3 subjects are much stronger. For example, as shown in Panel A, 23% of the subjects in Group-1 choose credit rating as the most important variables for their decisions. Once credit rating is highlighted prominently on the interface, 48% of them state that credit rating is the most important variable for their decisions. The difference is 25%, with a t-statistic of 2.96. This difference is clearly reflected in their loan choices and performances. As shown in Panel B, 63% of the loans chosen by Group-1 subjects have the *HR* rating, but only 48% of the loans chosen by Group-3 subjects have the *HR* rating. The t-statistic for the difference is 1.76. By avoiding loans with *HR* ratings, Group-3 subjects chose loans with slightly lower interest

rates. The average interest rate is 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 is much lower. While 31% of the loans chosen by Group 1 default, only 10% of the loans chosen by Group 3 default. The difference is 21% (t=2.98). That is, by simply highlighting credit rating on the interface, we can nudge subjects to pay more attention to credit rating, and reduce their exposure to default risk. Finally, the average decision time increases from 117.11 seconds for group 1 to 148.54 seconds for Group 2, and it further increases to 152.35 seconds for Group 3. This is also consistent with our hypothesis that when relevant information more visible, investors would slow down their decision process and try to incorporate it into their decisions.

VI. Learning under fast-thinking

In this fast-thinking environment, do investors learn and improve their decisions over time? Moreover, do investors learn differently when they observe the same data? The latter question is partly motivated by the recent intriguing findings in Malmendier and Nagel (2011, 2016) that rather than forming expectations based on all available data, people seem to rely more on the data they "experienced" during their life time. Hence, for the same data, two people respond differently because they were born in different cohorts and so form expectations based on different life-time experiences.

Our question is similar to the "cross-sectional counterpart" of the question analyzed in Malmendier and Nagel (2011, 2016). We want to examine whether a "participant" and an "observer" learn differently when they "experience" the same data, where the difference between a participant and an observer is whether they have a skin in the game. Specifically, observing the default of a loan, a participant (who has a position in the loan) may behave differently from an observer (who does not have a stake in the loan). In other words, we are interested in examining whether investors learn more from "first-hand" experience than from second-hand experience.

In Section VI.A., we examine these questions empirically, and find indeed that first-hand experience matters: participants learn more than observers. To further analyze those questions

and assess the potential explanations of 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 had until 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 an observer and a participant, we construct a dummy variable $Default3M_{it}$, which is 1 if investor *i* has invested in a loan that defaulted in the previous 3 months, and 0 otherwise. As shown in Panel A, it has a mean of around 0.25. $DecisionTime_{it}$ is the duration between the time when a loan is listed and the time when investor *i* bids to invest in the loan 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 invested 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. However, the magnitude of this effect is relatively small. On average, the experience of investing in an additional loan slows down the investor by 1.08 seconds.

Do participants learn differently from observers? That is, does an investor respond differently from a default of his loan and a default of someone else's loan? To test this, we include *Default3M* in the regression. As shown in the second column, its coefficient is 79.22 (*t*=2.21). That is, if an investor experienced a default of his loan, he would slow down by almost 80 seconds. Similarly, the third column shows that the coefficient of *CumBid* is 0.001 (t=2.80), suggesting that investors with more experiences tend to choose loans with higher interest rates. However, the magnitude is small. At the end of our sample, an average investor has invested in three loans, which means an increase of interest rate by 0.3 basis points.[9] On the other hand,

[9] 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 medium of this sample of *CumBid* is 15 and 3, respectively.

directly experiencing a recent default has a stronger effect on the investor's choices. As shown in column 4, the coefficient of *Default3M* is 0.035 (t=2.18). That is, the average interest rate of the loans chosen by investors who experienced default in the last 3 months is 3.5 basis points higher than the average interest rate of other loans. In the regression of *HR* on experience, as shown in columns 5, the coefficient of *CumBid* is insignificant. That is, on average, experience has a negligible effect on the choice of rating. Interestingly, a first-hand default experience has a much stronger effect. As shown in column 6, the coefficient of *Default3M* is -0.031 (t=-6.30), that is, the investors who 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 *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 a recent default increases an investor's return by 28 basis points per year.

In summary, our evidence suggests that, on average, experience has a small or negligible effect on investors' decisions. However, observers and participants appear to learn differently. After a first-hand experience of default, investors tend to significantly increase their decision time, choose loans with slightly higher interest rates while avoiding HR ratings, and receive higher future returns. In contrast, after observing others experiencing a default, the effects are significantly smaller or negligible. That is, the learning effects on participants are an order of magnitude larger than the learning effects on observers.

Why do participants learn differently from observers? First, one potential reason is wealth effect. A participant, not an observer, suffers a loss from the default. Hence, they may have different responses. However, this effect is unlikely to be significant because the loss from default is usually small. The mean and median bid size is RMB979 and RMB500. Moreover, with the principal guarantee, investors only lose interest payments, which are an order of magnitude smaller than the principals.

Second, the results might be due to a selection effect. After suffering from a default of his loans, the investors with low abilities may recognize it and choose to stop investing in future loans. As a result, the set of investors who choose to stay in the market after suffering from a default should have a higher average ability.[10] In principle, this selection effect can contribute to our result. But one might expect its magnitude to be small since, due to the principal guarantee, investors still have a profit even if their loans default, and so may have little incentive to exit the market. Moreover, as will be shown in the next section, in our experiment where this selection effect is absent, there is still a significant difference between observer learning and participant learning.

Third, one might attribute the results to inattention. If a defaulted loan is not in an investor's portfolio, it is likely that the investor would pay very little attention, if at all, to the default. Consequently, participants would respond more strongly than observers. While this interpretation is certainly feasible and might have contributed to the observed results, it is unlikely to explain the entire phenomenon. This is because, as will be shown in the next section, a similar phenomenon arises in our experiments, where all subjects are confronted with the outcome of all loans.

Finally, our conjecture is that there might different psychological reactions between participants and observers. Confronted with a default of one of their loans, participants are more responsive in reexamining their decision processes, and consequently improve their future decisions. After witnessing a default of others' loans, however, investors might be less eager to reexamine their decision process and hence are less responsive. That is, first-hand experience matters!

B. Experimental evidence

We recruited 60 undergraduate students from various departments and majors at Tsinghua University on June 10, 2017. All subjects went through a training session, which is the same as that in previous experiments. They are randomly divided into two groups of 30.

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

The subjects of the treatment group participated in two rounds of investments. In each round, subjects are asked to select one from five loans offered. The five loans for each round are chosen from those listed around November 4, 2017, such that there are three *HR* loans, one of which ends up in default. After subjects made their first-round choices, the outcomes of all five loans (i.e., their realized cash flows) were announced. Then, in the second round, subjects were shown another five loans and asked to choose one. After the second round of investment, we survey all subjects by asking the following questions:

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

   A. Interest Rate; B. Maturity; 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 pay their attention to, the second question is meant to estimate the extent to which the subjects make decisions based on System 1, i.e., rely on their intuition.

Our first test examines how experiences affect the way investors make decisions. Specifically, we test if investors focus on different variable across the two rounds of investments. Our surveys of the subjects of 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 outcome 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 the way subjects behave in the second round. Instead, we let the subjects of the control group go through the same training and investment decisions for the first round. Then, we survey them after they made their investment decisions but before they learned the outcome of the loans. Since subjects are randomly assigned to the treatment and control groups, the difference between the two surveys reflects the effect of

the investment experience. To avoid interference, experiments were conducted separately for the treatment group and the control group.

The comparison of the two surveys is reported in Panel A of Table 10. As shown in the first row, the percentage of subjects who select interest rate as the most important factor is substantially lower for the treatment group than for the control group (13.33% vs. 50.00%). The difference between the two is 36.67%, with a t-statistic of 3.27. 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 (66.67% vs. 23.33%). The t-statistic for the difference between the two percentages is 3.69.

Moreover, after observing loan performance, subjects appear to rely less on their intuition for their second round investment choices. The average score is 5.47/7 for the control group and 4.07/7 for the treatment group. The t-stat for the difference between the two average scores is 3.55. In contrast, as shown in the last three rows, the treatment and control groups do not have significantly different opinions about loan maturity, loan amount and other variables. In summary, consistent with our interpretation, participants pay more attention to credit ratings and less attention to interest rates after they gain more investment experience.

Our evidence in the previous section shows that observers and participants learn differently. That is, an investor who experiences a recent default would 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 the interpretations of our earlier empirical results.

In particular, we run cross-sectional regressions based on the survey data of the subjects of the treatment group. In the specification in column (1) of Panel B, the dependent variable is *Intuition Score* and the independent variable $Default_i$ is 1 if the loan chosen by investor *i* in the previous round defaults, and 0 otherwise. The coefficient of *Default* is -1.95 (t=3.50), suggesting that, relative to the investors who did *not* experience default in the first round, those who did

experience default rely less on their intuition when they choose their investment in the second round. In column (2), the dependent variable is *Credit Rating*$_{it}$, which is a dummy variable that is 1 if investor *i* chooses credit rating as the most important factor for his decision, and 0 otherwise. The coefficient of *Default* is 0.55 (t=3.49), suggesting that, relative to the investors who did *not* experience default in the first round, those who did are 55% 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 -0.40 (t=3.53), suggesting that, the subjects who experienced default in the first round are 40% 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 maturity and loan 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 choices of the subjects of the treatment group. The first column shows that relative to the investors who did not experience default in the first round, those who did spend an extra 37.15 seconds (t=2.69) to make their choices. Similarly, column (2) shows that subjects who experienced default in the first round are 45% less likely to choose loans with an *HR* rating. Since non-HR loans have lower interest rates, as shown in column 93), the average interest rate of the loans chosen by subjects who experienced default in the first round is 3.25% lower. The last two columns show that the effect is insignificant for maturity and marginally significant for loan amount.

These results not only corroborate our empirical evidence in the previous section, but also help narrow down their potential interpretations. Specifically, the wealth effect, selection effect, and inattention effect are either negligible or absent in our experimental setup. Finally, we conjecture that there might different psychological reactions between participants and observers. That is, first-hand experience matters! This adds to the literature on the effect of experience on belief formation. One intriguing finding in this literature is that rather than forming expectations based on all available data, people seem to rely more on the data they "experienced" during their life time (Malmendier and Nagel (2011, 2016)). Our evidence adds to this result by showing that

while investors learn from their experience as "observers," they appear to learn much more when they have a skin in the game, i.e., when they are participants.

VII. Conclusion

We have analyzed investment decisions under fast-thinking. In an online P2P lending market, under time pressure to make quick decisions, investors appear to focus mostly on interest rate without sufficiently examining other information such as credit rating. This simple rule of thumb is sensible since interest rate 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 are more under time pressure.

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

Finally, *first-hand experience* matters for learning: After a recent default of her loan, an investor tends to increase her decision time and avoids those loans with "High Risk" ratings, and hence obtains 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 wealth effect, selection effect, or attention. Our conjecture is that the psychological responses to first-hand experience are different from that to other experiences.

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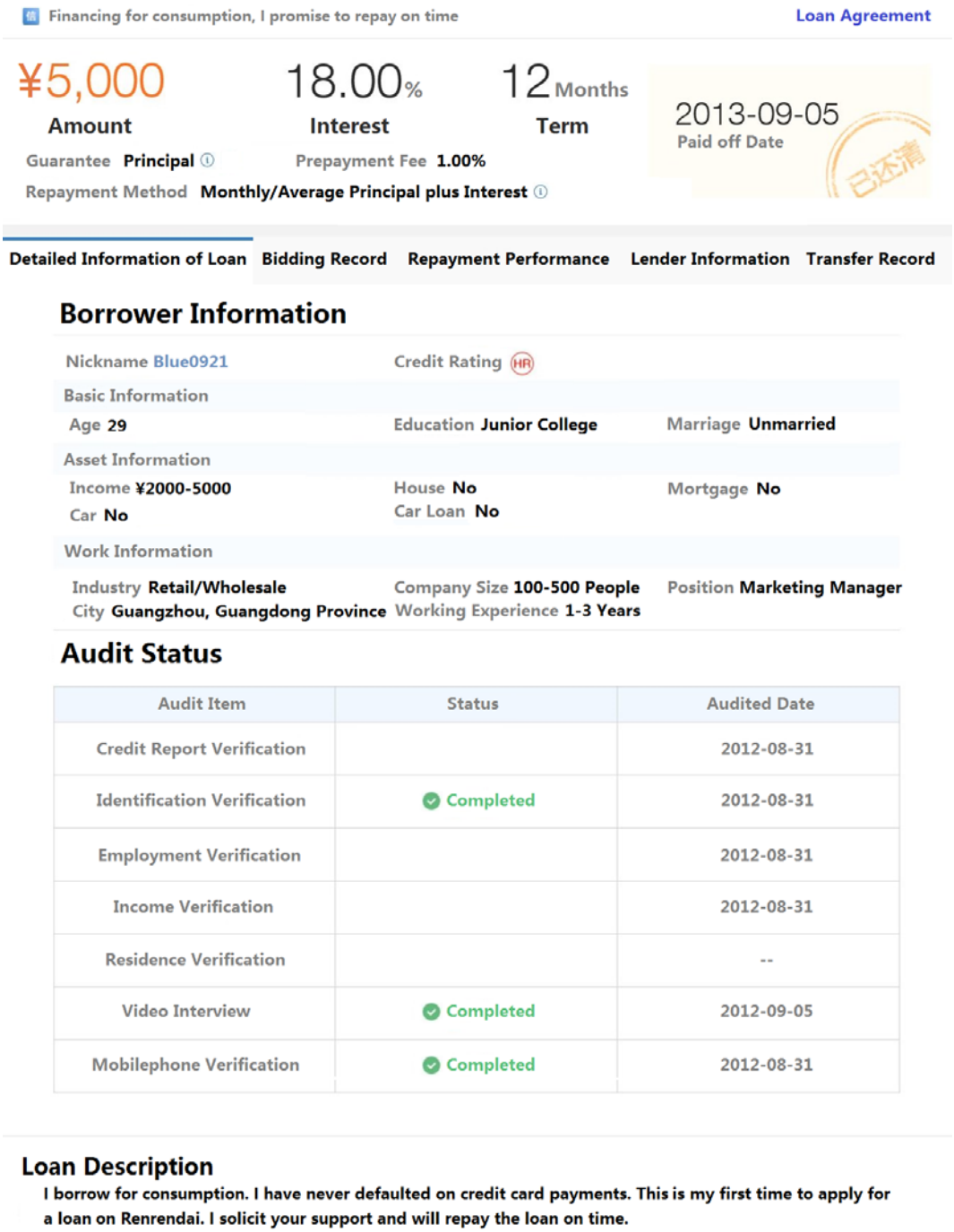
Figure 1. Computer screenshot of a sample loan



Financing for consumption, I promise to repay on time — Loan Agreement

¥5,000	18.00%	12 Months	2013-09-05
Amount	Interest	Term	Paid off Date

Guarantee **Principal** — Prepayment Fee **1.00%**

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

Detailed Information of Loan | 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 of *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 of *Interest Rate* from quantile regressions and the grey region is the 95% confidence interval for the coefficient estimate of *Interest Rate*.

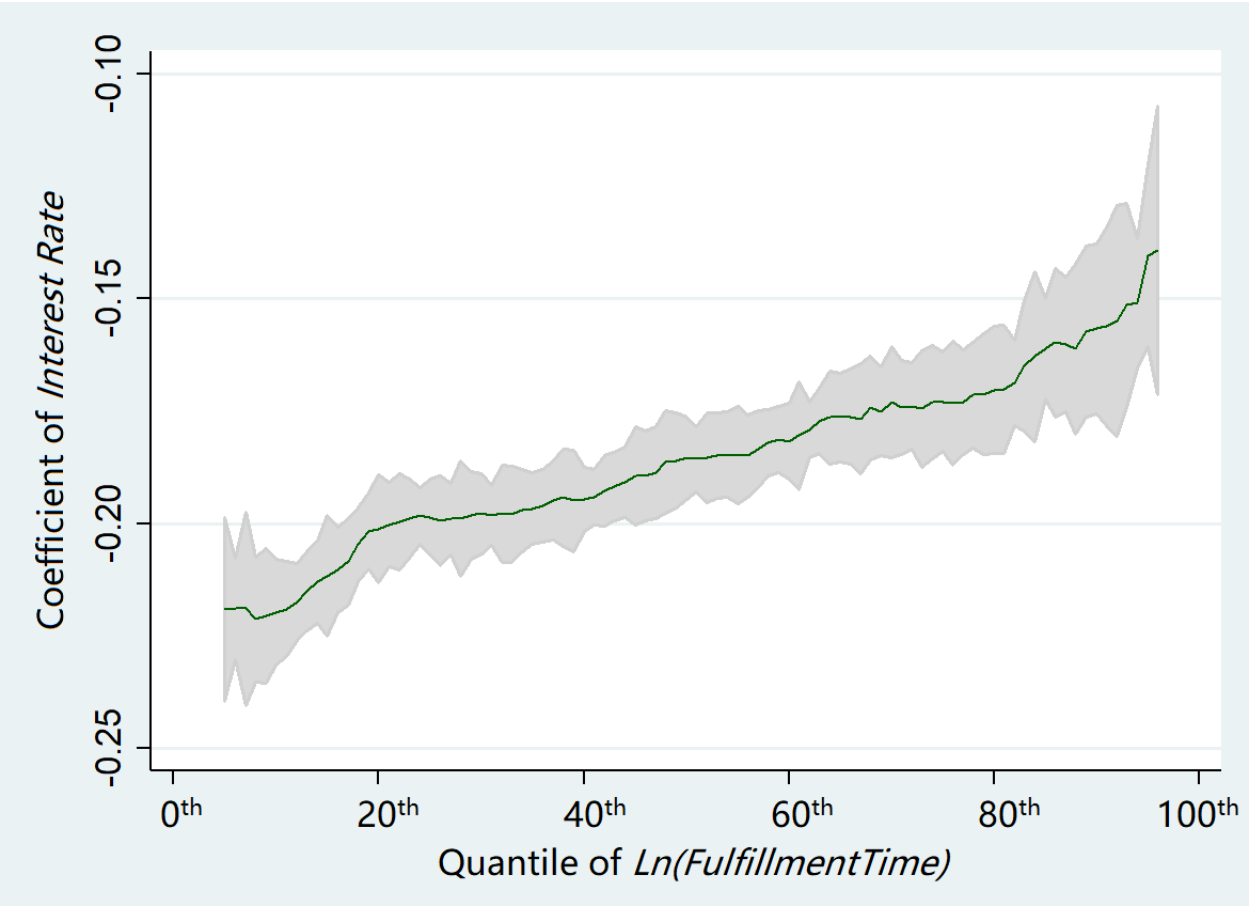


Figure 3. Mobile App screenshot of a sample loan

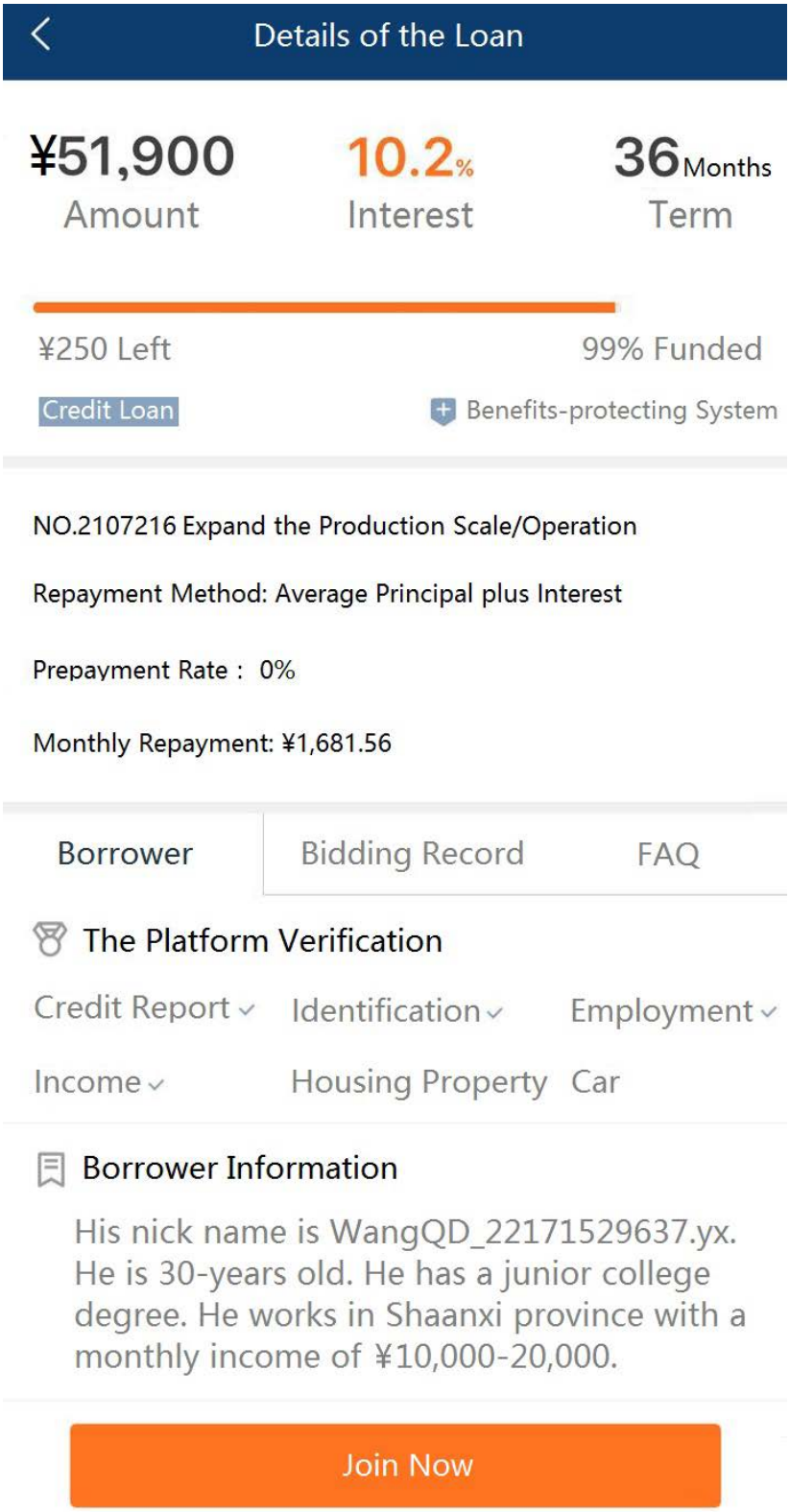


Figure 4. Computer screenshot of a sample loan for Group 1 (original)

For enterprise development and working capital management

Loan Agreement

¥80,000	14.00%	9 Months	2013-10-04
Amount	Interest	Term	Paid off Date

Guarantee Principal

Prepayment Fee 1.00%

Repayment Method Monthly/Average Principal plus Interest

已还清

Detailed Information of Loan | 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 (smaller font for interest rate)

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 Information of Loan | 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 (larger font for credit rating)

For enterprise development and working capital management — Loan Agreement

¥80,000	D	14.00%	9 Months
Amount	Credit Rating	Interest	Term

2013-10-04
Paid off Date
已还清

Guarantee **Principal** ⓘ Prepayment Fee **1.00%**

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

Detailed Information of Loan | 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** 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.

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.
Maturity (months)	The Maturity of the loan. At Renrendai, a borrower can choose the Maturity of a loan from eight alternatives: 3 months, 6 months, 9 months, 12 months, 15 months, 18 months, 24 months, and 36 months.
FulfillmentTime (seconds)	The time interval between the beginning and ending time of a loan's funding process.
IRR (%)	The internal rate of return (IRR) for the loan.
Default	is 1 if the loan defaults; 0 otherwise. Both overdue loans and advanced loans are classified as default loans. 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 Maturity as the loan.
HR	Take a value of 1 if the borrower's credit rating is HR (High Risk); 0 otherwise.
Male	is 1 if the borrower is male; 0 otherwise.
Age (in years)	Age of the borrower.
Bachelor	is 1 if the borrower's highest degree is a bachelor's degree; 0 otherwise.
MasterOrHigher	is 1 if the borrower's highest degree is a master's degree or higher; 0 otherwise.
Employ(3–5yrs)	is 1 if the borrower has work experience of 3 to 5 years; 0 otherwise.
Employ(5yrs+)	is 1 if the borrower has work experience of more than 5 years; 0 otherwise.
Income(¥5,000–10,000)	is1 if the borrower's monthly income is between ¥5,000 and 10,000; 0 otherwise.
Income(¥10,000–20,000)	is 1 if the borrower's monthly income is between ¥10,000 and 20,000; 0 otherwise.
Income(¥20,000–50,000)	is 1 if the borrower's monthly income is between ¥20,000 and 50,000; 0 otherwise.
Income(¥50,000+)	is1 if the borrower's monthly income is above ¥50,000; 0 otherwise.
House	is 1 if the borrower owns a house; 0 otherwise.
Mortgage	is 1 if the borrower has an unpaid mortgage; 0 otherwise.
Car	is 1 if the borrower owns a car; 0 otherwise.
CarLoan	is 1 if the borrower has an unpaid car loan; 0 otherwise.
Bid_t	is 1 if the investor invests in month t; 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
Maturity (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=2644)	Other (N=7741)	Fast minus Other Diff	t-stat
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***
Maturity (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***
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 10th, 25th, 75th, and 90th percentiles). The dependent variable is *Ln(FulfillmentTime).* All independent variables are defined in Table 1. Verifications fixed effects are captured by dummy variables on whether Renrendai verified the credit report, ID, employment, income, home deed, car title, marriage certificate, education diploma, mobile phone, Weibo account, address, and video interview. All continuous variables are winsorized at the 1st and 99th 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)
Maturity	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*, *CD Rate* the bank deposit rate in the same month as the loan and with the same time to maturity. 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)
Maturity	-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 period from the loan gets funded to the time when the loan defaults or gets repaid. The dependent variable is $Default_{it}$, which is a dummy variable that is 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)
Maturity	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* of *HR* and non-*HR* loans, for each quintile, and for 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. Experiment on time pressure

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. Their task is to select one from five offered loans to invest in. Subjects are randomly divided into two groups of 30. The subjects in treatment group were asked to select 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 that subjects choose from. 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
Interest Rate (%)	16.8	20	15	16	15	18
Amount (¥ '000)	12.4	10	10	12	5	25
Maturity (Months)	15	12	24	12	3	24
IRR(%)	15.40	12.99	15	16	15	18
Default	0.2	1	0	0	0	0
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)
Maturity (months)	14.90	14.10	0.80
			(0.32)
Amount (¥)	9,000	7,700	1,300
			(1.57)

Table 7. Introduction of Mobile Apps

Panel A reports the estimate of a panel regression of *Ln(DecisionTime$_{ij}$)* on *Mobile$_{ij}$*, where *DecisionTime$_{ij}$* is investor *i*'s the decision time for investing in loan *j*, and *Mobile$_{ij}$* is a dummy variable, which is 1 if investor *i*'s bid to loan *j* is through a mobile app, and 0 if it is through a computer. The first two columns report the estimates based on the overall sample, and the last two columns are based on the subsample, where all investors have used both mobile and 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 is 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)
Maturity	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 on March 19, 2018. The procedures for the two rounds of experiments are kept the same. For each round of experiment, subjects were divided randomly into three groups. The training session is the same as in Section IV.B, except that the screen shot for the loan information is presented differently across the three groups. For Group 1, the screenshot is original PC interface, as in Figure 4. For Group 2, we modified the original interface by reducing the font size of interest rate and moving it to a less prominent place, as in Figure 5. For Group 3, we modified the original interface by enlarging the font size of credit rating and changing its color to orange and moving it to the top of the screen, as in Figure 6. After the training session, subjects were asked to choose one out of the same five loans as in the experiment in Table 6. For all subjects, the format of the interface of those five loans matches to what they saw during the training session. We conduct the following survey at the end of the experiment.

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

A. Interest Rate; B. Maturity; 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）
Maturity	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 rate	Larger credit rating		
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)
Amount	12,492	11,857	13, 541	635	-1,049
				(0.51)	(-0.75)
Maturity	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 main variables. $CumBid_{it}$ is the total number of bids investor *i* has had until the end of day *t*. $Default3M_{it}$ is a dummy variable, which is 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 bid in 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
CumBids	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. First-hand experience in default and loan choices

Dependent variable:	*DecisionTime*	*DecisionTime*	*InterestRate*	*InterestRate*	*HR*	*HR*	*IRR-CD rate*	*IRR-CD rate*
CumBids	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 60 undergraduate students from various departments and majors at Tsinghua University on June 10, 2017. They were randomly divided into two groups of 30. All subjects went through the same training session described in Section IV.B, and participated in two rounds of investment decisions. At each round, all subjects faced the same five loans and were 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 were 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 investing decisions?*
   A. Interest Rate; B. Maturity; 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 contrast, we surveyed the subjects in the control group with 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 survey results of the treatment group on *Default*, which is one is 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 is one if credit rating is chosen as the most valued factor by a subject, 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 loan choices of the treatment group 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*=30)	Control group (*N*=30)	Diff (Treatment - control)
Interest Rate (%)	13.33	50.00	-36.67***
			(3.27)
Credit Rating (%)	66.67	23.33	43.33***
			(3.69)
Intuition Score	4.07	5.47	-1.40***
			(3.55)
Maturity (%)	10.00	16.67	-6.67
			(0.75)
Amount (%)	10.00	6.67	3.33
			(0.46)
Others (%)	0.00	3.33	-3.33
			(1.00)

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

Dependent variable:	*Intuition Score* (1)	*Credit Rating* (3)	*Interest Rate* (2)	*Maturity* (4)	*Amount* (5)
Default	-1.950***	0.550***	-0.400***	-0.150	0.000
	(-3.50)	(3.49)	(-3.53)	(-1.28)	(0.00)
Constant	5.700***	0.300**	0.400***	0.200**	0.100
	(12.54)	(2.33)	(4.32)	(2.10)	(1.02)
No. of Obs.	30	30	30	30	30
R-squared	0.305	0.302	0.308	0.056	0.000

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

Dependent variable:	*Decision Time* (1)	*HR* (3)	*Interest Rate* (2)	*Maturity* (4)	*Amount* (5)
Default	37.150**	-0.450**	-3.250***	-0.750	-5,400*
	(2.69)	(-2.54)	(-3.65)	(-0.24)	(-1.71)
Constant	67.30***	0.90***	18.50***	14.70***	18,800***
	(5.96)	(6.23)	(25.43)	(5.84)	(7.29)
No. of Obs.	30	30	30	30	30
R-squared	0.205	0.188	0.322	0.002	0.095