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User Interface and Firsthand Experience in Retail Investing

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Using data from a major online peer-to-peer lending platform, we document that, due to time pressure, investors appear to focus on interest rates and only partially account for credit ratings in their decisions. The effect is stronger for mobile-based investors than for PC-based ones. Our evidence suggests that this variation is caused by the difference in information content on the interfaces rather than differences in the devices' physical attributes *per se*. Investors improve their decisions by slowing down and paying more attention to credit ratings after experiencing a loan default firsthand, but not after observing others experiencing defaults. (*JEL* G12)

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FinTech has fundamentally transformed the household finance industry. Two features stand out in this trend. First, while the aggregate size of this market is enormous, a single financial decision tends to involve a small amount and is often made without much time for deliberation. To what extent do investors rely on simple decision rules when making such financial decisions? Second, much of retail finance is moving to the mobile channel, the adoption of which is likely to increase in acceleration as new areas are developed purely on mobile platforms.[1] How do people respond to information at their fingertips? Are the effects due to the physical attributes of mobile devices *per se* (e.g., small size, touch screen, navigation difficulty) or due to the information content of mobile apps? Distinguishing between these mechanisms would shed light on financial decision-making in the age of mobile investing and would have important policy implications. However, doing so presents empirical challenges, because in practice, information content goes hand in hand with the physical characteristics of the host devices.

We attempt to address these issues by examining investment decisions 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. Two unique features make this platform ideal for analyzing the questions raised earlier. First, although the market is sizable, each investment is small and the decision is made quickly. In 2017, the aggregate size of the P2P market in China is 2.8 trillion Yuan ($1 is worth around ¥7).[2] During our sample period, the cumulative principal of the loans in Renrendai is over ¥700 million, while the median investment size is only ¥500. Because of the market environment, which we explain in detail in Section 2, loans on this platform get funded quickly. For example, 25% of the loans are fulfilled within 42 seconds, and 90% are fulfilled in under eight minutes. Renrendai records time stamps for all transactions, allowing us to measure investors' decision time to analyze financial decisions under time pressure.

Second, during our sample period, Renrendai introduced a mobile app. Combining the empirical analysis of this change with a randomized controlled experiment, we examine the influence of mobile devices on investment decisions. More importantly, we are able to distinguish the effect of information content from that of the physical features of mobile devices.

Under time pressure, investors in this market appear to follow a rule of thumb: they focus on loans with high interest rates and partially overlook borrowers'

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1 According to the 2017 Global Findex Database, 52% of adults—or 76% of bank account owners—reported having made or received at least one digital payment using their account in the past year. In high-income economies, the share was as high as 91% of adults (97% of account owners).

2 These numbers are based on data from https://shuju.wdzj.com/industry-list.html.

credit ratings. Specifically, we find that, all else equal, loans with higher interest rates are funded more quickly. In contrast, credit ratings do not affect funding time, even though they can forecast loan performance after controlling for interest rates.

Focusing on interest rates is a sensible strategy for investors in this market, because Renrendai guarantees to repay the outstanding principal of a loan if the borrower fails to make a monthly payment. This principal guarantee mechanism, which was credible at the time, significantly limits investors' exposure to borrowers' credit risk. Even though incorporating credit rating information can increase investment returns, the improvement is limited, because investors only lose interest payments for up to 2 months upon a default. For example, we find that by avoiding loans with "High Risk" (HR) ratings, an investor can improve her annual returns by approximately 1% on average. For comparison, the average internal rate of return of the loans in this market is about 11%. In addition, an investor may miss the opportunity to invest in a loan if she spends much time pondering credit risk. The alternative investment for most Chinese households is bank deposits, for which the interest rate is only about 3%. Hence, the simple decision rule of focusing on interest rates can be interpreted as a near-optimal strategy to cope with time pressure.

We examine this interpretation by conducting a randomized controlled experiment. Subjects are provided institutional background on this market and asked to choose one out of five loans. For the treatment group, subjects were asked to make choices within 42 seconds (the 25th percentile of our sample), while the subjects in the control group were asked to make choices after 180 seconds (the 75th percentile). We find that treated subjects are more likely to choose loans with higher interest rates and are consequently exposed to greater risks. Moreover, our survey at the end of the experiment shows that treated subjects are more likely to rely on their intuition and view interest rates as the most important factor in their decisions.

Our empirical and experimental analyses uncover two factors that shape the decision rule: user interface and firsthand experience. We first analyzed the influence of the user interface on the decision rule. With the increasing reliance on mobile investing in household finance, a natural question is how people respond to information at their fingertips and how the positioning of information on the app affects decision-making. On a personal computer (PC) interface, interest rates are more prominent than credit ratings. This contrast is more striking on a mobile interface, where interest rates are displayed even more prominently and credit ratings are not shown at all. Hence, one hypothesis is that by suppressing credit rating information, the mobile interface encourages investors to make quicker decisions and focus even more on interest rates. Consistent with this hypothesis, we find that mobile-based investors (i.e., investors who use the mobile app) make decisions more quickly than PC-based investors, even after we control for investor fixed effects and loan fixed effects.

Moreover, we find that loans with higher interest rates obtain a larger fraction of funding from mobile-based investors.

To establish the causal relationship between user interfaces and investment decisions, we conduct an experiment by randomly assigning subjects to two groups, one with the mobile interface and the other with the PC interface. We find that the mobile group subjects tend to make decisions more quickly and choose loans with higher interest rates. Moreover, our survey at the end of the experiment shows that the mobile group subjects rely more on their intuition and are more likely to consider interest rates as the most important factor in their decisions.

What causes the mobile and PC groups to make different decisions? One possibility is the difference in the devices' physical features. Individuals may process information presented on mobile devices differently. For example, mobile devices are much smaller and more difficult to navigate. Also, people may be in a more distracted frame of mind and pay more attention to prominent features when making decisions on mobile devices (Brown, Grant, and Winn 2020). Another possibility is differences in information content. The mobile interface contains less information than the PC interface, perhaps because of the smaller screens. How can we distinguish between these two mechanisms when information content goes hand in hand with the physical attributes of the devices? We introduce a randomly assigned hybrid group that accesses the information content of the mobile app on PCs. We find that the decisions of these subjects are indistinguishable from those of the mobile group. This suggests that given the same information content, investors do not appear to process information differently on PCs than on mobile devices in our context. The difference between the mobile and PC groups' decisions is driven by the difference in the information content the two groups receive. This finding has important implications. Given the trend of the increasing use of mobile devices in financial markets, designing mobile apps to properly display key information is critical for their viability and success.

The contents of PC and mobile interfaces differ along multiple dimensions. To isolate the effect of the salience of a specific characteristic, we conduct another experiment. We modify the PC interface by enlarging the size of the credit rating information, changing its font color from black to orange, and moving it to a prominent spot on the interface for the treatment group, while keeping the original interface for the control group. Our evidence shows that relative to subjects in the control group, the treated subjects pay more attention to credit ratings, rely less on their intuition, and are less likely to choose HR-rated loans.

Finally, we examine the second factor that shapes the decision rule: *firsthand* experience. We find that after personally experiencing a loan default, an investor learns to improve her investment decisions by increasing decision time and avoiding loans with HR ratings. In contrast, observing *others* experiencing a default has a negligible effect on an investor's behavior. That is, investors who experience loan defaults as "participants" appear to learn more from those defaults than do investors who simply witness defaults as "observers."

One potential explanation for the difference in investors' learning is inattention. Investors naturally pay attention to the defaults on their own loans, and they may not even notice the defaults on other investors' loans. However, inattention cannot explain the firsthand experience effect entirely, because similar results arise in our experiment, in which *all* subjects, regardless of whether their selected loan defaults, are informed about the default event.[3] We conjecture that participants and observers *process* the same default information differently. Experiencing a default personally and suffering losses, participants are compelled to reexamine their decision processes and, consequently, improve future decisions. In contrast, investors do not respond strongly to defaults on their fellow investors' loans, perhaps because they do not believe they are subject to the same mistakes.

One prominent insight in the literature on decision-making is the so-called "two-system approach" (e.g., Stanovich and West 2000; Kahneman 2011). System 1 operates automatically and quickly, with little or no effort. It relies on intuition and generates simple decision rules that can cope with most scenarios reasonably well. For convenience, we use "fast thinking" to refer to decision-making under System 1. In contrast, System 2 is slow and deliberate, but it is usually inactive. The two-system theory suggests that fast thinking should influence most of our everyday decisions. However, most of the studies in this literature have been conducted in experimental settings. The extent to which fast thinking affects investment decisions in real financial markets remains an open question due to the inherent challenges of measuring decision time. To the best of our knowledge, we are the first to investigate the effect of fast thinking on investment decisions in a financial market.[4]

More broadly, our paper relates to the research on the role of bounded rationality, especially limited attention, in financial markets (e.g., Abel, Eberly, and Panageas 2013). Given the wealth of information and the scarcity of attention, investors tend to focus on the most salient features (e.g., Benartzi and Lehrer 2015; Frydman and Wang 2020).[5] Hirshleifer and Teoh (2003) show that salient information is absorbed more easily when time and attention are costly.

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

4 Hirshleifer et al. (2019) show that when making multiple forecasts on the same day, financial analysts resort to more heuristic decisions in their earnings forecasts. Heller et al. (2017) carry out large-scale randomized controlled trials and find that behavioral intervention and educational programs can help young people slow down and reflect on their automatic thoughts and behaviors. Such interventions reduce the rates of arrests and readmission to jail and improve school engagement and graduation rates. Using experimental and survey data, Butler, Guiso, and Jappelli (2014) show that intuitive thinkers tolerate more risk and ambiguity than effortful thinkers, and they outperform others in uncertain environments. In experimental settings, faster thinking has been associated with greater risk-taking (Cella et al. 2007; DeDonno and Demaree 2008; Chandler and Pronin 2012).

5 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

The literature on rules of thumb focuses primarily on the efficiency of simple decision rules and compares them with the optimal decisions (e.g., Lettau and Uhlig 1999). Our paper adds to this literature by empirically examining rules of thumb in a financial market and the factors that shape the decision rules.

Mobile apps emerged a decade ago and are well on their way to playing more and more important roles in the financial industry. We are only beginning to witness their influences. Mobile devices affect the availability of information as well as users' ability to process the information. Grant (2020) shows that decision quality using mobile devices is lower because of the screen size, spatial layout, and especially navigation difficulty. Mobile device users also may be in a distracted framed of mind, which increases the influence of prominent information (e.g., Benartzi and Lehrer 2015; Brown, Grant, and Winn 2020). We use market data and a randomized controlled experiment to show the inferior performance of mobile investing, and we identify the mobile app's information content (rather than investors' ability to process information on mobile devices) as the main cause. To the best of our knowledge, our paper is the first to analyze the influences of mobile devices on financial decisions and identify the underlying mechanism of such influences.[6]

Our paper adds to the literature on learning from experience (e.g., Malmendier and Nagel 2011, 2016).[7] Our results are related to those in Andersen, Hanspal, and Nielsen (2019), which show that individuals who lost money on their holdings in bank stocks during the recent global financial crisis subsequently shy away from risk in their investments. One key difference is the nature of the experienced losses: the shocks in Andersen etal. (2019) are rare and more substantial; as a result, investors stop investing in bank stocks.

negatively predicts future stock returns. Investors underreact more to earnings surprises when they are distracted, for example, when earnings announcements are made on Fridays (DellaVigna and Pollet 2009) or when multiple announcements are made on the same day (Hirshleifer, Lim, and Teoh 2009). Our paper shows that time pressure leads investors to fixate on interest rates and partially overlook other relevant information that is freely available on the trading interface.

6 Two recent papers examine investment decisions on mobile devices. Using retail investors' trading data in China, Cen (2018) shows that "going mobile" increases trading volume by aggravating investors' over-confidence and self-control problems. Cen shows that fund flows are more sensitive to fund performance in the prior week and more susceptible to market sentiment. Performance decreases as a result of heightening indirect illiquidity costs. Similarly, using proprietary data from a German retail bank, Kalda, Loos, and Previtero (2020) find greater risk and higher skewness for retail investing via mobile devices. This effect is nontransient and feeds back into investors' trading via computers. Neither paper distinguishes the information-content mechanism from the information-processing mechanism of mobile investing. We are the first to do so using a randomized controlled experiment.

7 A growing number of studies have analyzed the effect of experiences on expectation formation and investments in the stock market (Vissing-Jorgensen 2003; Greenwood and Nagel 2009; Kuhnen, Rudorf, and Weber 2017; Andersen etal. 2019), credit markets (Chernenko, Hanson, and Sunderam 2016), CEO decisions (Malmendier and Tate 2005; Malmendier, Tate, and Yan 2011; Dittmar and Duchin 2016; Schoar and Zuo 2017), leverage choice (Koudijs and Voth 2016), IPO investments (Kaustia and Knupfer 2008; Chiang et al. 2011), retirement savings (Choi et al. 2009), and policy-making (Grant 2020). Our findings also complement the literature demonstrating that investors form different beliefs based on differential interpretations of the same information (Hong and Stein 2007). For instance, investors' beliefs are shown to be strongly influenced by their prior portfolio choices (Kuhnen, Rudorf, and Weber 2017) and political leanings (Meeuwis et al. 2018). Our evidence suggests that firsthand experience can also contribute to differential interpretations of the same information in forming beliefs.

We consider smaller, more frequent shocks and show that investors learn from their experience to improve investment decisions. Our experimental evidence sheds further light on the potential mechanism for this effect.[8]

1. Institutional Background and Hypothesis

1.1 Institutional background

Our data are collected from Renrendai, a major P2P lending platform in China. Online P2P lending was first introduced in China in 2007 and rapidly grew from 2011 to 2015.[9] Renrendai was founded in 2010 and has an AAA rating, the highest rating for P2P lending platforms, from the Chinese Academy of Social Sciences. We focus on "credit loans," which have no collateral and compose 76% of all loans made on Renrendai during our sample period. We examine the behavior of individual investors.

To apply for a credit loan, a borrower is required to provide identification information, as well as information on income, employment, and creditworthiness. 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,[10] and ratings increase with the number of optional documents submitted, including home deed, car title, marriage certificate, diploma, cell phone number, Weibo account (Weibo is 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.[11]

Potential borrowers submit loan applications, specifying the requested amount, term, and interest rate. The maximum amount for each loan varies with the borrower's credit rating, ranging from ¥3,000 to ¥500,000. A borrower is allowed to have multiple loans outstanding as long as the total amount does not exceed a certain limit determined by her credit rating. Credit loans are available at different eight maturities: 3, 6, 9, 12, 15, 18, 24, and 36 months. Borrowers specify the interest rates of their loans, subject to the minimum interest rate

8 Agarwal et al. (2013) measure the learning behavior of credit card users after paying a late fee (a negative shock). Consumers learn to avoid paying future late fees, and such effects depreciate over time.

9 P2P lending has grown rapidly, more than doubling its market share in the U.S. personal lending market from 22.5% in 2015 to 49.4% in 2019 (see Tatham 2019). Most existing studies focus on Prosper.com. Investigating investor behavior, Zhang and Liu (2012) find evidence of rational herding among investors. Lin and Viswanathan (2015), Pope and Sydnor (2011), Ravina (2018), and Duarte, Siegel, and Young (2012) study the roles of home bias, racial bias, the beauty premium, and trust, respectively, in P2P lending decisions. Regarding borrowers, Iyer et al. (2016) show that lenders effectively use soft and nonstandard 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.

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

11 Each month, a borrower's credit score increases by 1 point if payments remain current. The credit score is reduced by 3 points if a payment is overdue by 1–30 days, and it is set to 0 if a payment is overdue by more than 30 days.

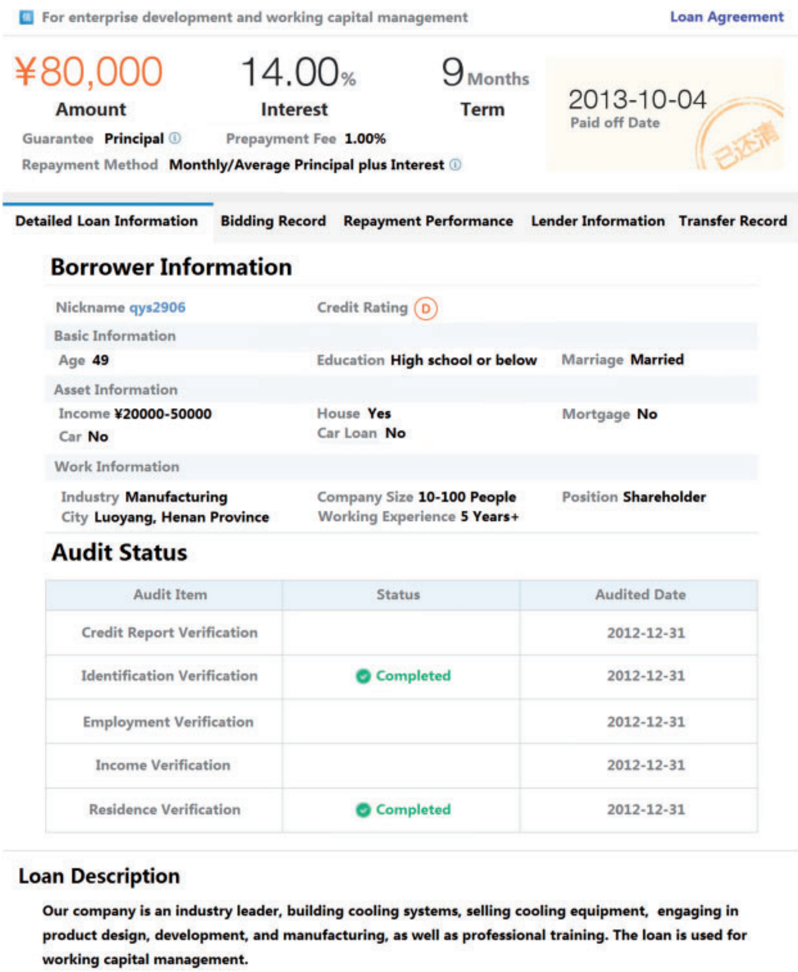

Figure 1
Computer screenshot of a sample loan

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 verification. Approved applications are listed on the platform and can be viewed by all potential investors. Each listing includes loan characteristics and borrower information, such as credit rating, age, education, marital status, monthly income reported as a range, ownership of a house (apartment) and/or a car, and the presence of a home mortgage or car loan. 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. An investor can choose to fund a portion of a listed loan in multiples of ¥50. The funding process of a loan stops once the requested amount is fully funded, or if the loan is not fully funded after 7 days. In the latter case, the loan listing is withdrawn. As a result, the borrower either receives 100% funding or is not funded. 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 feature enables us to calculate the timing of each loan's funding process to the second, which is not feasible on other P2P lending platforms, such as Prosper.com.

1.2 Hypothesis

Renrendai is an ideal context for studying financial decision-making with fast thinking, because investors are under pressure to make quick decisions. Bank deposit rates in China are highly regulated and kept artificially low, at about 3% during our sample period (e.g., Lardy 2008). Hence, the P2P lending market, if organized properly to limit borrowers' credit risk, is appealing to many households. Indeed, in our sample, more than 90% of loans are fully funded within eight minutes after they are listed on Renrendai. Because loan details are not observable until loans are publicly listed, investors have a short time frame for making decisions.

We hypothesize that under time pressure, investors' attention gravitates to interest rates and that they only partially account for other information, such as borrowers' credit ratings. This hypothesis is motivated by the following two considerations.

First, Renrendai guarantees that it will repay investors the outstanding principal of a loan within 31 days if a borrower fails to make a monthly payment. Hence, investors forgo only up to 2 months of interest payments when a default occurs. This guarantee is considered credible, because Renrendai not only has an excellent credit rating but also levies an up-front 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 0.1%–0.35% of the outstanding balance. This principal guarantee is akin to a credit default swap embedded in the loan contract, which significantly limits lenders' downside risk and the necessity of analyzing borrowers' credit risk. The insights in Kahneman and Tversky (1979) suggest that the principal guarantee is especially appealing to loss-averse investors. This further reduces the need to analyze credit risk.

Second, as Figure 1 shows, the interest rate is prominently displayed on the trading interface: it is presented in a large font at the top and in the center of the screen, attracting investors' attention. In contrast, credit ratings are displayed in a small font and in a much less prominent location. Hence, investors' attention would naturally gravitate to interest rates, and they may overlook less prominent information, such as borrowers' credit ratings.

Importantly, algorithmic trading is unlikely to have a big impact on retail investing in this market. Most of the participants in this market are retail investors with small amounts of holdings. They are unlikely to have the incentive or ability to do algorithmic trading. Moreover, Renrendai actively discourages the use of computer programs, and it may ban computerized bidders from investing on its platform for up to one year. One goal of this policy is to ensure the security and stability of the online platform. A computerized bidding strategy would visit the platform frequently in order to submit bids before others. The resulting heavy traffic could crash Renrendai's server. Conversations with the management at Renrendai further suggest that they believe banning algorithmic trading makes the platform more attractive to ordinary investors, who are critical to the platform's growth and viability in the long run.

2. Investing with Fast Thinking

2.1 Data

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

Panel B of Table 1 reports loan and borrower characteristics. Mean and median values of the interest rate are 12.70% and 12.00%, respectively. Mean and median loan amounts are ¥25,372 and ¥14,000, respectively. The loan term ranges from 3 to 36 months, with an average of 10.3 months and a median of 9 months. The mean and median numbers of investors for each loan are 19.8 and 14 (untabulated).

We find that 71.2% of Renrendai loans are categorized as having a high risk of default (HR), and 87.3% of borrowers are male. Borrowers' mean and median ages are 32.9 and 32 years old, respectively. About one-third of borrowers hold a bachelor's degree or higher, and 56.7% have 3 or more years of work experience. Financially, 41.3% of the borrowers have a monthly income exceeding ¥10,000. While 55.5% of borrowers are homeowners and 40.8% own a car, only 21.7% of borrowers have a mortgage and only 8% have an outstanding car loan.

2.2 Attention to interest rates

Because of low bank deposit rates and the principal guarantee mechanism, investors find Renrendai loans appealing and quickly snatch them up once they are listed. Indeed, 25% of loans are fully funded in 42 seconds, 75% in less than 3 minutes, and 90% in less than 8 minutes. For convenience, we refer to the period from the time a loan is listed to the time the loan is fully funded as *FulfillmentTime*.

We posit that investors primarily focus on the interest rates and quickly seize high-interest-rate loans without sufficiently examining other information in loan contracts, such as borrowers' credit risk. To investigate this conjecture, we first examine the sensitivity of investors' decision speed to interest rates. Specifically, we regress *FulfillmentTime* on *Interest Rate* and *HR*, where *Interest*

Table 1
Variable definitions and data descriptions

A. Definitions

Variable	Definition
Interest rate (%)	The interest rate of the loan
Amount (¥)	The amount of the loan
Term (months)	The term of the loan. At Renrendai, a borrower can choose from eight terms: 3, 6, 9, 12, 15, 18, 24, or 36 months
FulfillmentTime (seconds)	The time interval between the beginning and ending times of a loan's funding process
IRR (%)	The internal rate of return (IRR) for the loan
Default	Equals 1 if the loan defaults and 0 otherwise. Both overdue loans and advanced loans are classified as defaulted. Overdue loans are loans that have been overdue for less than 30 days; advanced loans are loans that have been overdue for more than 30 days, which Renrendai has repaid to the borrowers
Rm	The rate of return in the A-share market in China over the past 20 trading days
Rf (%)	The annualized rate of return of time deposits with the same term as the loan
HR	Equals 1 if the borrower's credit rating is HR (High Risk) and 0 otherwise
Male	Equals 1 if the borrower is male and 0 otherwise
Age (in years)	Age of the borrower
Bachelor	Equals 1 if the borrower's highest degree is a bachelor's degree and 0 otherwise
MasterOrHigher	Equals 1 if the borrower's highest degree is a master's degree or higher and 0 otherwise
Employ(3–5yr)	Equals 1 if the borrower has work experience of 3 to 5 years and 0 otherwise
Employ(5yr+)	Equals 1 if the borrower has work experience of more than 5 years and 0 otherwise
Income(¥5,000–10,000)	Equals 1 if the borrower's monthly income is between ¥5,000 and 10,000 and 0 otherwise
Income(¥10,000–20,000)	Equals 1 if the borrower's monthly income is between ¥10,000 and 20,000 and 0 otherwise
Income(¥20,000–50,000)	Equals 1 if the borrower's monthly income is between ¥20,000 and 50,000 and 0 otherwise
Income(¥50,000+)	Equals 1 if the borrower's monthly income is above ¥50,000 and 0 otherwise
House	Equals 1 if the borrower owns a house and 0 otherwise
Mortgage	Equals 1 if the borrower has an unpaid mortgage and 0 otherwise
Car	Equals 1 if the borrower owns a car and 0 otherwise
CarLoan	Equals 1 if the borrower has an unpaid car loan and 0 otherwise
Bid_t	Equals 1 if the investor invests in month t and 0 otherwise
$ProportionFastBids_t(\%)$	The proportion of fast loans among all loans made by an investor in month t
$CumBid_{it}$	The cumulative number of loans made by investor i up to day t
$Default3M_{it}$	Equals 1 if investor i has invested in a loan that defaulted in the previous 3 months and 0 otherwise
$Decision\ Time_{it}$	The duration between the time when a loan is listed and the time when investor i invests in the loan during week t

(*Continued*)

Table 1
(Continued)

B. Summary statistics (N = 10,385)

Variable	Mean	SD	p1	p25	p50	p75	p99
Loan characteristics							
Interest rate (%)	12.70	2.20	10	11	12	13	20
Amount (¥'000)	25.37	39.67	3.00	8.00	14.00	27.00	200.00
Term (months)	10.30	7.08	3	6	9	12	36
FulfillmentTime (seconds)	291	1,581	4	42	80	180	2,972
IRR (%)	10.82	3.80	0	8.02	10.77	13.00	21.97
Default	0.18	0.38	0	0	0	0	1
Market conditions							
Rm	0.037	0.068	−0.117	−0.004	0.025	0.063	0.247
Rf (%)	2.924	0.355	2.55	2.75	2.8	3	4.25
Borrower characteristics							
HR	0.712	0.453	0	0	1	1	1
Male	0.873	0.333	0	1	1	1	1
Age	32.889	7.024	23	28	32	37	52
Bachelor's	0.298	0.457	0	0	0	1	1
MasterOrHigher	0.023	0.151	0	0	0	0	1
Employ(3–5yr)	0.220	0.414	0	0	0	0	1
Employ(5yr+)	0.347	0.476	0	0	0	1	1
Income(¥5,000–10,000)	0.267	0.442	0	0	0	1	1
Income(¥10,000–20,000)	0.140	0.348	0	0	0	0	1
Income(¥20,000–50,000)	0.143	0.350	0	0	0	0	1
Income(¥50,000+)	0.130	0.336	0	0	0	0	1
House	0.555	0.497	0	0	1	1	1
Mortgage	0.217	0.412	0	0	0	0	1
Car	0.408	0.492	0	0	0	1	1
CarLoan	0.080	0.272	0	0	0	0	1

Panel A defines our main variables. Panel B reports their summary statistics.

Rate is the interest rate offered in the loan contract, and *HR* is a dummy variable that equals 1 if the loan has an HR rating and 0 otherwise. The first column of Table 2 presents the results.

The estimate of the coefficient for *Interest rate* is −40.23, with a t-statistic of −5.59. Hence, a one-standard-deviation increase in the interest rate (i.e., 2.20%) reduces *FulfillmentTime* by 89 seconds. In contrast, the coefficient estimate for *HR* is −27.50 ($t = -0.70$). Holding everything else constant, had investors avoided loans with *HR* ratings, this coefficient would be positive rather than negative. Hence, our evidence does not support the conjecture that holding everything else constant, investors are hesitant to invest in loans with *HR* ratings.

Note that if the information in credit ratings is fully reflected in interest rates, the results above can arise even if investors do not overlook any information in credit ratings. In the next section, however, we will see that the information in credit ratings is not fully reflected in interest rates: credit ratings can predict loan performances even after we control for interest rates.

Several control variables are worth mentioning. Naturally, the coefficient for *Amount* is significantly positive, since larger loans take longer to fund. Interestingly, investors also appear to respond to some borrower characteristics.

Table 2
Fulfillment time, IRR, and default

Dependent variable:	*Fulfillment time*	*IRR*	*Default*
Interest rate	−40.233***	0.791***	0.105***
	(−5.589)	(30.272)	(6.641)
HR	−27.503	−1.068***	2.122***
	(−0.700)	(−14.948)	(8.523)
Amount	0.013***	−0.000***	0.000***
	(4.352)	(−4.358)	(5.197)
Term	2.750	−0.139***	0.068***
	(0.470)	(−5.842)	(2.908)
Rm	1,341.901	−0.826	3.463**
	(0.892)	(−0.651)	(2.157)
Rf	−19.733	1.551***	−0.385
	(−0.188)	(3.554)	(−0.911)
Male	−74.250	−0.140**	0.196**
	(−1.414)	(−2.135)	(2.250)
Age	5.162	−0.019***	0.021***
	(0.989)	(−4.536)	(4.872)
Bachelor's	−49.592*	0.330***	−0.520***
	(−1.896)	(6.549)	(−8.819)
MasterOrHigher	−197.979***	0.827***	−1.093***
	(−3.006)	(5.306)	(−3.980)
Employ(3–5yr)	15.067	0.065	−0.080
	(0.490)	(1.056)	(−1.257)
Employ(5yr+)	−45.018	0.094	−0.197***
	(−0.981)	(1.256)	(−2.926)
Income(¥5,000–10,000)	−35.599	−0.197***	0.212***
	(−1.411)	(−2.884)	(3.619)
Income(¥10,000–20,000)	−72.104*	−0.193**	0.288***
	(−1.676)	(−2.442)	(3.448)
Income(¥20,000–50,000)	−135.914	−0.219***	0.600***
	(−1.447)	(−2.632)	(6.418)
Income(¥50,000+)	−152.418	−0.285***	0.690***
	(−1.328)	(−3.251)	(6.825)
House	−65.740	−0.056	0.108*
	(−1.445)	(−0.793)	(1.713)
Mortgage	40.551	0.329***	−0.416***
	(1.145)	(4.068)	(−5.623)
Car	0.013	0.168**	−0.295***
	(0.001)	(2.246)	(−3.345)
CarLoan	−37.817	−0.048	0.104
	(−0.978)	(−0.438)	(0.921)
Constant	1,293.937***	1.658	
	(3.238)	(1.229)	
Verification fixed effects	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes
Day-of-week fixed effects	Yes	Yes	Yes
Hour-of-day fixed effects	Yes	Yes	Yes
No. of obs.	10,385	10,385	10,385
Adjusted/Pseudo-R-squared	.196	.592	

This table reports the results of three regressions. The first two columns are based on OLS regressions, where the dependent variables are *FulfillmentTime* and *IRR*, respectively. The third column is based on the Cox Hazards model, where the dependent variable is *Default*. All variables are defined in Table 1. Verification fixed effects are captured by dummy variables indicating whether Renrendai verified the borrower's credit report, ID, employment, income, home deed, car title, marriage certificate, education diploma, mobile phone, Weibo account, address, and video interview. t-statistics, in parentheses, are based on standard errors clustered by week. $^{*}p<.1$; $^{**}p<.05$; $^{***}p<.01$.

For example, the coefficient for *MasterOrHigher* is −197.98 ($t=-3.00$), suggesting that if a borrower has a graduate degree, her loans are perceived to be less risky and get funded more quickly.

2.3 Loan performance

Given the principal guarantee, the performance of a loan should have a strong positive association with its interest rate. Hence, a sensible approach would be for investors to focus on interest rates. To examine this, we measure the performance of a loan by its internal rate of return, IRR, which can be computed as follows:

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

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

To test these hypotheses, we regress *IRR* on *Interest rate*, *HR* and other loan and borrower characteristics. As shown in the second column, the coefficient for *Interest rate* is 0.794 ($t=30.27$). That is, a 1% increase in the interest rate leads to a 79-basis-point (bp) increase in *IRR*. This evidence confirms our hypothesis: Renrendai investors' reliance on interest rates is a sensible response to the pressure to make quick decisions.

After we control for interest rate, *HR* is still negatively related to performance. The coefficient estimate for *HR* is -1.068 ($t=-19.95$). That is, all else equal, the average return is 1.068% lower for loans with *HR* ratings than for other loans.[12] This is consistent with the interpretation that the information in credit ratings is not fully reflected in loan prices (i.e., interest rates).

To further examine this interpretation, we estimate the gains an investor can achieve by paying more attention to credit ratings. For each week, we construct a principal-amount-weighted portfolio of HR-rated loans and a similar portfolio for non-HR loans. We find that the *HR* loan portfolios underperform non-*HR* loan portfolios by 1.121% (untabulated). The magnitude of this return difference is comparable to the *HR* coefficient in the regression.[13]

2.4 Loan default

Our interpretation of the above results is that if everything else (e.g., interest rates) is held constant, *HR* loans are more likely to default, leading to lower *IRR* due to the loss of interest payment upon default (the remaining principal is paid off by Renrendai). We now directly examine this interpretation by testing

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[12] Loan performance also appears to be correlated with other variables. For example, *IRR* is negatively correlated with the loan term. Since there is no secondary market for investors to unload their holdings, one might expect that investments in loans with longer maturities are less liquid and should command higher average returns. In our sample, however, loans with longer terms have lower average returns. *IRR* is also correlated with the loan amount and several borrower characteristics, even after we control for the interest rate and the borrower's credit rating.

[13] A related question is how the interest rates are set in the market. To examine this, we regress interest rate on credit category dummies and borrower- and loan-level controls, and we find that interest rates are lower for borrowers with higher credit ratings, better education, higher income, and home ownership.

whether a borrower's credit rating predicts loan default after we control for interest rate.

Specifically, we create a dummy variable $Default_{it}$, which equals 1 if loan i defaults on month t, and run a Cox proportional hazards model. We define a loan as in default if its payment is overdue.[14] As shown in the third column of Table 2, the coefficient for *Interest rate* is 0.105 ($t=6.64$). That is, loans with higher interest rates are more likely to default. However, consistent with our interpretation, even after we control for interest rate, an *HR* rating still predicts a higher likelihood of default. The coefficient for *HR* is 2.122 ($t=8.52$).

3. What Determines the Rule of Thumb?

The evidence presented in the previous section is consistent with the interpretation that in aggregate, investors appear to follow a simple rule of thumb: relying on interest rates to make quick decisions. In this section, we first examine this interpretation by showing that time pressure causes people to adopt this decision rule. We then examine two factors that shape the decision rule: user interface and investors' firsthand experience.

3.1 Experiment 1: Time pressure

The interpretation that investors adopt the decision rule to cope with time pressure implies that investors should rely more on interest rates when time pressure is stronger. To examine this prediction, we conducted a randomized controlled experiment on June 16, 2019. We recruited 72 subjects from a first-year graduate class at the People's Bank of China School of Finance (PBCSF), Tsinghua University.

Subjects were asked to select a loan to invest in from a pool of five loans. The five loans were chosen from the 16 loans listed on the Renrendai platform on November 4, 2013, an arbitrary day in the middle of our sample period. Of those loans, 10 had the *HR* rating; two ended up in default. We randomly chose three *HR* loans, one of which ultimately defaulted,[15] and two non-*HR* loans that were fully repaid. The fraction of *HR* loans and the default rate of these five loans are comparable to those of our full sample. Panel A of Table 3 provides details for these five loans.

Before making their loan choices, all subjects went through a training session. They were provided with Renrendai's institutional background and the experiment procedure, as well as loan characteristics, borrower characteristics, and the eventual outcomes for 50 loans listed from October 4, 2013 to November 3, 2013, the 30-day period prior to the date on which the five loans in the

[14] The results are similar if default is defined as a payment being overdue for more than 30 days.

[15] Loan 1 defaulted after the borrower made three monthly payments of ¥926.35. Renrendai paid off its remaining principal of ¥7,682.77 in the fifth month.

experiment are chosen. Those 50 loans were randomly selected from the 194 loans listed on Renrendai in that 30-day window. Subjects were provided two screenshots for each loan. The first provided basic details about the loan and the borrower, and the second gave the loan's repayment status. All subjects were given 30 minutes to study these 50 loans. Subjects were asked to think about what types of loans deliver higher returns and what types of loans are likely to default. Communication among subjects was prohibited.

After the training session, subjects were randomly assigned into two groups of 36. Those in the treatment group were asked to make their choices within 42 seconds (the 25$^{\text{th}}$ percentile of the *FulfillmentTime* in our sample). Those in the control group were asked to take a minimum of 180 seconds (the 75th percentile) to make their decisions. To avoid interference, the two groups made investment decisions in different rooms. After making their choices, subjects were asked the following two questions:

1. *Which factor did you value most when making choices?*
   A. Interest Rate; B. Term; C. Amount; D. Credit Rating; E. Other.

Table 3
Experiment 1: Time pressure

A. Details of the five loans

Variable	Mean	Loan 1	Loan 2	Loan 3	Loan 4	Loan 5
Loan characteristics						
Interest rate (%)	16.8	20	15	16	15	18
Amount (¥ '000)	12.4	10	10	12	5	25
Term (months)	15	12	24	12	3	24
IRR (%)	15.40	12.99	15	16	15	18
Default	0.2	1	0	0	0	0
Borrower characteristics						
HR	0.6	1	0	1	0	1
Age (in years)	32	35	36	32	29	28
Bachelor	0.8	0	1	1	1	1
MasterOrHigher	0	0	0	0	0	0
Employ(3-5yr)	0.4	0	0	0	1	1
Employ(5yr+)	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

B. Covariate balance

Dependent variable:	*Male*	*Age*	*Exemption*
Treatment	−0.083	0.222	0.028
	(−0.723)	(0.515)	(0.233)
Constant	0.417***	24.278***	0.444***
	(5.111)	(79.633)	(5.279)
No. of obs.	72	72	72
R-squared	.007	.004	.001

(*Continued*)

Table 3
Continued

C. Survey results

Dependent variable:	*Interest rate*	*Credit rating*	*Amount*	*Term*	*Intuition score*
Treatment	0.318***	−0.254**	0.056	−0.082	1.161***
	(3.004)	(−2.317)	(0.751)	(−0.937)	(2.794)
Male	0.100	−0.014	−0.076	0.009	0.666
	(0.880)	(−0.127)	(−0.920)	(0.106)	(1.558)
Age	−0.017	0.023	−0.022	−0.017	−0.097
	(−0.628)	(0.757)	(−1.282)	(−0.676)	(−0.827)
Exemption	−0.022	−0.072	−0.067	0.107	−0.007
	(−0.202)	(−0.662)	(−0.764)	(1.233)	(−0.018)
Constant	0.552	−0.081	0.674	0.565	5.798**
	(0.806)	(−0.107)	(1.477)	(0.879)	(1.999)
No. of obs.	72	72	72	72	72
R-squared	.125	.087	.037	.045	.126

D. Loan choices

Dependent variable:	*Interest rate*	*HR*	*Amount*	*Term*	*Decision time*
Treatment	0.987**	0.202*	867.270	0.974	−174.447***
	(2.354)	(1.829)	(0.716)	(0.441)	(−22.872)
Male	0.119	0.082	19.883	−2.170	−0.589
	(0.277)	(0.676)	(0.014)	(−0.907)	(−0.066)
Age	0.001	0.004	−75.194	0.032	−1.049
	(0.010)	(0.123)	(−0.214)	(0.056)	(−0.529)
Exemption	−0.196	−0.070	−560.504	0.183	3.719
	(−0.435)	(−0.592)	(−0.395)	(0.080)	(0.438)
Constant	15.505***	0.117	11,288.599	14.787	236.828***
	(4.474)	(0.140)	(1.222)	(1.016)	(4.872)
No. of obs.	72	72	72	72	72
R-squared	.084	.060	.010	.018	.889

The experiment was conducted on June 16, 2019. All 72 subjects were recruited from a first-year graduate class at the People's Bank of China School of Finance (PBCSF), Tsinghua University. After going through the training session described in Section 3.1, they were asked to select one of five offered loans to invest in. Subjects were randomly assigned into two groups of 36. The subjects in the treatment group were asked to select a loan within 42 seconds, while those in the control group were asked to take a minimum of 180 seconds to make their selections. At the end of the experiment, all subjects were asked the two questions described in Section 3.1. Panel A reports the details of the five loans from which the subjects chose. Panels B through D report the regression results of various variables on *Treatment*, which is a dummy variable that equals 1 if the subject is in the treatment group and 0 otherwise. In panel B, the dependent variables are subject characteristics. *Male* is a dummy variable that equals 1 if the subject is a male and 0 otherwise. *Age* is the subject's age, denominated in years. *Exemption* is a dummy variable that equals 1 if the subject was admitted without an entrance exam and 0 otherwise. In panel C, the dependent variables are survey results. In the first column, the dependent variable is a dummy variable that equals 1 if the subject chose interest rate as the most important variable for her selection and 0 otherwise. The dependent variables for columns 2 through 4 are defined similarly. The dependent variable in column 5 is the self-reported *Intuition score*, which is 1 (7) if the subject reported having the lowest (highest) possible reliance on intuition in her selection. In panel D, the dependent variable is a loan characteristic in columns 1 through 4, and it is the subject's decision time (denoted in seconds) in column 5. t-statistics are in parentheses. $*p<.1$; $**p<.05$; $***p<.01$.

2. *Please rate the extent to which you rely on intuition in making choices on a scale of 1 (lowest) to 7(highest): ______.*

The first question tries to elicit where investors direct their attention. The second question aims to estimate the extent to which subjects make decisions based on intuition.

We have information on three characteristics of the subjects: gender, age, and admission method, where the admission method indicates whether the graduate entrance exam was exempt when the student was admitted. To examine if our assignment to the treatment and control groups is random, we construct three variables for the characteristics: *Male* is a dummy variable that equals 1 if the subject is a male and 0 otherwise. *Age* is the subject's age, denominated in years. *Exemption* is a dummy variable that equals 1 if the subject was admitted into the program without taking the graduate entrance exam and 0 otherwise. We regress these three variables on *Treatment*, a dummy variable that equals 1 if the subject is in the treatment group and 0 otherwise. As shown in panel B, the coefficient for *Treatment* is not statistically different from zero in any of the three columns. That is, the random assignment procedure works well. Ex post, the treatment has no correlation with the subjects' characteristics.

Panel C suggests that facing time pressure, subjects in the treatment group pay more attention to interest rates. In the first column, the dependent variable is a dummy variable that equals 1 if the subject chooses interest rates as the most important factor in her choice. The coefficient for *Treatment* is 0.318 ($t=3.00$), suggesting that subjects in the treatment group are 31.8% more likely to choose interest rates as the most important factor. In contrast, the second column shows that the treated subjects are 25.4% ($t=2.32$) less likely to choose credit ratings as the most important factor. Columns 3 and 4 show that time pressure appears to have no effect on subjects' attention to loan amount and term. Finally, column 5 suggests that the time pressure increases the treated subjects' self-reported intuition score by 1.16 ($t=2.79$), which accounts for 27.2% of the average intuition score of 4.26.

The differences between the treatment and control groups in the survey are clearly reflected in their loan choices. As shown in the first column of panel D, the coefficient for *Treatment* is 0.987 ($t=2.35$). That is, the average interest rate of the loans chosen by treated subjects is 98.7 bps higher than that chosen by the subjects in the control group. This is consistent with the hypothesis that under time pressure, the subjects in the treatment group focus more on the interest rate in their choices. Since loans with high interest rates tend to be those with the HR rating, treated subjects are 20.2% more likely to choose *HR*-rated loans, as the second column confirms. Columns 3 and 4 show that time pressure does not affect subjects' choices of loan term and amount. Finally, the last column shows that, on average, subjects in the treatment group take 174 fewer seconds to make their choices.

3.2 User interface

The previous section shows that investors rely on heuristics to make investment decisions under time pressure. Thus, how information is presented may play an important role. In this section, we examine how user interfaces influence investors' decisions. We approach this question in several steps. In Section 3.1 , we contrast the mobile interface with the PC interface and examine how the interface influences investor decisions. In Section 3.2, we attempt to establish a causal relation between the interface and investment decisions, and we shed light on the underlying mechanism. In Section 3.3, we isolate the salience of one characteristic at a time to study its influence on decisions.

3.2.1 Mobile devices. On July 30, 2014, Renrendai launched its mobile app, which enabled individuals to invest through mobile phones. Mobile-phone screens are much smaller than PC screens, and the mobile app contains much less information than the PC interface. As one can see in Figure 1, the interest rate is more prominently displayed than the credit rating on the PC interface. This contrast is more striking on the mobile interface. As Figure 2 shows, the most salient aspect of a listed loan on the mobile app is its interest rate, which is not only located near the top-middle of the screen (easy-middle bias; see, e.g., Reutskaja et al. 2011; Milosavljevic et al. 2012) but also shown in orange (as the only information not in black). Additionally, the constantly updated funding status shown on the screen (e.g., "99% Funded") could pressure investors to make quick decisions. Interestingly, the credit rating of the borrower is not shown at all.

How does the mobile interface affect investment decisions? One hypothesis is that by suppressing credit rating information, the mobile interface encourages investors to make quicker decisions and focus even more on interest rates. This hypothesis translates into two predictions. First, mobile-based investors should make decisions more quickly than computer-based investors. Second, loans with higher interest rates should attract a larger fraction of mobile-based investors.

To test the first prediction, we run a panel regression of $Decision\ time_{ij}$ on $Mobile_{ij}$, where $Decision\ Time_{ij}$ is investor i's decision time for investing in loan j (from the time loan j is listed to the time of investor i's bid), and $Mobile_{ij}$ is a dummy variable that equals 1 if investor i's bid for loan j is made through the mobile app, and 0 otherwise. As shown in the first column of panel A of Table 4, where the specification includes loan fixed effects, the coefficient for $Mobile_{ij}$ is -100.184 ($t=-8.81$). That is, mobile bidders are about 100 seconds faster than PC bidders on average.

While this result is consistent with the hypothesis that the mobile interface makes investors bid more quickly, it could also result from selection: investors who tend to bid more quickly might have a higher likelihood of adopting the mobile app. To address this selection issue, we include investor fixed effects in the regression. As the second column shows, the coefficient for $Mobile_{ij}$ is -27.949 ($t=-2.65$). That is, holding the investor constant, we find that bidding through the mobile app is 28 seconds faster than bidding through the PC interface. Moreover, we repeat this analysis on a restricted sample consisting of investors who used both mobile and PC interfaces during our sample period. As columns 3 and 4 show, the mobile app is associated with faster decisions in both specifications. These results alleviate some concerns about the selection issue but cannot completely rule it out.[16] Hence, in the next two sections, we

[16] The specification with investor fixed effects addresses the concern that quick decision-makers may be more likely to adopt the mobile app. It does not, however, address the concern of time variation in preferences, that is, the concern that an individual's preference for speed may change over time, and that she may prefer to use a PC (the mobile app) when she makes slow (quick) decisions.

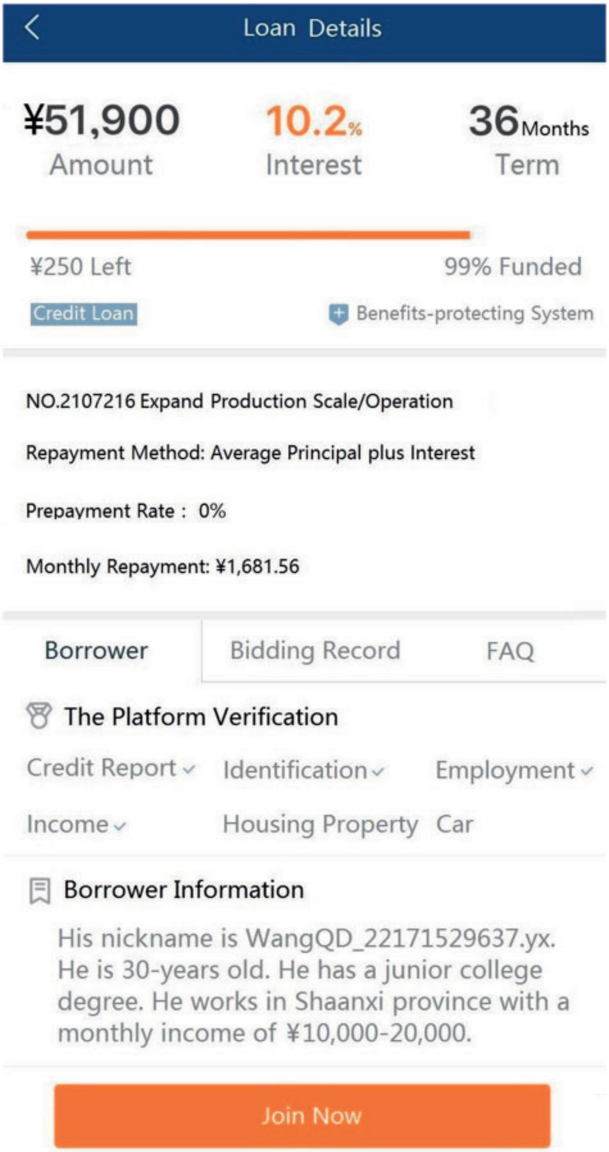

Figure 2
Mobile app screenshot of a sample loan

conduct two controlled experiments to examine the causal effect of the interface on investors' decisions.

To test the second prediction, for each loan we construct the variable *Mobile* $Share_i$, which is the fraction of the funding to loan i made through the mobile

Table 4
Mobile and PC interface
A. Faster mobile bids

	Decision time			
	Overall sample		Subsample (users of both mobile and PC)	
Dependent variable:	(1)	(2)	(3)	(4)
Mobile	−100.184***	−27.949***	−100.184***	−38.117***
	(−8.813)	(−2.650)	(−9.157)	(−4.449)
Constant	408.691***	−6.110	290.206***	−20.931
	(74.941)	(−0.083)	(35.461)	(−0.160)
Time fixed effects	*No*	Yes	No	Yes
Investor fixed effects	Yes	Yes	Yes	Yes
No. of obs.	204,872	204,872	69,358	69,358
R-squared	.198	.327	.086	.234

B. Fractions of bids from the mobile app

	Mobile share	
Dependent variable:	(1)	(2)
Interest rate	0.678***	0.641***
	(3.107)	(3.200)
Controls	Yes	Yes
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.	16,533	16,533
R-squared	.875	.875

Panel A reports the estimate of a panel regression of $\textit{Decision time}_{ij}$ on $\textit{Mobile}_{ij}$, where $\textit{Decision time}_{ij}$ is investor is decision time for investing in loan j (denominated in seconds) and $\textit{Mobile}_{ij}$ is a dummy variable that equals 1 if investor is bid for loan j is made through the mobile app and 0 otherwise. The first two columns are based on the overall sample, and the last two columns are based on the subsample where investors used both PC and the mobile interfaces during our sample period. Panel B reports the estimates of a regression of $\textit{Mobile Share}_i$, which is the fraction of the investment in loan i that comes from the mobile app, on *Interest rate* and the same set of control variables as those in Table 2. This regression is based on an extended sample period from September 2012 to March 2016. Standard errors are clustered by week. t-statistics are in parentheses. $*p < .1$; $**p < .05$; $***p < .01$.

app. We then regress it on *Interest rate* and control variables. Panel B reports the results. In both specifications, the coefficient for *Interest rate* is positive and statistically significant. This is consistent with our interpretation that mobile investors pay more attention to interest rates.[17]

3.2.2 Experiment 2: Content versus media. In this section, we conduct a randomized controlled experiment to examine the causal effect of mobile investing on investors' decisions and to identify the underlying mechanism. On January 8, 2020, we recruited 134 subjects from a first-year graduate class at the PBCSF and randomly assigned them to three groups of 45, 44, and 45

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

subjects. The training session was the same as in experiment 1, except that the user interfaces (devices and information content) were presented differently across the three groups. *Mobile group* subjects were shown the information content of the mobile app on their mobile phones. *MobileOnPC group* subjects were also shown the same information content as on the mobile app, but they viewed on their PCs. Finally, *PC Group* subjects were shown the PC interface on their laptops.

After the training session, all subjects were asked to choose one out of the same five loans as those in experiment 1. All subjects used the same type of device and received the same information content as they had during the training session. At the end of the experiment, all subjects were asked the same two questions as in experiment 1.

We first verify covariate balances of the subjects' characteristics. Specifically, we regress *Male, Age*, and *Exemption* on *PC* and *MobileOnPC*, where *PC* is a dummy variable that equals 1 if the subject is in the PC Group and 0 otherwise; *MobileOnPC* is a dummy variable that equals 1 if the subject is in the MobileOnPC Group and 0 otherwise. As shown in panel A of Table 5, the group assignment is uncorrelated with subjects' characteristics.

We then regress survey results on *PC* and *MobileOnPC* to compare the three groups. In the first column of panel B, the coefficient for *PC* is -0.270 ($t = -2.63$). That is, relative to PC group subjects, mobile group subjects are 27% more likely to choose interest rates as the most important factor in their decisions. This is consistent with the empirical result from the previous section showing that investors focus more on interest rates when bidding through the mobile app.

What causes this difference? We consider two possibilities. One possibility is differences in the physical attributes of the devices. For instance, smaller screens and touchscreen technology on mobile devices may shorten investors' attention span and direct their focus to a smaller number of salient features (Brown, Grant, and Winn 2020). Another possibility is differences in the information content of the interfaces. We note that the two might be intertwined: Perhaps because of the smaller size of mobile screens and the difficulty of navigating the screens, the mobile interface includes much less information. Hence, the interest rate is even more prominently displayed and attracts more investor attention. However, the distinction of the two possibilities is important, because they have different policy implications.

The data from the MobileOnPC Group help us assess these two hypotheses. The subjects in this group use PCs but base their decisions on the same information as that displayed by the mobile app. Hence, comparing their choices and those of the subjects in the Mobile Group isolates the effect of the media. Similarly, comparing their choices and those of the subjects in the PC Group isolates the effect of the information content.

As shown in the first column of panel B, the coefficient for *MobileOnPC* is -0.012 ($t = -0.12$). Holding information content constant, we find no detectable difference in the attention to interest rates between the subjects who use PCs and those who use mobile devices. That is, the difference between the PC Group and the Mobile Group is due to differences in the information content, rather than differences in the physical attributes of the devices.

The implication from the second column is similar. The subjects in the Mobile Group are 24.8% less likely to choose the credit rating as the most important factor in their decisions. This difference is almost entirely attributable to the difference in the interfaces' information content, since the responses of the MobileOnPC Group are indistinguishable from those of the Mobile Group. Columns 3 and 4 show no detectable difference among the three groups in their attention to *Amount* and *Term*. Finally, column 5 shows that, relative to the subjects in the PC Group, those in the Mobile Group rely more on intuition in their choices. Again, this difference is due to the difference in the information content instead of the media *per se*.[18]

[18] For each loan, loan and borrower information appears on a single page in the mobile app. Thus, no scrolling is needed to process the information of a loan either on mobile devices or on PCs. This might partially explain why we do not observe differences in investment decisions between the mobile and hybrid groups. We considered including a hybrid group that reads the more extensive PC content on mobile devices but decided against it. Fitting the PC content within a mobile screen makes the text illegible. To make it legible would require scrolling, which would create confounding effects.

Table 5
Experiment 2: Mobile and PC interface—Content versus media

A. Covariate balance

Dependent variable:	*Male*	*Age*	*Exemption*
PC	−0.022	0.200	−0.044
	(−0.209)	(0.548)	(−0.418)
MobileOnPC	0.033	0.077	−0.034
	(0.312)	(0.209)	(−0.321)
Constant	0.467***	24.378***	0.489***
	(6.208)	(94.479)	(6.508)
No. of obs.	134	134	134
R-squared	.002	.002	.001

B. Survey results

Dependent variable:	*Interest rate*	*Credit rating*	*Amount*	*Term*	*Intuition score*
PC	−0.270***	0.248***	−0.045	0.066	−0.657**
	(−2.630)	(2.620)	(−0.664)	(0.923)	(−2.144)
MobileOnPC	−0.012	0.074	−0.087	0.045	0.155
	(−0.115)	(0.781)	(−1.279)	(0.624)	(0.504)
Male	0.010	0.005	−0.028	0.035	−0.096
	(0.118)	(0.061)	(−0.507)	(0.596)	(−0.380)
Age	0.027	−0.006	−0.007	−0.004	−0.020
	(1.099)	(−0.268)	(−0.438)	(−0.255)	(−0.278)
Exemption	0.049	0.051	−0.026	−0.056	0.164
	(0.575)	(0.646)	(−0.469)	(−0.948)	(0.647)
Constant	−0.176	0.299	0.354	0.206	4.840***
	(−0.291)	(0.536)	(0.891)	(0.490)	(2.678)
No. of obs.	134	134	134	134	134
R-squared	.075	.056	.018	.017	.062

(*Continued*)

Table 5
Continued

C. Loan choices

Dependent variable:	*Interest rate*	*HR*	*Amount*	*Term*	*Decision time*
PC	−1.290***	−0.269***	578.419	1.716	40.271***
	(−2.701)	(−2.737)	(0.523)	(1.088)	(2.689)
MobileOnPC	−0.243	0.017	−485.444	−0.574	5.450
	(−0.506)	(0.175)	(−0.437)	(−0.362)	(0.362)
Male	0.076	−0.010	98.409	−0.224	0.983
	(0.193)	(−0.125)	(0.108)	(−0.172)	(0.080)
Age	0.087	0.028	−125.450	−0.637*	1.783
	(0.757)	(1.167)	(−0.473)	(−1.685)	(0.497)
Exemption	0.330	0.070	400.696	−0.140	−15.879
	(0.837)	(0.866)	(0.439)	(−0.107)	(−1.283)
Constant	15.912***	0.033	13,571.934**	30.177***	66.095
	(5.652)	(0.057)	(2.083)	(3.245)	(0.749)
No. of obs.	134	134	134	134	134
R−squared	.070	.090	.010	.038	.077

The experiment was conducted on January 8, 2020. All 134 subjects were recruited from a first-year graduate class at the People's Bank of China School of Finance (PBCSF), Tsinghua University. Subjects were randomly assigned into three groups of 45, 44, and 45 subjects. The training session was the same as in experiment 1 in Table 3, except that the device and the interface contents were presented differently across the three groups. *Mobile group* subjects were shown the mobile interface on their mobile phones. *MobileOnPC group* subjects were also shown the mobile interface, but on PC screens. Finally, *PC group* subjects were shown the PC interface on their laptop screens. After the training session, all subjects were asked to choose one out of the same five loans as those in experiment 1. For all subjects, the devices and interfaces matched what they had during the training session. At the end of the experiment, all subjects were asked the same two questions as in experiment 1. Panels A through C report the regression results of various variables on the treatment variables, *PC* and *MobileOnPC*, where *PC* is a dummy variable that equals 1 if the subject is in the PC group and 0 otherwise; *MobileOnPC* is a dummy variable that equals 1 if the subject is in the *MobileOnPC* group and 0 otherwise. In panel A, the dependent variables are subject characteristics. *Male* is a dummy variable that equals 1 if the subject is a male and 0 otherwise. *Age* is the subject's age, denominated in years. *Exemption* is a dummy variable that equals 1 if the subject was admitted without an entrance exam and 0 otherwise. In panel B, the dependent variables are survey results. In the first column, the dependent variable is a dummy variable that equals 1 if the subject chose interest rate as the most important variable for her selection and 0 otherwise. The dependent variables for columns 2 through 4 are defined similarly. The dependent variable in column 5 is self-reported *Intuition score*. In panel C, the dependent variable is a loan characteristic in columns 1 through 4, and it is the subject's decision time (denominated in seconds) in column 5. t-statistics are in parentheses. $*p<.1$; $**p<.05$; $***p<.01$.

The evidence in panel C shows that the loan choices of the subjects are consistent with their responses. For example, as the first column shows, the coefficient for *PC* is 1.290 (t=2.70), while the coefficient for *MobileOnPC* is insignificant. That is, the average interest rate of the loans chosen by the subjects in the PC Group is 1.29% lower than that of the loans chosen by the subjects in the Mobile Group, and this difference is almost entirely due to the difference in the information content. Similarly, the second column shows that the subjects in the PC Group are less likely to choose *HR*-rated loans, while there is no difference between the subjects in the Mobile and MobileOnPC groups. Consistent with the survey-based evidence, columns 3 and 4 do not show a detectable difference in *Amount* and *Term* across the three groups. Finally, consistent with the survey evidence on the reliance on intuition, column 5 shows that the subjects in the PC Group are slower in making decisions, while there is no significant difference between those in the Mobile Group and those in the MobileOnPC Group.

3.2.3 Experiment 3: Salience. The evidence in the previous section suggests that mobile devices *per se* do not worsen investors' decisions; rather, it is the information content exhibited on the interfaces that affects investors' behavior. If key information is presented properly, the performance of investments made via mobile apps may not be inferior to the performance of those made via PCs. Since mobile devices are increasingly used in household finance, this result is reassuring.

Given the importance of the information content, in this section we examine the effect of salience on investors' decisions by conducting a randomized controlled experiment. To obtain a sufficient sample size, the experiment was done in two trials. We recruited 105 graduate students from PBCSF for the first trial on January 10, 2018 and 77 graduate students from the School of Management and Engineering, Nanjing University for the second trial on March 19, 2018. The procedures for the two trials were the same.

For each trial, subjects were assigned randomly to three groups. The training session was the same as in experiment 1, except that the screenshot of the loan information was presented differently across the three groups. For the first group, which is the control group, the screenshot was the original PC interface, as in Figure 1. For the second group, we modified the original interface by reducing the font size of the interest rate and moving it to a less prominent location, as shown in Figure 3. For convenience, we will refer to this group as the "Small Interest Rate Group." For the third group, we modified the original interface by enlarging the font size of the credit rating, changing its color to orange, moving it to the top of the screen, and placing it to the immediate left of the interest rate, as shown in Figure 4. Reading from left to right, the subjects will naturally see credit ratings before interest rates. We will refer to this group as the "Large Credit Rating Group." Panel A of Table 6 suggests that the group assignment is random and is not correlated with the three characteristics of the subjects.

After the training session, subjects were asked to choose one of the same five loans shown in experiment 1. For all subjects, the interface for those five loans matched what they saw during their training session. At the end of the experiment, we asked all subjects the same two questions as in experiment 1.

We hypothesize that, relative to the control group, the subjects in the Small Interest Rate Group would pay less attention to interest rates, and those in the Large Credit Rating Group would pay more attention to credit ratings. Moreover, both treatment groups should make decisions more slowly, since the modified interfaces prompt subjects to be less fixated on interest rates and take other characteristics into account.

To test these hypotheses, we regress survey data on *SmallInterestRate* and *LargeCreditRating*, where *SmallInterestRate* is a dummy variable that equals 1 if the subject is assigned to the Small Interest Rate Group and 0 otherwise, and *LargeCreditRating* is a dummy variable that equals 1 if the subject is assigned to the Large Credit Rating Group and 0 otherwise.

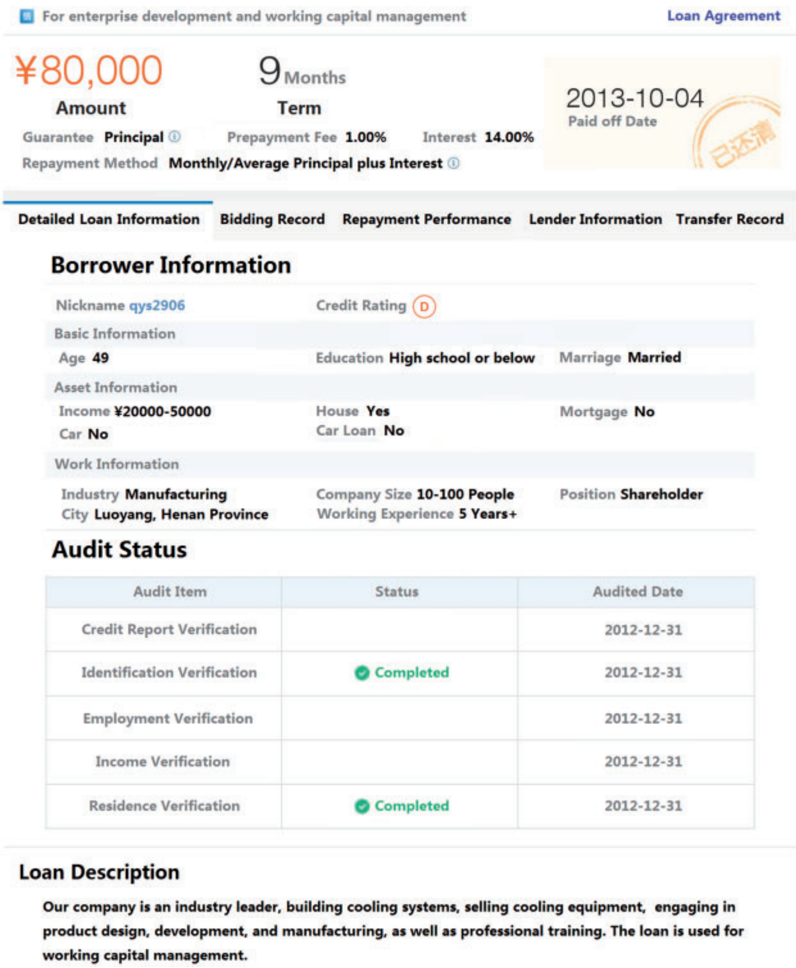

Figure 3
Modified computer screenshot: Small interest rate

The results, reported in panel B, are consistent with the hypotheses. In the first column, the coefficient for *SmallInterestRate* is 0.190 ($t = 2.31$), suggesting that relative to the control group, subjects in the Small Interest Rate Group are 19% less likely to choose interest rates as the most important factor in their decisions. Similarly, the second column suggests that relative to the control group, subjects in the Large Credit Rating Group are 24% ($t = 2.83$) more likely to choose credit ratings as the most important factor in their decisions. In contrast, columns 3 and 4 show that treatments appear to have no effect on the subjects' attention to amount and term. The last column shows that the treated subjects, especially

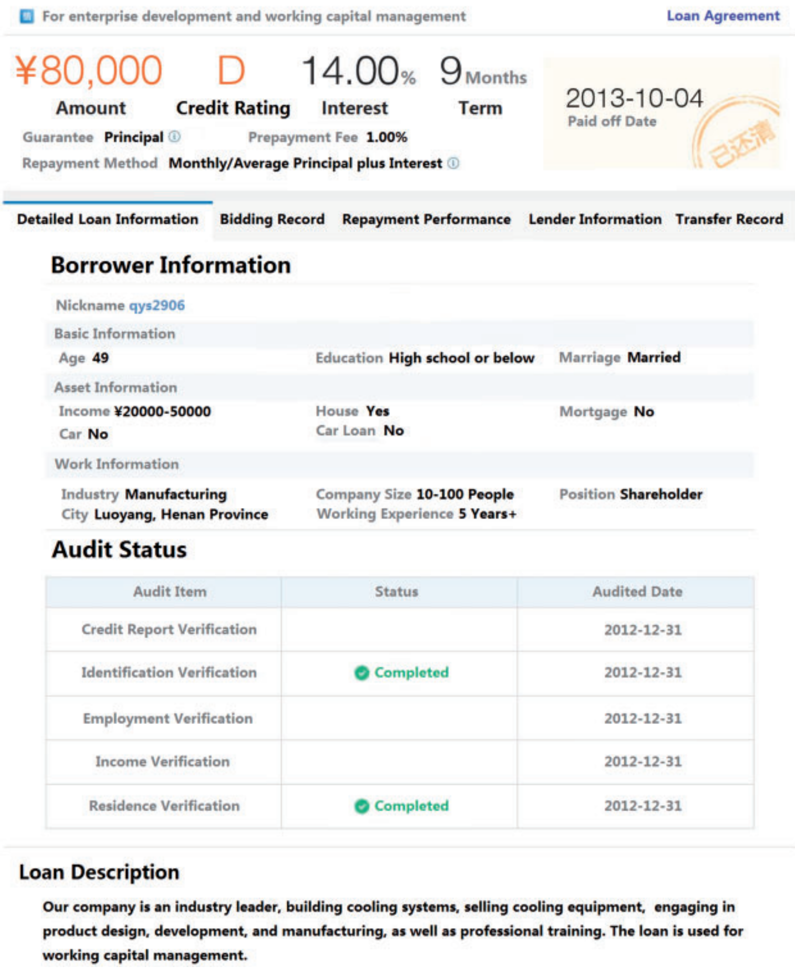

Figure 4
Modified computer screenshot: Large credit rating

those in the Large Credit Rating Group, rely less on their intuition when making decisions.

Subjects' loan choices display a similar pattern to their survey responses. The first two columns of panel C show that the loans chosen by the subjects in the Large Credit Rating Group tend to have lower interest rates and are less likely to be *HR* rated. In contrast, columns 3 and 4 show that treatment has no significant effect on the choices of loan amount and term. Finally, column 5 shows that treated subjects take more time to make decisions.

The above evidence suggests that by highlighting credit ratings on the interface, one can nudge subjects to pay more attention to this variable, reducing their risk-taking. When relevant information is more prominent, investors slow down their decision process and incorporate the additional information into their decisions. This finding is related to the literature on nudging (Thaler and Benartzi 2004). Reutskaja et al. (2011) show that individuals tend to pay attention to snacks located at eye level. Milosavljevic et al. (2012) show that a subtle change in visual prominence influences real food choices. Our results suggest that one can nudge investors to pay more attention to credit risk by increasing the salience of credit ratings.

3.3 Firsthand experience

The previous two sections showed that investors rely on simple decision rules under time pressure and that the design of the user interface affects their decisions. In this section, we examine how personal experience shapes the rule of thumb. Malmendier and Nagel (2011, 2016) find that rather than forming expectations based on all historical data, people tend to rely more on their own experiences. Two people born in different cohorts have had different experiences and thus may respond to the same data differently. We will examine whether a "participant" and an "observer" behave differently. Specifically, when a borrower defaults on a loan, investors may experience the event in two different ways. If an investor has exposure to the loan, she has a

Table 6
Experiment 3: Salience

A. Covariate balance

Dependent variable:	*Male*	*Age*	*Exemption*
SmallInterestRate	0.065	−0.075	−0.003
	(0.982)	(−0.313)	(−0.042)
LargeCreditRating	0.062	0.138	0.057
	(0.967)	(0.588)	(0.843)
Constant	0.302***	24.139***	0.458***
	(6.721)	(147.676)	(9.677)
No. of obs.	182	182	182
R-squared	.007	.004	.005

B. Survey results

Dependent variable:	*Interest rate*	*Credit rating*	*Amount*	*Term*	*Intuition score*
SmallInterestRate	−0.190**	0.122	−0.045	0.072	−0.529**
	(−2.309)	(1.404)	(−0.816)	(1.288)	(−2.056)
LargeCreditRating	−0.118	0.240***	−0.073	−0.077	−0.731***
	(−1.453)	(2.828)	(−1.354)	(−1.416)	(−2.895)
Male	0.019	0.076	−0.045	−0.011	0.331
	(0.204)	(0.763)	(−0.708)	(−0.170)	(1.122)
Age	−0.009	0.001	0.020	−0.001	−0.039
	(−0.349)	(0.049)	(1.144)	(−0.056)	(−0.480)
Exemption	−0.082	−0.010	0.002	0.057	0.403
	(−0.914)	(−0.101)	(0.028)	(0.938)	(1.443)
Constant	0.634	0.180	−0.324	0.109	4.837**
	(1.008)	(0.273)	(−0.774)	(0.255)	(2.462)
No. of obs.	182	182	182	182	182
R-squared	.036	.049	.022	.042	.061

(*Continued*)

Table 6
Continued

C. Loan choices

Dependent variable:	*Interest rate*	*HR*	*Amount*	*Term*	*Decision time*
SmallInterestRate	−0.451	−0.094	−722.901	1.770	32.620*
	(−1.219)	(−1.022)	(−0.527)	(1.121)	(1.890)
LargeCreditRating	−0.755**	−0.150*	1,317.995	1.613	37.076**
	(−2.079)	(−1.666)	(0.979)	(1.042)	(2.189)
Male	−0.315	−0.023	−703.993	0.550	−18.643
	(−0.744)	(−0.215)	(−0.448)	(0.304)	(−0.942)
Age	−0.067	0.004	1.265	0.479	0.249
	(−0.577)	(0.154)	(0.003)	(0.968)	(0.046)
Exemption	−0.252	−0.088	−924.859	−0.605	−12.097
	(−0.629)	(−0.883)	(−0.622)	(−0.354)	(−0.646)
Constant	19.151***	0.571	12,728.612	2.894	122.277
	(6.778)	(0.817)	(1.216)	(0.240)	(0.928)
No. of obs.	182	182	182	182	182
R-squared	.034	.022	.015	.015	.035

The experiment was conducted in two trials. We recruited 105 graduate students from PBCSF for the first trial on January 10, 2018, and 77 graduate students from the School of Management and Engineering, Nanjing University for the second trial on March 19, 2018. The procedures for the two trials were the same. For each trial, subjects were assigned randomly into three groups. The training session was the same as in experiment 1 in Table 3, except that the screenshot of the loan information was presented differently across the three groups. For group 1, which is the control group, the screenshot was the original PC interface, as in Figure 1. For group 2, we modified the original interface by reducing the font size of the interest rate and moving it to a less prominent location, as shown in Figure 3. For group 3, we modified the original interface by enlarging the font size of the credit rating, changing its color to orange, moving it to the top of the screen, and placing it to the immediate left of the interest rate, as shown in Figure 4. We will refer to this group as the "Large Credit Rating Group." After the training session, subjects were asked to choose one of the same five loans that were shown in experiment 1. For all subjects, the interface for those five loans matched what they saw during their training session. At the end of the experiment, we asked all subjects the same two questions as in experiment 1. Panels A through C report the regression results of various variables on the treatment variables, *SmallInterestRate* and *LargeCreditRating*, where *SmallInterestRate* is a dummy variable that equals 1 if the subject is in group 2 (i.e., using an interface with a less salient interest rate) and 0 otherwise; *LargeCreditRating* is a dummy variable that equals 1 if the subject is in group 3 (i.e., using an interface with a more salient credit rating) and 0 otherwise. In panel A, the dependent variables are subject characteristics. *Male* is a dummy variable that equals 1 if the subject is a male and 0 otherwise. *Age* is the subject's age, denominated in years. *Exemption* is a dummy variable that equals 1 if the subject was admitted to the graduate school without an entrance exam and 0 otherwise. In panel B, the dependent variables are survey results. In the first column, the dependent variable is a dummy variable that equals 1 if the subject chose interest rate as the most important variable for her selection and 0 otherwise. The dependent variables for columns 2 through 4 are defined similarly. The dependent variable in column 5 is self-reported *Intuition Score*, which is 1 (7) if the subject reported having the lowest (highest) possible reliance on intuition in her selection. In panel C, the dependent variable is a loan characteristic in columns 1 through 4, and it is the subject's decision time (denominated in seconds) in column 5. t-statistics are in parentheses. $^{*}p<.1$; $^{**}p<.05$; $^{***}p<.01$.

firsthand experience: suffering a loss and "feeling the pain." We refer to this as "experience as a participant." Alternatively, an investor may observe the default of a loan she has no position in, which we refer to as "experience as an observer." How do these two types of experiences affect investors' decision rules? In the next two sections, we first document empirically that firsthand experience indeed plays a role in shaping the rule of thumb, and then we conduct an experiment to assess potential explanations for those empirical results.

3.3.1 Evidence. We construct a proxy for an investor's experience, $CumBid_{it}$, which is the total number of bids investor i has made through the end of week t. As shown in panel A of Table 7, the mean and median of *CumBid* are 50 and 11,

Table 7
Firsthand experience and investment choices

A. Summary statistics

Variable:	No. of obs.	Mean	SD	p1	p25	p50	p75	p99
CumBid	114,975	50.34	106.56	1	3	11	43	629
Default3M	114,975	0.252	0.434	0	0	0	1	1
Decision time (seconds)	114,975	635	2,771	9	38	93	300	12,451
Interest rate (%)	114,975	12.703	1.542	10	11.98	13	13	18
HR	114,975	0.524	0.462	0	0	0.6	1	1
Default	114,975	0.151	0.358	0	0	0	0	1
IRR (%)	114,975	12.229	2.673	0	11.131	12.801	13.193	18.853

B. Loan choices

Dependent variable:	*Interest rate*	*HR*	*Default*	*IRR*	*Decision time*
CumBid	0.001**	0.000	0.000*	0.000	0.900***
	(2.60)	(0.08)	(1.893)	(0.312)	(2.26)
Default3M	0.035**	−0.031***	−0.034***	0.326***	79.216**
	(2.18)	(−6.30)	(−7.256)	(7.546)	(2.21)
Constant	13.287***	0.272***	0.094***	13.093***	982.488***
	(604.41)	(36.78)	(19.006)	(415.039)	(10.05)
Investor fixed effects	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes
No. of obs.	114,975	114,975	114,975	114,975	114,975
R-squared	.497	.391	.281	.337	.435

Panel A reports the summary statistics. $CumBid_{it}$ is the total number of bids investor i made through the end of week t. $Default3M_{it}$ is a dummy variable that equals 1 if investor i invested in a loan that defaulted in the previous 3 months and 0 otherwise. $Decision\ Time_{it}$ is the duration between the time when a loan is listed and the time when investor i bids to invest in the loan during week t. If an investor bids on multiple loans during week t, we use the principal-weighted average as the decision time. Panel B reports the results of regressions of various dependent variables on *CumBid* and *Decision time*. Standard errors are clustered by week. t-statistics are in parentheses. $^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$.

respectively.[19] To distinguish between observers and participants, we construct the dummy variable $Default3M_{it}$, which equals 1 if investor i has invested in a loan that defaulted in the previous 3 months, and 0 otherwise.[20] As panel A shows, this variable has a mean of 0.252. $Decision\ Time_{it}$ is the interval between the time when a loan is listed and the time when investor i invests in the loan in week t. Panel A shows that the mean and median of *Decision Time* are 635 seconds and 93 seconds, respectively. The table also reports the summary statistics of the characteristics of the loans, such as *Interest rate*, *HR* and *IRR*.

To analyze the effect of experience on decisions, we regress the decision variables on *CumBid* and *Default3M* and report the results in panel B. The main feature that stands out from this table is that the coefficient for *Default3M*

[19] Note that these two statistics are computed from the pooled panel of $CumBid_{it}$. If investor i funded n loans during our sample period, her observations would appear n times in the panel. Hence, these two statistics do not represent the number of loans funded by an average or median investor. To assess the number of loans funded by an average (median) investor, we calculate the *CumBid* on December 31, 2014—the last day of our sample—for all investors included in our sample. The mean and median of this sample of *CumBid* are 15 and 3, respectively. That is, the average (median) investor in our sample eventually funded 15 (3) loans at the end of our sample period.

[20] At least one loan defaulted in all rolling windows of 90 days over our sample period; that is, investors can always observe defaults of other investors' loans over the previous 3 months.

is substantially larger than that of *CumBid*. That is, the effect of personally experiencing a default is substantially greater than that of investing in an additional loan.

As the first column shows, the coefficient for *CumBid* is 0.001 (t= 2.60), suggesting that the experience of investing in an additional loan increases the interest rate of the investor's next chosen loan by 0.1 bps. In contrast, experiencing a recent default has a much stronger effect. The coefficient for *Default3M* is 0.035 (t = 2.18). That is, the average interest rate of the loans chosen by investors who have experienced a default in the last 3 months is 3.5 bps higher than that of other loans.

In the regression of *HR* on experience, shown in the second column, the coefficient for *CumBid* is insignificant. In contrast, experiencing a default firsthand has a much stronger effect. The coefficient for *Default3M* is −0.031 (t=−6.30). That is, investors who have experienced a recent default are 3.1% less likely to invest in *HR* loans.

Columns 3 and 4 show that if an investor personally experienced a default in the past 3 months, her next invested loan is 3.4% less likely to default and has a 32.6-bp higher *IRR* on average. In the last column, where the dependent variable is *Decision time*, the coefficients for *CumBid* and *Default3M* are 0.900 (t=2.26) and 79.216 (t=2.21), respectively. That is, on average, the experience of investing in an additional loan increases the decision time by less than one second. After experiencing a loan default, however, an investor takes almost 80 seconds longer to make investment decisions.

In summary, our evidence suggests that experience shapes the decision rule. After a firsthand 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 returns. In contrast, for investors whose loans have not defaulted recently, the experience effects are significantly smaller or negligible.

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

Participants may learn differently from observers due to a selection effect. After suffering a loan default, an investor with low ability may choose to stop investing in loans. As a result, the remaining investors have a higher ability on average (e.g., Seru, Shumway, and Stoffman 2010). In principle, this selection effect may have contributed to our results. However, we expect its magnitude to be small. Because of the principal guarantee mechanism, investors can still earn a return higher than 3% (the CD rate at the time) as long as borrowers make one payment, so investors have little incentive to exit the market. Moreover, we find similar results in our experiment in the next section, where this selection effect is absent.

Third, one might attribute the results to inattention. If a defaulting loan is not in an investor's portfolio, the investor might pay little attention to the default. Consequently, observers should respond less strongly than participants. While this interpretation is feasible, it is unlikely to explain the entire phenomenon. As the next section shows, a similar participant-versus-observer difference arises in our experiments, where all subjects are confronted with the performance of all loans, including the default event.

3.3.2 Experiment 4: Firsthand experience. Our evidence in the previous section reveals that participants and observers learn differently: an investor who experiences a recent default tends to choose loans with better credit ratings relative to investors who observe *others* experiencing defaults. To narrow potential interpretations of our findings, we conduct an experiment. The experiment also allows us to analyze investors' *thought process* through surveys.

We recruited 34 undergraduate students from Tsinghua University on June 23, 2018. All subjects went through the same training session as in experiment 1. Then, they participated in two rounds of choices. In each round, subjects were asked to select one of five loans offered. The five loans for the first round were chosen from loans issued in the 2-week period before November 4, 2013, and included three *HR* loans, one of which ultimately defaulted. Then the outcomes of all five loans were announced to all subjects. In the second round, subjects were asked to select one out of the same five loans as in experiment 1. At the end of the experiment, we asked all subjects the same two questions as in experiment 1.

Our first test examines how firsthand experience affects the way investors make decisions. Specifically, we test whether investors focus on different variables after personally experiencing a default. We run cross-sectional regressions based on the survey data. In the specification in the first column of panel A in Table 8, the dependent variable is *Interest rate* and the independent variable is $Default_i$, which equals 1 if the loan chosen by investor i in the previous round defaults and 0 otherwise. The coefficient for *Default* is -0.413 ($t=-2.40$), suggesting that relative to the subjects who did not experience a default in the first round, the subjects who did are 41% less likely to choose the interest rate as the most important factor for the second-round investment.

In the second column, the dependent variable is $Credit\ rating_{it}$, which is a dummy variable that equals 1 if investor i chooses credit rating as the most important factor for her decision and 0 otherwise. The coefficient for *Default* is 0.422 ($t=2.08$), suggesting that, relative to the subjects who did not experience a default in the first round, those who did are 42.2% more likely to choose credit rating as the most important factor in the second round. In contrast, columns 3 and 4 show that default experience does not affect subjects' views on loan term and amount.

Finally, we run a similar regression for *Intuition score*. As shown in the last column, the coefficient for *Default* is −1.233 ($t=-2.28$), suggesting that, relative to the subjects who did not experience a default in the first round, those who did experience one rely less on their intuition when making investments in the second round.

Panel B shows that the subjects' investment choices are consistent with the survey evidence in panel A. Specifically, we run cross-sectional regressions based on the loan choices of the subjects in the second round. The first column of panel B shows that the average interest rate of the loans chosen by subjects who experienced a default in the first round is 1.80% lower than that of the loans chosen by subjects who did not experience a default. The second column shows that subjects who experienced a default in the first round are 54.5% less likely to choose loans with an *HR* rating. Columns 3 and 4 show that experiencing a default does not affect loan term and amount choices. Finally, column 5 shows that subjects who experienced a default in the first round spent 48 more seconds ($t=3.63$) making decisions in the second round than those who did not experience a default.

Table 8
Experiment 4: Firsthand experience

A. Survey results

Dependent variable:	*Interest rate*	*Credit rating*	*Amount*	*Term*	*Intuition score*
Default	−0.413**	0.422**	−0.028	0.023	−1.233**
	(−2.404)	(2.078)	(−0.165)	(0.181)	(−2.284)
Male	−0.267	−0.096	0.287*	0.012	−0.201
	(−1.695)	(−0.516)	(1.835)	(0.102)	(−0.405)
Age	−0.014	−0.014	0.008	0.033	−0.048
	(−0.309)	(−0.256)	(0.187)	(0.994)	(−0.336)
Exemption	0.020	−0.019	−0.025	−0.043	−0.028
	(0.137)	(−0.110)	(−0.172)	(−0.413)	(−0.061)
Constant	0.778	0.708	−0.089	−0.699	4.987
	(0.698)	(0.537)	(−0.081)	(−0.861)	(1.425)
No. of obs.	34	34	34	34	34
R-squared	.191	.174	.123	.039	.161

B. Loan choices in the second round

Dependent variable:	*Interest rate*	*HR*	*Amount*	*Term*	*Decision time*
Default	−2.449***	−0.545***	−1,785.939	5.736	48.234***
	(−3.178)	(−3.050)	(−0.821)	(1.461)	(3.632)
Male	−1.798**	−0.308*	−456.859	1.250	8.573
	(−2.542)	(−1.878)	(−0.229)	(0.347)	(0.703)
Age	−0.046	0.016	1,336.290**	1.001	−3.368
	(−0.228)	(0.334)	(2.345)	(0.973)	(−0.968)
Exemption	0.039	0.080	1,299.389	1.575	0.454
	(0.061)	(0.533)	(0.711)	(0.478)	(0.041)
Constant	18.765***	0.168	−23,076.445	−13.983	165.033*
	(3.755)	(0.145)	(−1.636)	(−0.549)	(1.916)
No. of obs.	34	34	34	34	34
R-squared	.306	.281	.203	.103	.334

(*Continued*)

Table 8
Continued

C. Changes in loan choices

Dependent variable:	Δ*Interest rate*	Δ*HR*	Δ*Amount*	Δ*Term*	Δ*Decision time*
Default	−6.009***	−1.012***	−3,068.860	3.476	41.086***
	(−12.227)	(−8.515)	(−0.952)	(0.742)	(5.970)
Male	−1.289***	−0.203*	−2,440.327	−0.258	−4.470
	(−2.858)	(−1.861)	(−0.825)	(−0.060)	(−0.707)
Age	−0.007	0.012	942.101	0.760	−0.830
	(−0.052)	(0.372)	(1.116)	(0.619)	(−0.460)
Exemption	0.448	0.174*	1,106.247	1.908	−2.188
	(1.086)	(1.749)	(0.409)	(0.485)	(−0.378)
Constant	1.167	−0.308	−21,829.223	−17.745	−7.149
	(0.366)	(−0.400)	(−1.045)	(−0.584)	(−0.160)
No. of obs.	34	34	34	34	34
R-squared	.845	.739	.098	.044	.609

The experiment was conducted on June 23, 2018. We recruited 34 subjects from a graduate class at the People's Bank of China School of Finance (PBCSF), Tsinghua University. After going through the same training session, described in experiment 1, all subjects were asked to select one out of five loans, whose details are described in Section 3.3.2. After this round of selection, the outcomes of all five loans (i.e., their realized cash flows) were announced to the subjects. Then, the subjects were asked to choose one out of same five loans as those in experiment 1. After the second round of selections, all subjects were asked the same two questions as in experiment 1. The table reports the results from cross-sectional regressions. In panel A, the dependent variables are based on survey results. *Interest rate* is a dummy variable that equals 1 if the subject chose interest rate as the most important variable for her selection and 0 otherwise. *Credit rating*, *Amount*, and *Term* are dummy variables that are defined similarly. *Intuition score* is the self-reported reliance on intuition in decision decision-making and ranges from 1 (lowest) to 7 (highest). In panel B, the dependent variables, which are based on the loan choices in the second round, are the loan characteristics chosen by the subjects in columns 1 through 4 and the subject's decision time (denominated in seconds) in column 5. In panel C, the dependent variables are based on the changes in the loan choices across the two rounds. All three panels have the same independent variables. *Default* is a dummy variable that equals 1 if the loan selected by the subject in the first round defaults and 0 otherwise. *Male* is a dummy variable that equals 1 if the subject is a male and 0 otherwise. *Age* is the subject's age, denominated in years. *Exemption* is a dummy variable that equals 1 if the subject was admitted into the graduate program without an entrance exam and 0 otherwise. t-statistics are in parentheses. *$p<.1$; **$p<.05$; ***$p<.01$.

Panel B focuses on the choices in the second round, and panel C takes into account the choices in both rounds. Specifically, for each subject, we compute the changes in her choices across the two rounds and then run a cross-sectional regression of the changes on *Default*. Consistent with the evidence in panel B, these regressions also show that relative to the subjects who did not experience a default in the first round, those who did experience one tend to slow their decisions, avoid *HR*-rated loans, and choose loans with lower interest rates. Moreover, experiencing a default does not affect investors' choices of loan term and amount.

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

This finding adds to the literature on how experience affects belief formation along two dimensions. First, we show that firsthand experience plays a special role in affecting an investor's decisions. This is consistent with the findings in Andersen etal. (2019), who show that investors who suffered losses from investments in banks that defaulted following the 2008 financial crisis are more likely to shy from risk. One key difference between their study and ours is the nature of the firsthand experience. The experience in Andersen etal. (2019) is based on rare shocks that can generate substantial losses. In response, investors who had experienced the shock completely avoided the investment subsequently. In our study, however, the negative experience comprises more frequent but smaller shocks. Instead of avoiding risk altogether, investors pay more attention to risk and hence improve their future investments. Second, and more importantly, our experiment suggests that the firsthand experience effect cannot be entirely attributed to inattention. An investor is less responsive to other investors' losses not because she is unaware of such losses, but perhaps because she is less likely to learn from others' mistakes when planning her investments.

4. Conclusion

This paper analyzes how investors make decisions in a financial market without much time for deliberation. Under time pressure, investors in an online P2P lending market appear to focus on interest rates and only partially account for other information, such as credit ratings. This rule of thumb is near-optimal, because interest rates and loan performance are highly correlated in this market. Although the information contained in credit ratings can help improve performance, the magnitude is only around 1% per year.

Our empirical and experimental evidence suggests that mobile-based investors are more likely to focus on interest rates than PC-based investors. Further analysis suggests that this difference is due to differences in the interfaces' information content, rather than differences in the devices' physical attributes. Moreover, when credit rating information becomes more salient, it nudges investors into paying more attention to credit risk and hence influences their investment decisions. Finally, the decision rule is influenced by firsthand experience: after experiencing a loan default personally, investors tend to increase their decision time and avoid risky loans. In contrast, observing *others* experiencing a default has a negligible effect. Our research offers insights into how to design user interfaces of online marketplaces to improve decision-making in financial markets.

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