Are All Heuristics Created Equal? Evidence from P2P Investments[1]

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Abstract

Heuristics have a ubiquitous influence on decision-making. Despite a large strand of literature on various heuristics, scant research addresses the concurrent applications of different heuristics or the interplay between them. Using detailed peer-to-peer (P2P) investment data with more than 7.5 million bidding records of around 742 thousand loan applications from Renrendai, a leading Chinese P2P lending platform, we make the first attempt to uncover the relationship between two important numerological heuristics: the round-number heuristic and the lucky-number heuristic, with prevalent application from about 80% of investment choices on loan amounts and bid amounts. Using Bivariate Probit models that simultaneously estimate a borrower's choice of round-number heuristic and lucky-number heuristic, we first find that the selection of round numbers versus lucky numbers for the loan amount reveals borrowers' credit quality and affects the loan funding success rate, though the ex post performance of funded loans is similar. We also document a substitution relationship between the two heuristics. Moreover, lenders also apply heuristics in setting their bid amounts, revealing information about their activeness and risk preference. As lenders become more experienced, they form more sophisticated judgments about the loan quality from borrowers' use of heuristics. Overall, our paper examines the heterogeneities and interlacing of heuristics by establishing a framework to extract information about individuals' characteristics and preferences from the heuristics they use. Our findings shed light on the use of granular investment choice data in predictive analytics and are generalizable to many other real-life situations.

Keywords: Round-number heuristic; Lucky-number heuristic; Information asymmetry; P2P lending

JEL code: G20, G21, G23, G40, G41, D91

1. Introduction

Are all heuristics created equal? Are various heuristics independent of each other? Do they have an identical impact on decision-making? What can we learn about people's characteristics from their choice of heuristics? In this paper, we answer these questions by examining the heterogeneities of two important numerological heuristics—the round-number heuristic and the lucky-number heuristic—using unique bidding-level, peer-to-peer (P2P) lending data. Our research shows that people do not adopt heuristics randomly, and that specific heuristics affect how individuals make decisions differently. Most importantly, we show that agents' choice of heuristics reveals valuable information about their characteristics and preferences.

Since Simon's (1955) seminal work, which questions the rationality of the "economic man," various studies investigate how human decisions are made in real life. Given decision makers' limited knowledge and bounded rationality, heuristics have a ubiquitous influence on individuals' decision-making, such as in health care (Kc, 2020), privacy protection (Dinev, McConnell, and Smith, 2015), gambling behavior (Ma et al, 2014), design theory generation (Gregory and Muntermann, 2014), etc. Evidence abounds that heuristics induce biases in various personal and corporate decisions (Hirshleifer, 2001; Shiller 2003; and Hirshleifer, 2015); for example, borrowing and saving (Benartzi and Thaler, 2007; Stango and Zinman, 2009); corporate operations (Ramiah et al., 2016; Luan et al., 2019); stock investments (Kaustia et al., 2008); diversification strategies (Benartzi and Thaler, 2001); and asset pricing (Hirshleifer, 2001), among others.

Although there is abundant evidence that heuristics can induce biases and result in suboptimal decisions, evidence is scant on concurrent applications of different types of heuristics. In prior literature, different heuristics are either analyzed on a standalone basis or regarded as one big behavioral bias, with little attention paid to the heterogeneities within them. Different individuals adopt different heuristics based on their past experiences, even when facing the same problem, which could lead to different decisions. Thus, the choice of heuristics itself is informative in revealing individuals' characteristics and preferences.

In this study, we shed light on this issue by answering the following questions. First, we examine whether individuals indeed apply certain heuristics when making borrowing and lending decisions, and how individuals choose a certain type of heuristic on a marketplace lending platform. Specifically, we focus on two important numerological heuristics—the round-number heuristic and the lucky-number heuristic—because these are common heuristics that platform participants adopt. Second, we examine whether different heuristics are independent of each other when they are concurrently available, and identify whether adopting one heuristic affects the likelihood of using another at the same time. Third, we analyze how certain borrowers' or lenders' characteristics and preferences affect their choice of heuristics. Fourth, we study the implications on funding outcomes and repayment performance. In particular, we examine how borrowers' adoption of certain heuristics affects funding success and loan repayment performance.

We examine the above questions using data from Renrendai (RRD), one of the largest Chinese P2P lending platforms. The P2P investment data provide an ideal laboratory for our research questions for two reasons. First, both borrowers and investors in Chinese P2P lending platforms have limited experience and expertise, and are especially prone to behavior biases. Consequently, we are able to observe widespread application of heuristics and analyze the implications and potential biases they may entail. In our sample, 80.77% of borrowers and 76.65% of lenders use either the round-number heuristic or the lucky-number heuristic or both.

Second, our data include detailed information on borrower characteristics, the bidding process, and monthly loan repayment, which allows us to conduct a comprehensive analysis of the influence of heuristics from various angles. Using the monthly repayment records of every funded loan, we are also able to test how the use of heuristics affects loan performance. Moreover, detailed bid-level investment records enable us to investigate how investors adopt the two main types of numerological heuristics and respond to the heuristics usage in loan amounts set up by borrowers. The lender-side analysis, together with analysis of the funding success rate and loan performance, offers a complete understanding of the role of heuristics in the P2P lending process.

The two heuristics we examine—the round-number heuristic and the lucky-number heuristic—are widely used by platform participants, as seen from the overrepresentation of round and lucky numbers in the loan amounts and bidding amounts. For example, for the loan amounts and bid amounts with the top-10 highest occurrence rates, most are round numbers. Further, the occurrence rate of round numbers is 77.02% in loan amounts and 75.6% in bid amounts. This is in stark contrast to a hypothetical situation in which there is no adoption of a round-number heuristic; in that case, both the loan amount and the bid amount follow a uniform distribution, in which each number has an equal chance of occurrence: Round numbers should only make up 5% of the loan amount records and 7.5% of the bid amount records. For the lucky-number heuristic, we find that the lucky number 8 appears more frequently than its neighboring numbers 7 and 9 in the loan amount, whereas the unlucky number 4 has a much lower frequency than numbers 3 and 5 in both loan amounts and bid amounts, which shows the prevalent use of the lucky-number heuristic among participants on this Chinese P2P lending platform.

More importantly, we show that borrowers' choice of heuristics is not random. Psychological theories show that round numbers are cognitively more accessible (Schindler and Kirby, 1997) and easier to process (Thomas et al., 2010). Using round numbers in decision-making is a mental shortcut that allows cognitively constrained individuals to make easier but less accurate decisions. We find that the round-number heuristic is more likely to be used by borrowers with worse credit ratings and lower asset levels. This pattern is consistent with prior literature that documents the inferior quality and performance associated with the use of round numbers in financial markets (Kuo et al., 2014; Gao et al., 2019; Lin and Pursiainen, 2019).

The use of lucky numbers is associated with superstitious and optimistic beliefs (Darke and Freedman, 1997; Day and Maltby, 2003). Superstitious lenders and consumers are willing to pay a premium for lucky numbers (Agarwal et al., 2014; Shum et al., 2014; Fortin et al., 2014; Wong et al., 2019). Given the preference for lucky numbers, the lucky-number heuristic is intentionally used by sophisticated fundraisers to attract investors (Hirshleifer et al., 2018). We find that borrowers with better credit quality and a larger asset base tend to use the lucky-number heuristic, by setting lucky borrowing amounts in their loan applications. This is in line with Hirshleifer et al. (2018), who document that Chinese firms intentionally use lucky IPO listing codes to cater to investors' lucky preference. Quantitatively, a one-notch increase in credit grade[2] reduces the likelihood of using round numbers in loan amounts by 10.44% and increases the probability of using lucky numbers in loan amounts by 14.39%.

The use of heuristics by borrowers is also not independent. We document a substitution effect between the two heuristics; that is, when a borrower uses a certain heuristic in setting the loan amount, they are less likely to use the other at the same time. Resorting to the round-number heuristic by a borrower reduces the probability of using a lucky-number heuristic by 16.87%, and having a lucky loan amount lowers the probability of using the round-number heuristic by 5.71%.

Next, we examine the implications of using these two heuristics in the loan amount on the bidding and funding process for each loan application. Specifically, we focus on two variables: the

[2] RRD assigns each borrower a credit grade. There are seven grades—AA, A, B, C, D, E and HR—in which AA is the highest rating and HR the lowest.

funding success rate and time to funding completion. Interestingly, we find that use of the round-number heuristic and of the lucky-number heuristic in loan amounts has opposite effects on the funding success rate. On the one hand, having a lucky-number loan amount in the loan application increases funding success probability by around 24.05 percentage points. On the other hand, having a round-number loan amount reduces the funding success rate by 19.13 percentage points. Loans in the lucky amount take a shorter time to get fully funded: 0.084 hours less than non-lucky loans, using the funded sample. In contrast, loans in the round amount, on average, take 0.08 hours longer to be fully funded. Given the average funding time of 0.716 hours, this is 11.17% more time. The findings are robust to including borrower and loan characteristics as control variables.

In addition to the funding process, we examine the implications of using different heuristics in the loan amount on loan performance. To our surprise, neither of the two heuristics seems to have a significant impact on the loan delinquency rate. Although the choice of heuristics is associated with different borrower profiles ex ante, loan performance ex post appears similar. One explanation could be that loan applications with round-number loan amounts are initiated by borrowers with lower credit quality, and these applications are subject to tighter screening by investors (as seen from the lower funding success rate and longer time to funding completion). As a result, only those round-number loans with other positive attributes survive the screening, and hence their loan performance is not much worse than that of loans in non-round numbers.

For the lucky-number heuristic, although we find that borrowers with higher credit quality are more likely to use lucky loan amounts in loan applications, lucky-number loans face relatively lax screening, as seen from the higher funding success rate and shorter time to completion. The combination of the two effects could explain the insignificant impact of heuristic adoption on loan performance, which suggests that the better credit quality of lucky-amount loans is offset by lax screening.

This explanation requires that lenders to be able to fully extract information on the quality of borrowers from their choice of heuristics. In unreported regressions, we find that lenders are more likely to invest in loans with lucky amounts compared with round-amount loans as they become more experienced, which proves that lenders are learning to understand the information behind borrowers' use of heuristics and adjust their investment decisions accordingly.

For lenders' adoption of heuristics, we also find that their choice of round-number or lucky-number heuristics in setting the bid amount reveals certain characteristics of their investment style.

We find that cognitively constrained lenders who set round-number bid amounts pay less attention to portfolio diversification. Instead, they resort to the naïve diversification strategy (Benartzi and Thaler, 2001) by investing an equal amount across different loans. Lenders who set lucky bid amounts are less likely to do so.

Lenders' choice of heuristics also reveals their risk preference. We use two proxies to measure lenders' risk preference. The first is the credit grade of the loan on which a bid is placed, which reflects the risk undertaken in investing. The second proxy is the bid amount, which reflects a lender's diversification preference, since smaller bid amounts reflect higher degrees of diversification. We find that lenders who make round bids are more risk-averse in general, because they invest in loans with higher credit ratings. They also tend to invest a smaller amount in each loan for better diversification. Lenders who make lucky bids, in contrast, invest in loans of lower credit quality and hold more concentrated portfolios. This pattern is consistent with that of Jiang et al. (2009), who find that people are more aggressive in taking risks when they feel lucky.

This paper makes the following important contributions. First, it is the first attempt to investigate individuals' choice of different heuristics. To the best of our knowledge, we are the first to examine the heterogeneities of different heuristics and their implications for the funding success rate and investment performance in P2P marketplace loans. It is of great value to uncover the information behind the use of heuristics, as the choice of heuristics reveals the credit quality and risk preferences of borrowers and lenders. In many cases, we only observe whether people adopt different heuristics in decision-making, without knowing their innate cognitive attributes. Since various heuristics are preferred by individuals with different characteristics, based on our findings we can infer individuals' cognitive attributes by the heuristics they use. Our findings have wide application in real life. In addition to the context of P2P loan application and investment, they may be valuable in situations such as loan screening, credit ratings, and job interviews. More generally, our findings shed light on the use of highly granular investment behavior data in predictive analytics (Martens et al., 2016).

Second, we examine the relationship between different heuristics and study them simultaneously. Although Goldreich (2004) and Hedesstrom et al. (2004) document the existence of various heuristics in decision-making, most prior studies focus on one heuristic at a time, rather than the interaction between different heuristics. Motivated by Alexander and Peterson (2007), who apply a Bivariate Probit model to examine the presence of the round-number heuristic in both the price and quantity of stock trading, we adopt a similar estimation methodology to examine individuals' choice of different heuristics. The model estimates the determinants of the round-number heuristic and lucky-number heuristic simultaneously, which allows for the interaction between them.

Third, the paper adds to the burgeoning literature on P2P lending by focusing on lenders' and borrowers' behavioral biases. Crowd funding, and P2P lending in particular, have experienced rapid growth in the past decade (Hildebrand et al., 2017), and have been widely used by households and entrepreneurs (Roma et al., 2018; Burch and Chan, 2019). Literature shows that the lender's and borrower's investment behaviors are affected by culture and geographic similarity (Burch et al., 2014), social capital pro-sociality (Hong et al., 2018; Du et al., 2020), campaign quality (Geva et al., 2019), soft and nonstandard information (Duarte et al., 2012; Iyer et al., 2016; Jagtiani and Lemieux, 2019), investors' experience (Kim and Viswanathan, 2019); friendship (Lin et al., 2013; Liu et al., 2015), pricing mechanism (Wei and Lin, 2017), wealth level (Paravisini et al., 2017), and etc. Different from well-developed financial markets, the P2P lending market is still in an emerging stage in most countries, including China, and most participants in this market are retail investors and borrowers with limited expertise and experience. Thus, behavioral biases are likely to prevail. Researchers have documented the existence of various biases in P2P lending and crowdfunding, including herding (Zhang and Liu, 2012; Liu et al., 2015; Astebro et al., 2017); home bias (Lin and Viswanathan, 2016); cognitive simplification and myopia (Hu et al., 2018); round-number bias (Lin and Pursiainen, 2019); gambling (Demir et al., 2019); and biases due to perceptions of impact (Burch et al., 2013; Kuppuswamy and Bayus, 2017). This paper provides additional evidence on the use of the round-number heuristic and the lucky-number heuristic.

The rest of the paper is organized as follows. Section 2 introduces the borrowing and lending process on RRD, as well as the round-number and lucky-number heuristics used on the platform. Section 3 reviews related literature and develops major hypotheses. Section 4 describes the data. The loan level analysis and bid level analysis are presented in Sections 5 and 6, respectively. Section 7 describes the robustness tests, and Section 8 concludes.

2. Institutional Background

2.1 P2P Platform RRD

Established in 2010, RRD is one of the largest P2P lending platforms in China. We collect all available information on registered users and loan applications—including borrowers, lenders, listings, bids, and loans—on the platform. A registered borrower can post a loan listing to request funding of a specific amount. The total amount must be in multiples of RMB 50. The minimum application amount is RMB 1,000 and the maximum in our sample is RMB 300 million.

The platform conducts an initial screening of all applications to verify the authenticity of documents provided by borrowers. Applicants who are found to use false information will be denied by the platform, and qualified applications are posted on the platform's website. Although the People's Bank of China has a credit reference system that maintains the credit records of different borrowers, it does not offer a credit rating or score, such as the FICO score in the U.S. For ease of reference, RRD calculates an internal credit grade for each borrower. Interested lenders can then browse the profiles and bids on the listings. The bid amount must be in multiples of RMB 50 as well. Each bid represents a commitment to provide capital in the amount of the bid if the listing achieves funded status and is converted into a loan.

Each application has a given funding period. If the cumulative bidding volume on the application reaches the requested amount within the time limit, the loan is materialized: The borrower receives the funds and is obligated to make monthly repayments. Otherwise, the application fails, with the money invested returned to bidders. Figure 1 illustrates the borrowing and funding process on RRD.

[INSERT FIGURE 1 ABOUT HERE]

2.2 Round Numbers and Lucky Numbers

Different from a well-developed financial market, in which the participants are sophisticated, users of the P2P platform are inexperienced borrowers and retail investors who are prone to heuristics. In particular, when borrowers and lenders decide their borrowing and investment amounts, respectively, they resort to numerological heuristics. As shown in the data description, we find an overrepresentation of round numbers and lucky numbers in both loan amount and bid amount, which indicates use of the round-number heuristic and the lucky-number heuristic.

The definition of round numbers varies slightly in different studies. For example, Bhattacharya et al. (2012) and Kuo et al. (2014) identify round numbers by focusing on the last two digits, and Lin and Pursiainen (2019) define round numbers as divisible by 1,000 or 500. For the platform we study, the loan amount and bid amount must be multiples of RMB 50, such as 1,050, 2,000, etc., and 87.33% of the amounts applied for are divisible by 1,000. It is also noteworthy that defining roundness by focusing on the last several digits is affected by the order of magnitude. For example, it is beyond question that a 4-digit number divisible by 1,000 is round, but this may not hold for an 8-digit number. Although 54,321,000 is a multiple of 1,000, it is questionable whether it should be classified as round. Given this concern, we apply a stricter criterion and recognize an amount with a nonzero number in the leftmost digit, and zero in all other digits as round.

The luckiness of numbers is culture specific. In most of Western countries, the number 13 is considered unlucky (Dyl and Maberly, 1988), whereas in China 8 is considered lucky and 4 is unlucky. The number 6 is also liked, because people believe it means that everything will go smoothly (possibly from the *I Ching*). Simmons and Schindler (2003) document a disproportionately higher frequency of the number 8 in Chinese advertisements than the number 4. Block and Kramer (2009) show an illogical result whereby Chinese consumers are willing to pay more for a package of 8 tennis balls than 10 in Taiwan. Following the literature, we designate lucky numbers as those having 8 and not 4 in the loan or bid amount.[3]

3. Literature Review and Hypothesis Development

3.1 Round-number Heuristic

Since the seminal work of Ginzberg (1936) which finds that adjusting the commodity price to round numbers is associated with remarkable changes in the sales amount, numerous studies have documented the prevalence of round-number heuristics in various contexts. For example, there is significant clustering in round numbers in the bank deposit rate (Khan et al., 1999); the gold market (Ball et al., 1985); the real estate market (Palmon et al., 2004; Leib et al., 2020); credit card repayment (Keys and Wang, 2019); financial misreporting (Thomas, 1989; Jorgensen et al., 2014; Garmaise, 2015; Pursiainen, 2020); analyst forecasts (Hirshleifer et al., 2019); IPOs (Kandel

[3] Some researchers also recognize the number 6 as lucky. In unreported robustness tests, we define lucky numbers as having 8 or 6 and no 4, and the results are consistent.

et al., 2001; Bradley et al., 2004); SEOs (Mola and Loughran, 2004); mergers and acquisitions (M&As) (Hukkanen and Keloharju, 2019); foreign exchange markets (Bessembinder, 1999; Sopranzetti and Datar, 2002; Osler, 2003); and savings and loans (Khan et al., 1999).

The psychology literature shows that round numbers often serve as reference points in human decision-making (Rosch, 1975; Pope and Simonsohn, 2011) because they are cognitively more accessible (Schindler and Kirby, 1997) and easier to process (Thomas et al., 2010)[4]; also, individuals make decisions subject to limited cognitive abilities (Simon, 1955; Kahneman, 1973). The cognitive accessibility of round numbers allows decision makers to make subjective judgments more easily (Tversky and Kahneman, 1974). However, the use of round numbers is associated with feeling-based decision-making, compared with cognitive-based decision-making using sharp (i.e. non-round) numbers (Wadhwa and Zhang, 2015).

The use of round numbers provides borrowers and lenders with cognitive convenience in decision-making, and is generally associated with limited cognitive ability and inferior decision outcomes. Alternatively, a busy individual engaged in multiple decision tasks could intentionally take a mental shortcut to save limited cognitive resources (see Kuo et al., 2015 for interpretation of investors' use of the round-number heuristic). In both cases, the use of round numbers indicates that an individual is cognitively constrained and can only pay limited attention to the current decision problem.

On the borrower side, Lin and Pursiainen (2019) find that inexperienced entrepreneurs are more likely to set round amounts in reward-based crowdfunding, and the use of round goal amounts reduces campaign success rates. Pursiainen (2020) shows that round numbers in loan amounts can be used to detect both deliberate and inadvertent misreporting by borrowers in P2P lending, along with other indicators. Along the same lines, we expect that lower-quality borrowers prefer to use round numbers in setting loan amounts and have inferior funding outcomes on P2P platforms.

The relationship between loan roundness and ex post repayment is complicated. On the one hand, loans of round numbers are applied for by borrowers of lower credit quality, and thus should have worse performance if funded. On the other hand, lower funding success indicates tighter screening by lenders, which is associated with better repayment. The combination of these

[4] Stiving (2000) presents an alternative explanation for the use of round numbers in pricing, focusing on the signaling role of high prices. Our paper focuses on the use of round numbers in loan amount, instead of the loan interest rate.

two forces leads to three possible situations, depending on the relative strength of the borrower's credit quality disparity and the lender's tightness in screening.

The first possible scenario is that if screening is not enough to offset the difference in credit quality ex ante, then the use of a round number would still be negatively related to loan performance. Second, if the screening effect dominates the credit quality effect, using a round number will be associated with lower delinquency rates. Third, it is also possible that screening would only cancel out the credit quality differences, and the use of the round-number heuristic would have a neutral influence on delinquency.

On the lender side, when investors are cognitively constrained, the attention paid to diversification is also limited. Instead of holding a portfolio that maximizes individual utility, an investor diversifies their portfolio in the most cognitively conserving manner. In particular, capital is evenly partitioned across different investment options, which is also known as the naïve diversification strategy in Benartzi and Thaler (2001). In the P2P market in particular, lenders subject to the naïve diversification strategy simply invest a fixed amount in all bids.

We formally summarize the above analysis as our first set of testable hypotheses:

Hypothesis 1 (H1): Users of the round-number heuristic are cognitively constrained and pay limited attention to P2P borrowing/investment.

Hypothesis 1A (H1A): Borrowers' use of the round-number heuristic in setting loan amounts is negatively associated with their credit quality and subsequent funding success.

Hypothesis 1B (H1B): Lenders who use a round bid amount are more likely to resort to naïve diversification strategies.

3.2 Lucky-number Heuristic

Lucky numbers are also frequently used in financial markets. For example, Hirshleifer et al. (2018) find that lucky listing codes appear abnormally frequently in Chinese IPO market, and Bhattacharya et al. (2018) show, using trading data from the Taiwan Futures Exchange, that individual investors submit significantly more limited orders at 8 than 4.

The lucky number preference is associated with superstitious beliefs (Hirshleifer et al., 2018) and optimism (Darke and Freedman, 1997; Day and Maltby, 2003), which has strong implications on risk-taking. For example, Fisman et al. (2020) show that individuals buy more insurance when feeling unlucky, and when a chairman of a firm feels unlucky, the firm significantly reduces its R&D. Jiang et al. (2009) provide experimental evidence that Asians who hold superstitious beliefs makes higher estimates of their chances of winning a lottery, express greater willingness to participate in a lottery, and are more willing to make risky financial investments associated with lucky numbers.

Apart from greater risk-taking, it is documented that investors are willing to pay a premium for lucky numbers. Wong et al. (2019) find that Chinese motorists in Malaysia are willing to pay a higher price for plates that include the number 8. Drawing on evidence from the Singapore housing market, Agarwal et al. (2014) show that housing prices are inflated when the floor number or the number in the address is a lucky one. Shum et al. (2014) and Fortin et al. (2014) find similar evidence in China and the US.

In response, developers cater to homebuyers' lucky number preference in their building design. Anecdotal evidence shows that real estate developers in Vancouver purposefully skip floor numbers that include 4 and 13, which are unlucky numbers in Chinese and Western culture.[5] Simmons and Schindle (2003) show that advertisements in China include 8 with disproportionately higher frequency, while 4 appears far less often, to cater to the preference of consumers.

Empirical evidence demonstrates that luckiness can be used to cater to the lucky preference of investors in order to attract more interest (Guryan and Kearney, 2008; Kong et al., 2020). For example, Guryan and Kearney (2008) document a *lucky store effect* where a store that recently sold a lottery ticket that won the Lotto prize experiences a 12% to 38% increase in sales. Hirshleifer et al. (2018) also document that Chinese IPO firms intentionally choose lucky listing codes to appeal to investors' lucky number preference, which results in larger price run-ups and more active trading on the secondary market. On the P2P platform, sophisticated borrowers can intentionally set lucky loan numbers to cater to investors' preference, and we expect that these loans would have better funding performance.

The influence of the lucky-number heuristic on loan repayment is also subject to two contradictory forces: the higher credit quality of applicants using lucky numbers and the lax screening by bidders. Similar to the case of the round-number heuristic, if the credit quality difference plays a dominating role, then use of the lucky-number heuristic should imply lower delinquency rates. If the screening has a stronger impact, then lucky amount loans should have

[5] For example, see this media report: https://vancouversun.com/news/local-news/no-more-skipping-4-13-14-24-in-vancouver-floor-numbers/

higher delinquencies; and if screening tightness offsets the disparity in borrowers' qualities, use of the lucky-number heuristic should be irrelevant to loan repayment performance.

We propose a second set of hypotheses on the lucky-number heuristic, as follows:

Hypothesis 2A (H2A): Borrowers who set lucky loan amounts to cater to lenders' lucky preference have better credit quality and enjoy better funding success.

Hypothesis 2B (H2B): Lenders who prefer lucky numbers in bid amounts are more superstitious and more aggressive in risk-taking.

4. Data

4.1 Data and Variables

There are three layers of samples in our data: listing level, loan level, and bid level. Listings are loan applications that lenders can choose from and bid on. At the listing level, lenders can look at borrowers' detailed descriptions and loan listing information, including interest rate, loan amount, and duration. There is a rich list of borrower characteristics, including borrower age, income level, employment status, education level, marital status, city and province of origin, home ownership status, home loan status, car ownership status, car loan status, and a credit grade assigned by the platform, consisting of seven grades: AA, A, B, C, D, E, and HR (i.e., high risk).

We can also observe each borrower's credit history on the platform, such as the number of loans applied for in the past. In addition, lenders can observe the actions of other lenders on this listing, such as the combined amount funded and percentage funded, as well as the elapsed and remaining funding time.

After a listing successfully converts to a loan, we can further observe the loan repayment performance or the delinquency rate. The loan's post-lending performance can also be observed from the platform, including whether the loan is ongoing, repaid, or overdue. Bid-level data contain the size and timing of each bid, as well as the bidder's encrypted account ID.

4.2 Heuristics in P2P Lending

We begin our analysis of borrowers' and lenders' use of heuristics by demonstrating the overrepresentation of round numbers and lucky numbers in both loan amount and bid amount. Table 1 lists the top 10 most frequent loan amounts and bid amounts. The number 50,000 is the most frequently loan amount used by borrowers, with a frequency of 131,220 (or 16.41% of the entire loan sample). Other top-frequency loan amounts are also round, indicating borrowers' prevalent use of the round-number heuristic in setting the loan amount.[6] On the lender side, bid amounts are also concentrated in round numbers: 18.58% of the bid amounts is 50, followed by other round numbers, such as 500, 100, 200, etc. The complete frequency distributions of loan amounts and bid amounts are presented in Online Appendix 1.

[INSERT TABLE 1 ABOUT HERE]

We provide further evidence of extensive use of the round-number heuristic in setting loan amounts and bid amounts by comparing the "hypothetical" and observed occurrence rates of round numbers. Since the borrowing and bidding amounts must be multiples of RMB 50, the rightmost digit must be 0 and the tens digit can be either 5 or 0. The rest of the digits can take values from 0 to 9 with the same probabilities, and the leftmost digit cannot be 0.[7]

Following this rule, we calculate the "hypothetical" ratio of round numbers by different orders of magnitude. As shown in Table 2 Panel A, there is a remarkable overrepresentation of round numbers. The comparison for loan amounts starts from the 10^3 level, since the minimum borrowing amount is RMB 1,000. For the 10^6 level, we consider only the numbers below the maximum borrowing amount, RMB 3,000,000. Compared with the hypothetical round numbers percentage of 5%, we find that 77.02% of the listings used round numbers as loan amounts, which clearly proves the wide application of a round-number heuristic in setting the loan amount. The bid amount ranges from RMB 50 to RMB 1,200,000. We also find an overrepresentation of round numbers: 75.60% of the bids are round, compared with the hypothetical percentage of 0.18%.

[INSERT TABLE 2 ABOUT HERE]

In Table B, we list the frequency of lucky numbers in loan amounts and bid amounts and compare them with their hypothetical frequency. However, we find that lucky numbers are not used more frequently than the hypothetical probability in either loan amount or bid amount. One potential explanation is that there is a substitution relationship between the round-number heuristic and the lucky-number heuristic in setting the loan and bid amounts, which will be elaborated on in Section 5. The prevalent use of round-number heuristic reduces the use of lucky-number heuristic,

[6] We note that an unlucky loan amount, 40,000, is in ninth place. This indicates that a small proportion of borrowers use the lucky-number heuristic in setting loan amounts; the majority of borrowers are not sophisticated enough to intentionally use lucky number 8 and avoid unlucky number 4 to attract investors.

[7] The hypothetical percentages are calculated under the assumption that no heuristic is adopted, and that loan amounts and bid amounts follow a uniform distribution.

which results in the observed frequencies of lucky numbers in loan amounts and bid amounts being lower than their hypothetical probabilities.

To analyze the preference for lucky numbers, we compare the relative frequency of lucky numbers with non-lucky ones. We find that lucky numbers have a higher frequency than non-lucky ones, especially in loan amounts. Figure 2 Panel A illustrates the frequency of nonzero figures in loan amounts. Since the platform requires that loan amounts must be multiples of RMB 50, the only nonzero number the tens digit can take is 5, and hence the number 5 has the highest appearance frequency of 34.9% in all loan amounts. It is also observed that as the number increases, the probability of occurrence decreases. This is consistent with a mathematical principle, Benford's law, which states that smaller numbers occur more frequently than larger ones (Benford, 1938).

Following Benford's law, a number's frequency is compared with that of its neighbors (excluding 5) to ascertain the lucky number preference. The lucky number 8 is observed more frequently than its neighboring figures 7 and 9, while the unlucky number 4 does not appear as often as number 3. In unreported univariate tests, we show that the above differences are statistically significant at the 1% level. The overrepresentation of the lucky number 8 and the underrepresentation of the unlucky number 4 reflect the active use of the lucky-number heuristic in setting loan amounts. In Panel B, we examine the bid amount and find consistent, albeit weak, evidence of the use of the lucky-number heuristic by lenders.

[INSERT FIGURE 2 ABOUT HERE]

Further, we show that the round-number heuristic and lucky-number heuristic encompass most of the numerological choices made by borrowers and investors, which highlights the prevalence of the two heuristics. We find that 77.02% of borrowers adopt the round-number heuristic and 6.68% adopt the lucky-number heuristic in setting their borrowing amounts, as shown in Table 3 Panel A. We also find there are 80.77% of borrowers who resort to at least one of the heuristics[8]. On the lender side, the bidding amount frequency analysis is presented in Table 3 Panel B. Bids in either round numbers or lucky numbers make up 75.60% and 1.74% of the bidding sample, respectively. The frequent use of these two heuristics by both lenders and borrowers underscores the importance of this study and ensures the representativeness of our results.

[8] Listings with loan amounts that are both round and lucky account for 2.93% of the total.

[INSERT TABLE 3 ABOUT HERE]

4.3 Summary Statistics

Table 4 provides summary statistics of the loan-level variables in Panels A and B, and the bid-level data are used in Panel C. Our focal variables are LoanRound and LoanLucky at the loan level, which indicate whether the loan amount is a round number or lucky number, respectively. Round loans account for 77% of the full loan application sample, and 6.7% of the loans are lucky. These percentages change to 24.1% and 18.5%, respectively, in the funded subsample. In general, the median borrower is 31 years old, post-tertiary educated, earns a wage of RMB 5,000 to RMB 10,000 per month, has 1 to 3 years of working experience, comes from one of the top 20 provinces by GDP, and has the lowest credit grade, HR. For borrowers, 40% own assets, such as cars or houses, and 16.6% have loans from traditional financial intermediaries.

[INSERT TABLE 4 ABOUT HERE]

Next, we look at loan characteristics. The mean (median) loan duration is 17.69 (18) months. While the maximum loan amount is as high as RMB 3 million, the minimum is only RMB 1,000, and the median amount is around RMB 40,000. The financing cost on RRD is high, as seen from the average (median) interest rate of 13.11% (13.00%). The interest rate premium is calculated as the difference between the loan's interest rate and the benchmark rate for the same duration from the People's Bank of China. The average (median) interest premium is 7.38% (7.00%).

At the bidding level, we are interested in two variables: RoundBid and LuckyBid, which indicate whether the bid amount is a round number or a lucky number, respectively. The percentages of round and lucky bids in the bidding sample are 75.6% and 1.7%. In general, an average (median) lender has 147.51 (54) bidding records on the platform, with an average (median) bid amount around RMB 1,191 (RMB 450).

To measure lenders' investment performance at each time point, we form an investment portfolio for each lender at the time of each bid, based on all prior bids a lender placed before the current bid. If a bid is placed on a loan that is fully repaid, the internal rate of return (IRR) is simply the loan interest rate. In case of delinquency, we derive the IRR for this specific bid from the loan repayment record. The portfolio return is calculated as the weighted average IRR of all previous bids made by the lender, using the bid amount as the weight.

On average, the average prior portfolio return (i.e., weighted average IRR) is 11.17%. Benartzi and Thaler (2011) show that investors tend to make a naïve diversification by equally dividing the investment amount across projects. We construct a dummy variable, Lazy, which equals 1 if a borrower puts the same amount in each bid throughout their investment history, and 0 otherwise. About 1.0% of bidders take this shortcut and never adjust their investment amount.

4.4 Univariate Analysis

We present the univariate test results in Table 5. In Panel A, we compare loans associated with at least one of the two heuristics in the loan amount, i.e., the round-number heuristic or lucky-number heuristic, with heuristic-free loans. The number of observations, the means of the variables in each group, and the differences in mean are presented along with *t*-test significance. Our finding is consistent with prior studies: The use of a heuristic, as a behavioral bias, is associated with worse quality and leads to suboptimal decision outcomes.

In Panel B, we report the univariate test results on the differences in key loan and borrower characteristics between round loans and non-round loans. Consistent with our hypothesis, *t*-test results show that the use of a round number in the loan amount is associated with the borrower's negative attributes. Specifically, those who borrow round-amount loans, on average, have a worse credit grade, a more junior education certificate, less working experience, and earn lower income from employment. They are less likely to own a home or car. Those loans are also charged a higher interest rate.

[INSERT TABLE 5 ABOUT HERE]

Consequently, round-amount loans have a significantly lower funding success rate than non-round loans, with a difference of -65.7%. For successfully funded loans, round loans also need on average 1.11 more hours to be fully funded. The average maturity of round loans is significantly shorter, by 9.0 months, and the interest rate is significantly higher than non-round loans, by 0.68 percentage points. In terms of loan performance, round loans are more likely to be delinquent by 6.3 percentage points.

Next, we examine the differences between lucky and non-lucky loans. In Panel C, we find that borrowers who apply for lucky loans, on average, have a better credit profile, as indicated by a higher credit grade, higher education level, more worker experience, and higher income from employment. Lucky loans are also more likely to be fully funded, with a significant difference in the probability of 41.7 percentage points. We also find that lucky loans are associated with shorter bidding time. In terms of loan contracts, a lucky loan has a lower interest rate and longer duration. As for loan performance, lucky loans are less likely to be delinquent by 1.8 percentage points.

5. Loan-level Analysis

5.1 How Borrowers Use Heuristics in Setting Loan Amounts

We begin with our analysis of determinants of the use of heuristics by borrowers without differentiating round-number heuristic and lucky-number heuristic. We present Probit regression results in the first two columns of Table 6, in which the dependent variable, Heuristic, is a dummy variable that equals 1 if the loan amount is either a round or lucky number, and 0 otherwise. Dependent variables are the borrower's credit grade along with other borrower and loan characteristics.

To investigate heuristics heterogeneity further, we examine determinants on the occurrence of round numbers and lucky numbers in loan amounts using bivariate Probit models. The model estimates the adoption of round and lucky loan amounts simultaneously and incorporates their correlations. The model is specified as follows:

$$\text{Prob}\{\text{Round amount}\} = \Phi(X'\beta_1 + \varepsilon_1)$$
$$\text{Prob}\{\text{Lucky amount}\} = \Phi(X'\beta_2 + \varepsilon_2)$$
$$Cov(\varepsilon_1, \varepsilon_2) = \rho$$

where X is a matrix of independent variables, β_1 and β_2 are coefficients vectors, and ε_1 and ε_2 are the error terms. Instead of estimating two binary Probit models separately, the bivariate Probit model allows for correlation between error terms. Specifically, instead of assuming independence between ε_1 and ε_2, the error terms are assumed to follow a joint distribution:

$$\begin{pmatrix}\varepsilon_1\\ \varepsilon_2\end{pmatrix} \sim N\left\{\begin{pmatrix}0\\ 0\end{pmatrix}, \begin{bmatrix}1 & \rho\\ \rho & 1\end{bmatrix}\right\}$$

In unreported results, we find that the correlation coefficient between the round number and the lucky number in loan amounts is -0.211, which is statistically significant at the 1% level. Thus, the use of the round-number heuristic and that of the lucky-number heuristic are not independent of each other. Using one heuristic reduces the possibility of using the other one. Therefore, separate estimations of the two binary Probit models may yield biased results, since the relationship between these two heuristics is ignored. Instead, the assumptions of the bivariate Probit model are more appropriate for our data.

The dependent variables in the bivariate Probit model are LoanRound and LoanLucky, which indicate where the loan amount is a round number or a lucky number, respectively; the determinants on the use of these two heuristics are estimated simultaneously. We start from a simple model that includes only the borrower's credit grade along with year-quarter fixed effects in matrix X. Other borrower and loan characteristics are further incorporated in the full model. Regression results are presented in Table 6.

[INSERT TABLE 6 ABOUT HERE]

Our focal variable is CreditGrade, which is assigned to each borrower by the platform based on a proprietary algorithm. Results in the first two columns confirm the univariate test result that heuristics, as a whole, are more likely to be adopted by borrowers with lower credit quality. Bivariate Probit regressions indicate that while borrowers with higher credit grade are less likely to use the round-number heuristic, they are more likely to use the lucky-number heuristic, consistent with the expected relationship between borrower quality and heuristics usage. The last row of the table reports the Wald Chi statistics, along with significance levels. The null hypothesis that the error terms are independent (i.e., ρ=0) is strongly rejected, justifying use of the Bivariate Probit model. [9]

This finding is robust to the inclusion of other borrower characteristics and loan characteristics in columns 5 and 6. Quantitatively, a one-notch increase in credit grade is associated with a 10.44% lower likelihood of using a round loan amount and a 14.39% higher likelihood of using a lucky number.[10] The findings indicate that heuristics are not adopted randomly by different borrowers. Instead, the choice of heuristics reflects the borrowers' characteristics and is affected by borrowers' credit qualities. That is, heuristics are not created equal and the use of heuristics reveals individuals' attributes.

[9] Nevertheless, we find that the findings remain robust to separate estimation of two binary Probit models. Results are not reported for brevity and are available upon request.

[10] We first convert the coefficients to changes in odds ratios of -33.63% (=$1 - e^{-0.410}$) and 15.72% (=1-$e^{0.146}$). Next, the 77.0% and 6.7% probabilities of using round numbers and lucky numbers in the full sample indicate that the original odds of using round numbers and lucky numbers are 3.3478 and 0.0718, respectively. Third, we derive the new odds ratios with a one-notch increase in credit grade as 3.3478*(1-33.63%)=2.222 and 0.0718*(1+15.72%)=0.0831. Fourth, we translate the new odds ratios into probabilities of 68.96% and 7.66%. Lastly, we compare the new probabilities with the original funding probabilities (i.e., 77.0% and 6.7%) to get the 10.44% decrease and 14.39% increase in the probability of using round numbers and lucky numbers, respectively.

We further investigate the relationship between the use of the round-number heuristic and the lucky-number heuristic, and estimate the extent of the substitution effect quantitatively using Probit regression. In the first two columns of Table 7, the dependent variable is LoanRound; LoanLucky is used as the focal variable, whose coefficient reflects how the use of a lucky amount affects the probability of having a round loan amount. The second specification switches these two variables to reveal the impact of the round-number heuristic on the use of lucky numbers. The determinants studied in Table 6 are included as control variables across all specifications. The outcomes show that when a borrower resorts to the lucky-number heuristic, they are 5.71% less likely to use a round number. Similarly, the probability of applying for a lucky-number loan is decreased by 16.87% when an individual uses a round-number heuristic.[11]

The above estimation may be subject to endogeneity issues, since the use of these two heuristics is determined simultaneously. We address this concern in columns 3 to 6 using the weighted percentage of the round (i.e., PriorRoundLoan%) and lucky (i.e., PriorLuckyLoan%) loans applied for by the borrower in the past, where the weight of each application is the loan amount. Sample size decreases, because these proxies are only applicable to repeat borrowers. The finding that the use of one heuristic reduces the probability of using the other remains unchanged. In the last two specifications, we find that borrowers who frequently used round numbers in the past are more likely to apply for a round-number loan than a lucky-number loan in the future. In addition, the use of lucky numbers in the past increases the probability of using lucky numbers in the next application, but is negatively related to the use of round numbers.

The substitution relationship is driven by disparities in the cognitive limitations of different borrowers. Specifically, borrowers with inferior credit quality tend to use round numbers more often to conserve cognitive resources, whereas higher credit quality borrowers use lucky numbers to cater to investors' lucky preference. [12]

[11] We convert regression coefficients to changes in probabilities using the same methodology as in footnote 6.

[12] Another potential reason for the observed substitution between the two heuristics is the inherent incompatibility between the use of round numbers and the use of lucky numbers. For example, consider a borrower who needs 2,599 RMB for a cell phone. As the loan amount must be in a multiple of 50, the borrower can set the loan amount as 2600, where neither heuristic is used. Alternatively, the borrower can apply for 2,800, driven by a lucky-number heuristic, or for 3,000, using a round-number heuristic. The chance is slim, however, to set a loan amount consistent with both heuristics, e.g., 8,000, as it would deviate too much from the original point. However, the incompatibility cannot explain the substitution effects observed in the last four columns, in which prior usage of round numbers and lucky numbers are examined . Thus, the mutual incompatibility cannot rule out the behavioral explanation emphasized in this paper.

[INSERT TABLE 7 ABOUT HERE]

5.2 Heuristics Used in Setting Loan Amounts and Their Effects on Funding Outcomes

We further investigate the impacts of the choice of heuristic by relating them to funding success. Table 8 Panel A reports the results of the Logit regressions in which the dependent variable is FundingSuccess, which equals 1 if the loan is fully funded and 0 otherwise. The focal explanatory variables are LoanRound and LoanLucky, which indicate whether the loan amount is round or lucky, respectively. Borrower characteristics and loan characteristics are also included as control variables. Year-quarter fixed effects are added in all specifications. A discrete variable, CreditGrade, which takes values from 1 (for HR rating) to 7 (for AA rating) is included in specifications (1), (3), and (5) to control for the borrower's credit quality. Specifications (2), (4), and (6) replace this with credit grade fixed effects. Specifications (1) to (4) examine the influence of our focal variables, LoanRound and LoanLucky, along with other controls as introduced above, while in specifications (5) and (6), both LoanRound and LoanLucky are included.

[INSERT TABLE 8 ABOUT HERE]

Estimated coefficients for round-amount loans are negative and statistically significant in all specifications, while those for lucky-amount loans are significantly positive. In the last specification, in which both heuristic dummies and two sets of fixed effects are included, the baseline observations are loans in neither a round nor lucky amount. Results show that compared with borrowers who use neither of these heuristics, use of the round-number heuristic reduces the funding success rate by 19.13 percentage points, and setting lucky loan amounts increases funding probability by 24.05 percentage points.[13]

The coefficients on other control variables also make intuitive sense. Borrowers' positive attributes, such as higher credit grade, higher education level, and greater income and assets levels, are also associated with larger funding probabilities. Listings that require larger amounts are less likely to be funded. And loan premium, which is a comprehensive measure of loan riskiness, is negatively related to funding success.

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[13] We first convert the coefficients to changes in odds ratios of -89.5% (=$1-e^{-2.255}$) and 202.5% (=$e^{1.107}$-1). Next, the full sample funding probability, 22.0%, indicates the original funding odds of 0.2821. Third, we derive the new funding odds ratios associated with the use of round numbers and lucky numbers as 0.2821*(1-89.5%)=0.0296 and 0.2821*(1+202.5%)=0.8534. Fourth, we translate the new odds ratios into funding probabilities of 2.87% and 46.05%. Lastly, we compare the new probabilities with the original funding probability (i.e., 22.0%) to get the 19.13 percentage point decrease and the 24.05 percentage point increase in funding probability.

In addition to the funding success rate, we examine the effects of loan roundness and luckiness on the funding time for funded loans. If loans in a round amount are less favored by investors than lucky loans, the round loans should take longer to get fully funded, and vice versa for lucky loans.

Table 8 Panel B reports OLS regression results on the effects of loan roundness and luckiness on bidding time, in which the funded loans subsample is used. The first two columns present the results for round amounts, the next two columns for lucky amounts, and the last two specifications include both focal variables. Borrower characteristics, loan characteristics, and year-quarter fixed effects are controlled. The coefficients on LoanRound are significantly positive across all specifications, and the coefficients on LoanLucky exhibit the opposite sign, consistent with previous results. While having round numbers in the loan amount increases funding time by 0.08 hours, the use of lucky loan amounts reduces funding time by a similar magnitude.

5.3 Heuristics Used in Setting Loan Amounts and Implications for Loan Performance

The results in Tables 6 and 8 show that loan applications in round numbers are from borrowers of worse credit quality and are subject to stricter screening, as shown by the lower funding success rate, whereas lucky loan amounts are associated with better borrower credit quality and lax screening. The relative strength of these two forces leaves the impact of heuristics on loan performance an open question. Three possible scenarios are discussed in the development of our hypotheses, and we formally check which scenario is in play in Table 9. We examine how the use of heuristics in setting loan amounts affects loan performance using logit regressions, controlling for other relevant loan and borrower characteristics. The main explanatory variables of interest are the two heuristic measures: LoanRound and LoanLucky. The dependent variable is Delinquent, a dummy variable that equals 1 if there is a late payment associated with the loan and 0 otherwise. The coefficients of our two focal variables are statistically insignificant across all specifications, which is in line with the rationale that the disparity in the credit quality of borrowers using different heuristics is simply offset by the tightness in screening.

[INSERT TABLE 9 ABOUT HERE]

We also notice that larger loan amounts, higher loan-interest premium, and longer loan duration are associated with worse loan performance, which is consistent with the findings of Karlan and Zinman (2009); Hertzberg et al. (2018); and Cespedes (2019). In addition, superior borrower credit quality, such as a better credit grade and higher education level, reduces delinquencies.

6. Bid-level Analysis

6.1 Heuristics Used in Setting Loan Amounts and Lenders' Response

Using bid-level data, we examine how lenders adjust their investment behavior in response to borrowers' use of round numbers and lucky numbers in the loan amount. We test whether lenders make more sophisticated responses as they accumulate more experience on the platform. In particular, we examine whether lenders are aware of the disparities in borrowers' qualities through the heuristics used in setting the borrowing amount and adjust their investment decisions accordingly.

In Online Appendix 3, we perform a Bivariate Probit regression, in which the dependent variables are BidtoLucky and BidtoRound, which indicate whether the bid goes to a lucky-amount loan or a round-amount loan, respectively. The focal variable is the logarithm of the number of previous bids made by the bidder. The results show that lenders impose stronger screening on round loans and are less likely to invest in them as they gain more experience. These findings confirm that investors learn from past experience and are able to extract quality information about borrowers from the heuristics they use. This pattern is consistent with the *learning by trading* phenomenon documented in Bhattacharya et al. (2018). More importantly, the observation that experienced investors impose stricter screening on borrowers who set round loan amounts provides further evidence that the level of screening tightness offsets the ex ante quality difference of borrowers using different heuristics.

6.2 Lenders' Use of Heuristics in Setting Bid Amounts

Bidding records of each lender with detailed timestamps at each second is used to examine lenders' choice of numerological heuristics. We investigate the relationship between lenders' choice of heuristics and their activeness in investment activity, with a focus on the variation in bid amounts across loans. Investors who are passive in setting their investment amounts are subject to naïve diversification strategies (Benartzi and Thaler, 2001). Since an active lender would formulate a bid amount specific to each loan request, which is less likely to be constant across all loans invested in, we measure a lender's laziness by a dummy variable, Lazy, that equals 1 if the lender invests a fixed amount in each loan in all bids and 0 otherwise. Our hypothesis suggests a positive relationship between the use of a naïve diversification strategy and adoption of the round number heuristic by cognitively constrained lenders.

Table 10 reports regression results. We find that lazy investors prefer to use round numbers in bid amounts rather than lucky numbers, as shown in Panel A. Compared with investors who actively adjust their investment quantity across loans, lazy investors are 12.75% more likely to place a round bid and 49.41% less likely to place a lucky bid.[14] In Panel A Model 1, we only include our focal variable, the Lazy dummy, along with year-quarter fixed effects. Model 2 further controls for lenders' past bidding history, as well as the logarithm of the bid amount and credit grade of the loans in which they invest. We also include the average prior portfolio return measured as the weighted average IRR from all previous bids made by each lender, which reflects their prior investment performance.

We find the average prior portfolio return reduces the likelihood of submitting a round-number bid amount, which implies that lenders using a round bid amount are associated with worse investment performance. The relationship between laziness, worse investment performance, and the use of the round-number heuristic in setting bid amounts is again consistent with evidence from the loan amount analysis, where the round-number heuristic is adopted by cognitively constrained individuals.

[INSERT TABLE 10 ABOUT HERE]

Our results also reveal that lenders display inertia in using heuristics. Similar to the borrower-side results presented in Table 7, lenders who used the round-number heuristic more frequently in the past are more likely to choose a round amount in the next bid. Similarly, those lenders who placed lucky bids in the past have a higher chance of placing a lucky number in the current bid.

In addition to lenders' laziness, we are interested in the relationship between a lender's use of heuristics and their risk preference, which is measured by two proxies. The first variable concerns a lender's risk-taking behavior, which is the credit grade of the loan application in which the lender invests. The second variable is the logarithm of the bid amount, which potentially

[14] We convert regression coefficients to changes in probabilities using the same methodology as in footnote 6.

reflects a lender's diversification across loans.[15] Our focal variables are RoundBid and LuckyBid, which indicate whether the bid amount is a round or lucky number, respectively. Lender fixed effects and year-quarter fixed effects are incorporated to control for lender characteristics and the time trend. Note that the dummy variable Lazy is omitted, as it is invariant within each lender.

The estimation results are reported in Panel B. Lenders who place round bids, on average, invest in loans of higher credit grade by 0.04 notches, and they actively diversify the risk, since the bid amount is 34.6% less. Lucky bids, in contrast, are associated with more aggressive risk-taking by investors, as the loans on which they bid have lower credit ratings. Also, the bid amount is 34.4% larger, which may lead to more concentrated portfolios. The aggressive risk-taking associated with lucky bid amounts is consistent with the literature, which finds that users of the lucky-number heuristic tend to be overoptimistic (Darke and Freedman, 1997; Day and Maltby, 2003) or hold superstitious beliefs (Hirshleifer et al., 2018).

7. Robustness Checks

7.1 Alternative Definition of Lucky Numbers

As stated in the institutional background part, some studies also consider the number 6 to be a lucky number (Shum et al., 2014), because it suggests that everything will go smoothly in traditional Chinese wisdom. We modify the definition of lucky numbers as having 8 or 6 but not 4, and re-estimate all of the empirical models using the updated definition. In unreported results, the outcomes are highly similar to our main tables.

7.2 Removing Auto Bids

RRD began providing an auto-bidding service to investors and managing investors' funds through algorithm-based auto investment in March 2012, and the proportion of auto bids keeps increasing. Online Appendix 2 presents the percentages of auto bids across time. Since only humans are subjective to heuristics, including auto bids in our sample may potentially weaken our results.

We argue that although auto bids are executed by machines, the algorithms are still designed by humans who are subject to heuristics. Thus, the influence of auto bids on our analysis

[15] In unreported regressions, we also measure a lender's diversification by the Herfindahl-Hirschman Index (HHI) of previous bids and find consistent outcomes. Results are available upon request.

may not be a serious concern. Even if auto bids were different from traditional human bids, they should be less affected by heuristics, therefore biasing the results against us. Our results from the full sample would still hold in the human-bid-only subsample.

To further confirm the robustness of our results, we estimate the major models using only a subsample of human bids. Table 11 Panel A reports results from the baseline Bivariate Probit model estimation used in Table 6. We again find that use of the round-number heuristic is negatively related to the borrower's credit grade and that the choice of a lucky number is associated with the borrower's positive attributes. The coefficients of our focal variables remain significant at the 1% level. The relationship between the round-number heuristic and the lucky-number heuristic is examined in Panel B. Consistent with the results in Table 7, we still find a substitution effect between these two heuristics within the human-bid sample.

We also examine the impact of heuristics on funding success and loan performance in Panel C. The first two columns use a sample of all loans that do not receive any auto bids and examine how borrowers' use of heuristics is associated with funding success. Not surprisingly, we find that loans of a round amount are less likely to be fully funded, whereas lucky-amount loans have higher funding success rates. The last two columns examine the influence of heuristics on loan performance using the sample of funded loans by human bids only. Similar to the results in Table 9, we find that the use of heuristics has little impact on loan delinquencies ex post.

On the bid amount side, we perform subsample regressions using human bids only to examine the robustness of our findings. We focus on the relationship between human lenders' characteristics and their choice of heuristics. Panels D and E relate lenders' activeness and risk preference to their choice of heuristics. Panel D confirms that lazy lenders prefer making round bids over lucky bids. Panel E shows that the use of lucky bids is associated with lenders who are more aggressive in risk-taking and have more concentrated portfolios.

[INSERT TABLES 11 ABOUT HERE]

Overall, we estimate all of the previous models using a subsample of funded loans with human bids only (at the loan level) or a subsample of human bids (at the bid level). The signs and significance of our focal variables remain qualitatively similar, which confirms that our findings from the full sample are not driven by auto bids and are robust.

7.3 Financial Constraints and the Minimum-amount Heuristic

A potential concern is that use of the lucky-number heuristic is influenced by investors' financial constraints. According to the platform rule on investment amounts, the bid amount must be in multiples of RMB 50. As a result, the smallest lucky number an investor can bid is 800, which is relatively large, given the median bid amount of 450[16]. In unreported regressions, we define lucky numbers as having an 8 or a 6 but no 4, which further reduces the smallest lucky bid amount to 600. The results are qualitatively similar to our main result in Table 10, which indicates that the influence of a lucky bid is not likely to be driven by financial constraints. To formally rule out the effect of lenders' financial constraints, we redo our main tests using a subsample of unconstrained lenders whose cumulative investment amount in the past 3 months is larger than 800 (i.e., the smallest lucky amount available to lenders).[17]

Table 12 Panel A presents the estimation results on the determinants of heuristic choice by unconstrained lenders in columns 1 and 2. We find that while active lenders like to place lucky bid amounts, lazy investors are more likely to choose a round bid amount, consistent with the result in Table 10 Panel A. It is also observed in columns 3 and 4 that a round bid amount is associated with more conservative risk-taking and better diversification, and bidders who make lucky bids take more risk and invest larger amounts in a single loan.

Notably, results using the unconstrained subsample are very similar to those in the models that use the full sample. Unconstrained lenders are capable of making lucky bids if they wish to do so. Therefore, the nonconflicting results alleviate concern about the impact of financial constraints.

Another concern regarding findings related to the round-number heuristic in bid amount is that it could be capturing the minimum-amount heuristic, whereby a lender invests the lowest amount allowed on the platform in each bid for better diversification. As shown in Table 1, RMB 50 is indeed the most frequently used bid amount on the platform, accounting for 18.58% of all bids.

We formally address this concern by excluding all bids of RMB 50 and re-estimate bid-level results using the remaining sample. We report regression outcomes in Table 12 Panel B. Our

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[16] Note that the mean of bid amount is 1,191, much greater than the median of 450 and also the minimum lucky number 800 in multiples of 50.

[17] We also test a stricter criterion and define unconstrained lenders as making a cumulative investment amount in the past week that exceeds 800. The results are consistent and omitted for brevity.

main findings still hold using this subsample: Lenders using the round-number heuristic tend to be more passive and adopt the naïve diversification strategy, whereas lenders using the lucky-number heuristic are more aggressive in their investments.

[INSERT TABLE 12 ABOUT HERE]

8. Conclusion

Heuristics play an important role in decision making. A large strand of the literature documents the heuristics adopted by people and analyzes their impacts separately. The evidence is scant, however, when it comes to the concurrent application of different heuristics. In this paper, we use data on detailed borrowing and lending activities on a P2P lending platform to investigate the heterogeneities between two main types of numerological heuristics, the round-number heuristic and the lucky-number heuristic.

First, we find that the two heuristics are not independent of each other. Borrowers' use of the round-number heuristic in the loan amount reduces the likelihood of using the lucky-number heuristic by 16.87%; using the lucky-number heuristic in the loan amount lowers the probability of using the round-number heuristic by 5.71%. Collectively, around 80.77% of borrowers and 76.65% of lenders use at least one of the two heuristics in setting their borrowing and bidding amounts. This finding demonstrates that heuristics of different kinds should not be investigated on a standalone basis in decision analysis.

Second, we find that these two heuristics are adopted by borrowers and lenders with different cognitive attributes and credit quality. While borrowers with higher credit quality are more likely to set lucky loan amounts to attract investors, borrowers with lower credit quality use the round-number heuristic more often, since it is cognitively more accessible. We also observe that loans with lucky numbers are more likely to be funded, whereas round-number loans have a lower funding success rate, consistent with the evidence on borrower credit quality. For funded loans, lucky loans also take a shorter time to get fully funded than round loans. In terms of loan performance, we do not find that the two heuristics have a conclusive impact. We argue that screening by lenders offsets the disparity in credit quality. As a result, the ex post performance of funded loans is not influenced by the heuristics used by borrowers.

Third, our findings indicate that the use of heuristics by investors has implications for investors' risk attitude. We find that lenders who use lucky bid amounts are more aggressive in taking risks. In contrast, lenders who use the round-number heuristic in bid amounts are more likely to be cognitively constrained and more passive, and adopt the naïve diversification strategy. This pattern is consistent with the psychological theory whereby the use of lucky numbers is associated with optimistic beliefs and excess risk-taking.

Our findings have a profound implication for credit quality inference. In more general situations, agents at an information disadvantage can predict the quality of other participants by observing their use of heuristics. In addition, the platform can benefit from our findings to improve its credit rating and pricing algorithms by incorporating information from borrowers' use of heuristics.

To the best of our knowledge, this is the first paper to reveal the concurrent application and interplay of multiple heuristics. We document the heterogeneities of heuristics in a holistic setting and provide empirical evidence that the choice of heuristics is related to individuals' characteristics and preferences. The heuristics a person adopts are informative of their credit and risk profiles. Our findings shed light on the use of highly granular investment decision data in predictive analytics (Martens et al., 2016), and could be further applied to similar frameworks to address information asymmetry problems. Apart from the loan-screening scenario this paper studies, the framework could also be applied to situations such as credit ratings and job interviews, among others.

References

Agarwal, S., He, J., Liu, H., Png, I. P., Sing, T. F. & Wong, W. K. (2014). *Superstition and asset markets: Evidence from Singapore housing.* Working paper.

Alexander, G. J. & Peterson, M. A. (2007). An analysis of trade-size clustering and its relation to stealth trading. *Journal of Financial Economics*, 84(2), 435-471.

Astebro, T. B., Fernández Sierra, M., Lovo, S. & Vulkan, N. (2017). Herding in equity crowdfunding. *Available at SSRN 3084140*.

Ball, C. A., Torous, W. N. & Tschoegl, A. E. (1985). The degree of price resolution: The case of the gold market. *Journal of Futures Markets*, 5(1), 29-43.

Benartzi, S. & Thaler, R. H. (2001). Naive diversification strategies in defined contribution saving plans. *American economic review*, *91*(1), 79-98.

Benartzi, S. & Thaler, R. (2007). Heuristics and biases in retirement savings behavior. *Journal of Economic perspectives*, *21*(3), 81-104.

Benford, F. (1938). The law of anomalous numbers. *Proceedings of the American philosophical society*, 551-572.

Bessembinder, H. (1999). Trade execution costs on Nasdaq and the NYSE: A post-reform comparison. *Journal of Financial and Quantitative Analysis*, 34(3), 387-407.

Bhattacharya, U., Holden, C. W. & Jacobsen, S. (2012). Penny wise, dollar foolish: Buy–sell imbalances on and around round numbers. *Management Science*, 58(2), 413-431.

Bhattacharya, U., Kuo, W. Y., Lin, T. C. & Zhao, J. (2018). Do superstitious traders lose money?. *Management Science*, 64(8), 3772-3791.

Block, L. & Kramer, T. (2009). The effect of superstitious beliefs on performance expectations. *Journal of the Academy of Marketing Science*, *37*(2), 161-169.

Bradley, D. J., Cooney, J. W., Jordan, B. D. & Singh, A. K. (2004). Negotiation and the IPO offer price: A comparison of integer vs. non-integer IPOs. *Journal of Financial and Quantitative Analysis*, 39(3), 517-540.

Burtch, G., & Chan, J. (2018). Investigating the relationship between medical crowdfunding and personal bankruptcy in the United States: Evidence of a digital divide. *MIS Quarterly (Forthcoming)*.

Burtch, G., Ghose, A., & Wattal, S. (2013). An empirical examination of the antecedents and consequences of contribution patterns in crowd-funded markets. *Information Systems Research*, *24*(3), 499-519.

Burtch, G., Ghose, A., & Wattal, S. (2014). Cultural differences and geography as determinants of online prosocial lending. *Mis Quarterly*, *38*(3), 773-794.

Cespedes, J. (2019). Heterogeneous Sensitivities to Interest Rate Changes: Evidence from Consumer Loans. *Available at SSRN 3022332*.

Day, L. & Maltby, J. (2003). Belief in good luck and psychological well-being: The mediating role of optimism and irrational beliefs. *The Journal of psychology*, *137*(1), 99-110.

Darke, P.R. & Freedman, J.L. (1997). "The Belief in Good Luck Scale", *Journal of Research in Personality*, 31, 486-511.

Demir, T., Mohammadi, A. & Shafi, K. (2019). Crowdfunding as Gambling: Evidence from Repeated Natural Experiments. *Available at SSRN 3430744*.

Dinev, T., McConnell, A. R., & Smith, H. J. (2015). Research commentary—informing privacy research through information systems, psychology, and behavioral economics: thinking outside the "APCO" box. *Information Systems Research*, *26*(4), 639-655.

Du, N., Li, L., Lu, T., & Lu, X. (2020). Prosocial compliance in P2P lending: A natural field experiment. *Management Science*, *66*(1), 315-333.

Duarte, J., Siegel, S., & Young, L. (2012). Trust and credit: The role of appearance in peer-to-peer lending. *The Review of Financial Studies*, *25*(8), 2455-2484.

Dyl, E. A. & Maberly, E. D. (1988). The anomaly that isn't there: a comment on Friday the thirteenth. *The Journal of Finance*, *43*(5), 1285-1286.

Fisman, R., Huang, W., Ning, B., Pan, Y., Qiu, J. & Wang, Y. (2020). Superstition and risk-taking: Evidence from "zodiac year" beliefs in China. Unpublished working paper

Fortin, N. M., Hill, A. J. & Huang, J. (2014). Superstition in the housing market. *Economic Inquiry*, 52(3), 974-993.

Gao, S., Lu, R. & Ni, C. (2019). Institutional investors' cognitive constraints during initial public offerings. *Journal of Banking & Finance*, *108*, 105627.

Garmaise, M. J. (2015). Borrower misreporting and loan performance. *The Journal of Finance*, 70(1), 449-484.

Geva, H., Barzilay, O., & Oestreicher-Singer, G. (2019). A Potato Salad with a Lemon Twist: Using Supply-Side Shocks to Study the Impact of Low-Quality Actors on Crowdfunding Platforms. *Mis Quarterly*, 4*3*(4), 1227-1248.

Ginzberg, E. (1936). Customary prices. *The American Economic Review*, *26*(2), 296-296.

Goldreich, D. (2004). Behavioral biases of dealers in US Treasury auctions. *Available at SSRN 545822*.

Gregory, R. W., & Muntermann, J. (2014). Research note—heuristic theorizing: proactively generating design theories. *Information Systems Research*, *25*(3), 639-653.

Guryan, J. & Kearney, M. S. (2008). Gambling at lucky stores: Empirical evidence from state lottery sales. *American Economic Review*, *98*(1), 458-73.

Hedesstrom, T. M., Svedsater, H. & Garling, T. (2004). Identifying heuristic choice rules in the Swedish premium pension scheme. *Journal of Behavioral Finance*, 5(1), 32-42.

Hertzberg, A., Liberman, A, & Paravisini, D. (2018). Screening on loan terms: evidence from maturity choice in consumer credit. *The Review of Financial Studies*, *31*(9), 3532-3567.

Hildebrand, T., Puri, M., & Rocholl, J. (2017). Adverse incentives in crowdfunding. *Management Science*, *63*(3), 587-608.

Hirshleifer, D. (2001). Investor psychology and asset pricing. *The Journal of Finance*, *56*(4), 1533-1597.

Hirshleifer, D. (2015). Behavioral finance. *Annual Review of Financial Economics*, *7*, 133-159.

Hirshleifer, D., Jian, M. & Zhang, H. (2018). Superstition and financial decision making. *Management Science*, *64*(1), 235-252.

Hirshleifer, D., Levi, Y., Lourie, B. & Teoh, S. H. (2019). Decision fatigue and heuristic analyst forecasts. *Journal of Financial Economics*, 133(1), 83-98.

Hong, Y., Hu, Y., & Burtch, G. (2018). Embeddedness, pro-sociality, and social influence: Evidence from online crowdfunding. *MIS Quarterly, Forthcoming*.

Hu, M. R., Li, X. & Shi, Y. (2018). Adverse Selection and Credit Certificates: Evidence from a P2P Platform. *Available at SSRN 3315146*.

Hukkanen, P. & Keloharju, M. (2019). Initial offer precision and M&A outcomes. *Financial Management*, 48(1), 291-310.

Iyer, R., Khwaja, A. I., Luttmer, E. F., & Shue, K. (2016). Screening peers softly: Inferring the quality of small borrowers. *Management Science*, *62*(6), 1554-1577.

Jagtiani, J., & Lemieux, C. (2019). The roles of alternative data and machine learning in fintech lending: evidence from the LendingClub consumer platform. *Financial Management*, *48*(4), 1009-1029.
Jiang, Y., Cho, A. & Adaval, R.. (2009). The unique consequences of feeling lucky: implications for consumer behavior. *Journal of Consumer Psychology*, 19(2), 171-184.
Jorgensen, B. N., Lee, Y. G. & Rock, S. (2014). The shapes of scaled earnings histograms are not due to scaling and sample selection: Evidence from distributions of reported earnings per share. *Contemporary Accounting Research*, 31(2), 498-521.
Kahn, C., Pennacchi, G. & Sopranzetti, B. (1999). Bank deposit rate clustering: Theory and empirical evidence. *The Journal of Finance*, 54(6), 2185-2214.
Kahneman, D. (1973). *Attention and effort* (Vol. 1063). Englewood Cliffs, NJ: Prentice-Hall.
Kandel, S., Sarig, O. & Wohl, A. (2001). Do investors prefer round stock prices? Evidence from Israeli IPO auctions. *Journal of banking & finance*, 25(8), 1543-1551.
Karlan, D. & Zinman, J. (2009). Observing unobservables: Identifying information asymmetries with a consumer credit field experiment. *Econometrica*, *77*(6), 1993-2008.
Kaustia, M., Alho, E. & Puttonen, V. (2008). How much does expertise reduce behavioral biases? The case of anchoring effects in stock return estimates. *Financial Management*, *37*(3), 391-412.
Kc, D. S. (2020). Heuristic thinking in patient care. *Management Science*, *66*(6), 2545-2563.
Keys, B. J. & Wang, J. (2019). Minimum payments and debt paydown in consumer credit cards. *Journal of Financial Economics*, 131(3), 528-548.
Kim, K., & Viswanathan, S. (2019). The experts in the crowd: the role of experienced investors in a crowdfunding market. *MIS Quarterly*, *43*(2).
Kong, Q., Granic, G. D., Lambert, N. S., & Teo, C. P. (2020). Judgment Error in Lottery Play: When the Hot Hand Meets the Gambler's Fallacy. *Management Science*, *66*(2), 844-862.
Kuo, W. Y., Lin, T. C. & Zhao, J. (2014). Cognitive limitation and investment performance: Evidence from limit order clustering. *The Review of Financial Studies*, 28(3), 838-875.
Kuppuswamy, V. & Bayus, B. L. (2017). Does my contribution to your crowdfunding project matter?. *Journal of Business Venturing*, *32*(1), 72-89.
Leib, M., Köbis, N. C., Francke, M., Shalvi, S., & Roskes, M. (2020). Precision in a Seller's Market: Round Asking Prices Lead to Higher Counteroffers and Selling Prices. *Management Science*.
Lin, M., Prabhala, N. R., & Viswanathan, S. (2013). Judging borrowers by the company they keep: Friendship networks and information asymmetry in online peer-to-peer lending. *Management Science*, *59*(1), 17-35.
Lin, M. & Viswanathan, S. (2016). Home bias in online investments: An empirical study of an online crowdfunding market. *Management Science*, *62*(5), 1393-1414.
Lin, T. C. & Pursiainen, V. (2019). The Round Number Heuristic and Entrepreneur Crowdfunding Performance. *Available at SSRN 3224543*.
Liu, D., Brass, D., Lu, Y. & Chen, D. (2015). Friendships in online peer-to-peer lending: Pipes, prisms, and relational herding. *Mis Quarterly*, *39*(3), 729-742.
Luan, S., Reb, J., & Gigerenzer, G. (2019). Ecological rationality: Fast-and-frugal heuristics for managerial decision making under uncertainty. *Academy of Management Journal*, *62*(6), 1735-1759.
Ma, X., Kim, S. H., & Kim, S. S. (2014). Online gambling behavior: The impacts of cumulative outcomes, recent outcomes, and prior use. *Information Systems Research*, *25*(3), 511-527.

Martens, D., Provost, F., Clark, J., & de Fortuny, E. J. (2016). Mining Massive Fine-Grained Behavior Data to Improve Predictive Analytics. *MIS quarterly*, *40*(4).

Mola, S. & Loughran, T. (2004). Discounting and clustering in seasoned equity offering prices. *Journal of Financial and Quantitative Analysis*, 39(1), 1-23.

Osler, C. L. (2003). Currency orders and exchange rate dynamics: an explanation for the predictive success of technical analysis. *The Journal of Finance*, *58*(5), 1791-1819.

Palmon, O., Smith, B. & Sopranzetti, B. (2004). Clustering in real estate prices: determinants and consequences. *Journal of Real Estate Research*, *26*(2), 115-136.

Paravisini, D., Rappoport, V., & Ravina, E. (2017). Risk aversion and wealth: Evidence from person-to-person lending portfolios. *Management Science*, *63*(2), 279-297.

Pope, D. & Simonsohn, U. (2011). Round numbers as goals: Evidence from baseball, SAT takers, and the lab. *Psychological science*, *22*(1), 71-79.

Pursiainen, V. (2020). Borrower Misreporting in Peer-to-Peer Loans. *Available at SSRN 3326588.*

Ramiah, V., Zhao, Y., Moosa, I. & Graham, M. (2016). A behavioural finance approach to working capital management. *The European Journal of Finance*, *22*(8-9), 662-687.

Roma, P., Gal-Or, E., & Chen, R. R. (2018). Reward-based crowdfunding campaigns: Informational value and access to venture capital. *Information Systems Research*, *29*(3), 679-697.

Rosch, E. (1975). Cognitive reference points. *Cognitive psychology*, 7(4), 532-547.

Schindler, R. M. & Kirby, P. N. (1997). Patterns of rightmost digits used in advertised prices: implications for nine-ending effects. *Journal of Consumer Research*, 24(2), 192-201.

Shiller, R. J. (2003). From efficient markets theory to behavioral finance. *Journal of economic perspectives*, *17*(1), 83-104.

Shum, M., Sun, W. & Ye, G. (2014). Superstition and "lucky" apartments: Evidence from transaction-level data. *Journal of Comparative Economics*, 42(1), 109-117.

Simmons, L. C. & Schindler, R. M. (2003). Cultural superstitions and the price endings used in Chinese advertising. *Journal of International Marketing*, 11(2), 101-111.

Simon, H. A. (1955). A behavioral model of rational choice. *The quarterly journal of economics*, *69*(1), 99-118.

Sopranzetti, B. J. & Datar, V. (2002). Price clustering in foreign exchange spot markets. *Journal of Financial Markets*, *5*(4), 411-417.

Stango, V. & Zinman, J. (2009). Exponential growth bias and household finance. *The Journal of Finance*, *64*(6), 2807-2849.

Stiving, M. (2000). Price-endings when prices signal quality. *Management Science*, *46*(12), 1617-1629.

Thomas, J. K. (1989). Unusual patterns in reported earnings. *The accounting review*, 64(4), 773.

Thomas, M., Simon, D. H. & Kadiyali, V. (2010). The price precision effect: Evidence from laboratory and market data. *Marketing Science*, *29*(1), 175-190.

Tversky, A. & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *science*, *185*(4157), 1124-1131.

Wadhwa, M. & Zhang, K. (2015). This number just feels right: The impact of roundedness of price numbers on product evaluations. *Journal of Consumer Research*, *41*(5), 1172-1185.

Wei, Z., & Lin, M. (2017). Market mechanisms in online peer-to-peer lending. *Management Science, 63*(12), 4236-4257.

Wong, W. C., Abdullah, N. A. H. & Lim, H. E. (2019). The value of Chinese superstitions in Malaysia: evidence from car plate auctioning. *The Singapore Economic Review*, *64*(01), 115-137.

Zhang, J. & Liu, P. (2012). Rational herding in microloan markets. *Management science*, *58*(5), 892-912.

Figure 1: Borrowing and Bidding Process on Renrendai

This figure presents the borrowing and bidding process on Renrendai, one of the largest online P2P platforms in China.

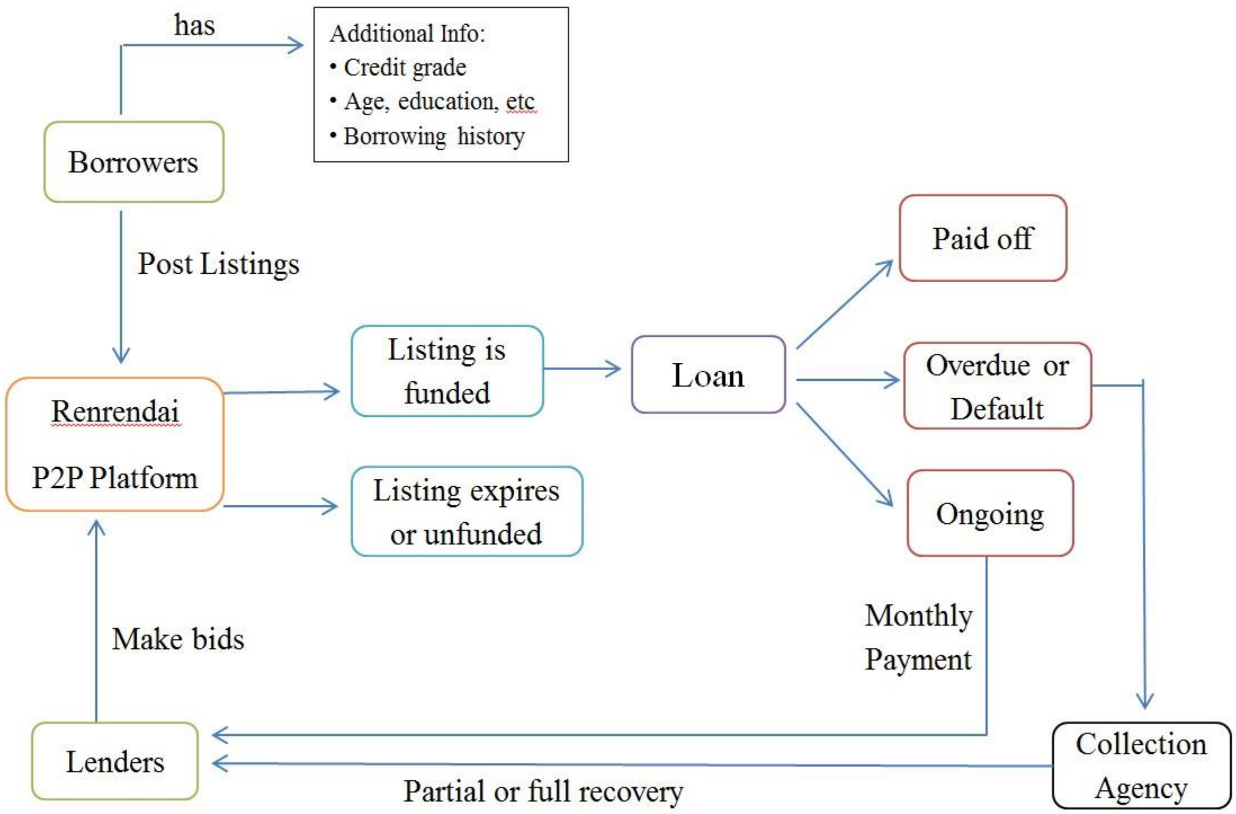
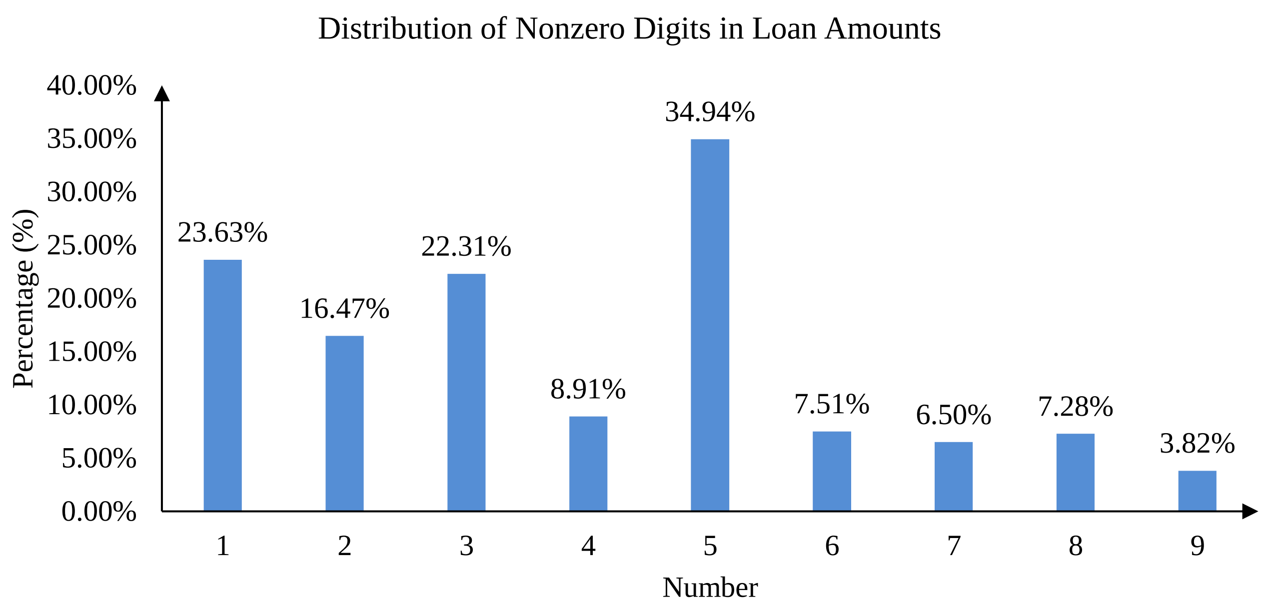


Figure 2: Distribution of Numbers in Loan and Bid Amounts
This figure shows the percentage of nonzero digits in loan amounts and bid amounts in Panel A and Panel B, respectively.

Panel A: Percentages of All Nonzero Digits in Loan Amounts



Panel B: Percentages of First Nonzero Digits in Bid Amounts

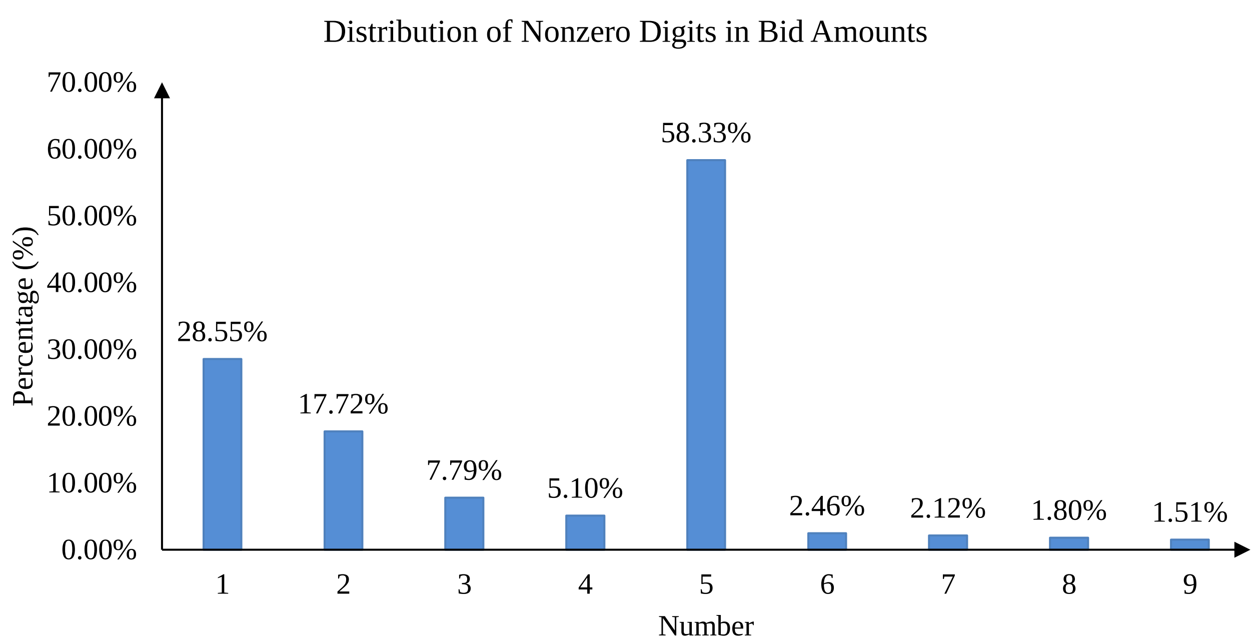


Table 1: Loan Amounts and Bid Frequencies

This table presents the frequency count and percentage of the top 10 most frequent loan amounts and bid amounts based on the loan application sample and the bid sample for funded loans.

	Loan Amount (full sample of Loan applications)			***Bid Amount (Funded sample)***		
Rank	**Amount**	**N**	**Percentage**	**Amount**	**N**	**Percentage**
1	50,000	131,220	16.41	50	1,402,123	18.58
2	10,000	61,719	7.72	500	1,265,260	16.77
3	30,000	59,058	7.38	100	777,220	10.30
4	3,000	58,393	7.30	200	601,717	7.97
5	20,000	55,615	6.95	1,000	548,296	7.27
6	100,000	50,748	6.34	150	284,928	3.78
7	5,000	40,843	5.11	300	254,698	3.38
8	200,000	16,490	2.06	2,500	234,131	3.10
9	40,000	16,317	2.04	1,500	163,973	2.17
10	60,000	15,274	1.91	2,000	159,060	2.11
Total		**505,677**	**63.22**		**569,1406**	**75.42**

Table 2: Percentage of Round and Lucky Amounts by Orders of Magnitude

This table presents the observed ratios and hypothetical ratios under a uniform distribution of round numbers and lucky numbers in loan amounts and bid amounts. The results are presented by orders of magnitude. ***Round amount*** is defined as having only one nonzero number at the leftmost digit, and ***Lucky amount*** is defined as having an 8 but no 4. Panel A presents the percentages of round numbers. The maximum loan amount in our sample is 3,000,000 RMB, so for loan amounts in order of 10^6, we only consider values between 1,000,000 and 3,000,000. Panel B the percentages of lucky numbers. The maximum bid amount in our sample is 1,200,000 RMB, so for bid amounts in order of 10^6, we only consider values between 1,000,000 and 1,200,000.

The hypothetical percentage of round numbers is calculated as $\mathrm{P(Round)} = \frac{\sum I_{round}(i)}{(^{n-m}/_{50})+1}$, with

$$I_{round}(i) = \begin{cases} 1, & i \text{ has only one non} - \text{zero number in the leftmost digit} \\ 0, & \text{otherwise} \end{cases},$$

The theoretical probability for lucky numbers is calculated as $\mathrm{P(Lucky)} = \frac{\sum I_{lucky}(i)}{(^{n-m}/_{50})+1}$, with

$$I_{lucky}(i) = \begin{cases} 1, & i \text{ has } 8 \text{ but does not have } 4 \\ 0, & \text{otherwise} \end{cases},$$

where n and m are the largest and smallest number within each order of magnitude, respectively.

Panel A: Round Number

Orders of Magnitude	N(Round Number)	Observed%	Hypothetical %
Loan Amount			
10^3	119,279	98.52	5[18]
10^4	360,411	72.27	0.50
10^5	91,583	75.05	0.05
10^6	462	94.48	0.0075
Overall	742,274	77.02	0.05
Bid Amount			
10^1	1,402,123	100	100
10^2	3,242,943	79.50	50
10^3	983,250	51.63	5
10^4	76,133	47.65	0.50
10^5	290	46.77	0.05
10^6	0	100	0.025s
Overall	5,704,739	75.60	0.175

Panel B: Lucky Numbers

Orders of Magnitude	N(Lucky Number)	Observed%	Theoretical %
Loan Amount			
10^3	6,990	5.78	18.89
10^4	18,793	4.72	25.11
10^5	898	0.80	30.09
10^6	1	0.21	29.52
Overall	26,682	4.23	29.53
Bid Amount			
10^1	0	0.00	0.00
10^2	71,852	1.76	11.11
10^3	52,237	2.74	18.89
10^4	7,003	4.38	25.11
10^5	25	4.03	30.09
10^6	0	0.00	29.52
Overall	131,117	1.74	28.67

[18] For example, the 10^3 group contains 9 round numbers, including 1,000, 2,000, …, and 9,000. The total number of possible loan amounts is 180 = ((9,950-1,000)/50+1). Thus the hypothetical probability equals 5% = 9/180.

Table 3: Round-number Heuristic and Lucky-number Heuristic

This table describes use of the round-number heuristic and lucky-number heuristic in the choice of loan and bid amounts. Every amount is classified into one of four categories by whether it is round or lucky. Panels A and B report the distribution of the loan amount and the bid amount, respectively.

Panel A: Percentages of Loan Amount

	Round Loan (%)	Non-Round Loan (%)	Total (%)
Lucky Loan (%)	2.93	3.75	6.68
Not Lucky Loan (%)	74.10	19.22	93.32
Total (%)	77.02	22.98	100

Panel B: Percentages of Bid Amount

	Round Bid (%)	Non-Round Bid (%)	Total (%)
Lucky Bid (%)	0.68	1.05	1.74
Not Lucky Bid (%)	74.91	23.35	98.26
Total (%)	75.60	24.40	100

Table 4: Summary Statistics

Panel A reports the summary statistics of borrower and loan characteristics in the full sample of all loan applications, and Panel B uses the funded subsample. Panel C uses bid-level data and presents lender and bid characteristics. Refer to Appendix 1 for the definition of other control variables.

Panel A: Borrower and Loan Characteristics (Full Sample)

Variable	N	mean	sd	p25	p50	p75	min	max
Borrower Characteristics								
Age	742,276	33.529	7.373	28	31	37	18	89
CreditGrade	742,292	1.988	1.957	1	1	1	1	7
EduLevel	670,281	1.857	0.780	1	2	2	1	4
JobIncomeLevel	594,069	4.068	1.218	3	4	5	1	7
JobLength	560,468	2.168	1.039	1	2	3	1	4
Single	723,459	0.521	0.500	0	1	1	0	1
Top20Province	560,191	0.876	0.329	1	1	1	0	1
HasAsset	742,292	0.400	0.490	0	0	1	0	1
HasLoan	742,292	0.166	0.372	0	0	0	0	1
NPriorLoan_Applied	742,292	0.703	2.248	0	0	1	0	147
Loan Characteristics								
LoanRound	742,274	0.770	0.421	1	1	1	0	1
LoanLucky	742,274	0.067	0.250	0	0	0	0	1
Loan_Amount (k)	742,274	59.648	86.885	12	40	62	1	3,000
Loan_Rate	742,292	13.113	2.674	12.000	13.000	13.200	3.000	24.400
Loan_Premium	742,039	7.376	2.547	6.000	7.000	7.750	-3.100	19.540
Loan_Duration (month)	742,292	17.689	100.095	12	18	24	1	48
FundingSuccess	742,292	0.220	0.414	0	0	0	0	1

Panel B: Borrower and Loan Characteristics (Subsample of Funded Loans only)

Variable	N	mean	sd	p25	p50	p75	min	max
Borrower Characteristics								
Age	163,149	38.417	8.396	32	37	44	21	75
CreditGrade	163,152	5.360	1.571	6	6	6	1	7
EduLevel	163,142	1.987	0.742	1	2	2	1	4
JobIncomeLevel	163,141	4.504	1.289	3	4	5	1	7
JobLength	162,952	1.737	1.039	1	1	2	1	4
Single	163,152	0.289	0.453	0	0	1	0	1
Top20Province	162,542	0.896	0.305	1	1	1	0	1
HasAsset	163,152	0.571	0.495	0	1	1	0	1
HasLoan	163,152	0.320	0.467	0	0	1	0	1
NPriorLoan_Applied	163,152	0.413	3.128	0	0	0	0	147
Loan Characteristics								
LoanRound	163,152	0.241	0.428	0	0	0	0	1
LoanLucky	163,152	0.185	0.388	0	0	0	0	1
Loan_Amount (k)	163,152	55.067	49.941	30.000	47.500	77.800	3	3,000
Loan_Rate	163,152	12.130	1.390	11.000	12.000	13.200	3.000	24.400
Loan_Premium	163,074	6.357	1.215	5.650	6.400	7.050	-2.100	19.540
Loan_Duration (month)	163,152	24.005	10.198	18	24	36	1	48
BidTime (h)	163,152	0.716	5.399	0.001	0.004	0.037	0.000	167.510
Delinquent	163,152	0.037	0.188	0	0	0	0	1

Panel C: Bid-level Lender Characteristics

Variable	N	mean	sd	p25	p50	p75	min	max
BidAmount (k)	7,546,180	1.191	3.631	0.100	0.450	1.000	0.050	1,200
NPriorBids	7,546,182	147.509	283.193	17	54	152	0	4,979
RoundBid	7,546,182	0.756	0.430	1	1	1	0	1
LuckyBid	7,546,180	0.017	0.131	0	0	0	0	1
BidtoRound	7,546,182	0.205	0.404	0	0	0	0	1
BidtoLucky	7,546,182	0.215	0.411	0	0	0	0	1
PriorRoundBid%	7,385,250	0.689	0.303	0.478	0.780	0.963	0	1
PriorLuckyBid%	7,385,250	0.027	0.068	0.000	0.000	0.031	0	1
Porior_Return	7,385,250	11.166	3.318	10.921	11.605	12.540	-100.000	24.000
Lazy	7,528,731	0.010	0.100	0	0	0	0	1

Table 5: Univariate Tests

Panel A partitions the loan sample by whether a borrower resorts to either the round-number heuristic or lucky-number heuristic in setting loan amounts. Round loans are those that have only one nonzero figure at the leftmost digit. For example, 1,000 is a round loan and 1,200 is not a round loan. Lucky numbers are defined as having the lucky number 8 but not the unlucky number 4. For example, 8,300 is a lucky number, but 8,400 and 7,300 are not. Panels B and C partition the loan sample by the roundness and luckiness of the loan amount, respectively. As Delinquent and BidTime are only observable for funded loans, the subsample of funded loans is used for these two variables. Number of observations, sample mean, difference in means, and t-test significance are presented. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Refer to Appendix 1 for the definition of other control variables.

Panel A: Univariate Test by the Use of Heuristics

	Heuristic-affected Loans		Heuristic-free Loans		Difference
Variable	N	mean	N	mean	diff
FundingSuccess	599,579	0.108	142,695	0.690	-0.582***
Delinquent	64,697	0.056	98,455	0.024	0.032***
BidTime (h)	64,697	1.102	98,455	0.462	0.641***
CreditGrade	599,579	1.459	142,695	4.210	-2.751***
Age	599,567	32.776	142,691	36.693	-3.917***
EduLevel	531,735	1.830	138,528	1.958	-0.127***
JobIncomeLevel	460,160	3.981	133,891	4.365	-0.384***
JobLength	428,709	2.266	131,741	1.846	0.420***
Single	581,774	0.558	141,667	0.371	0.187***
Top20Province	428,529	0.873	131,645	0.886	-0.013***
HasAsset	599,579	0.369	142,695	0.529	-0.160***
HasLoan	599,579	0.138	142,695	0.281	-0.143***
NPriorLoan_Applied	599,579	0.769	142,695	0.429	0.340***
Loan_Amount (k)	599,579	58.094	142,695	66.181	-8.087***
Loan_Rate	599,579	13.230	142,695	12.623	0.606***
Loan_Premium	599,391	7.505	142,630	6.833	0.673***
Loan_Duration (month)	599,579	16.239	142,695	23.782	-7.543***

Panel B: Univariate Test by Loan Roundness

	Round Loans		Non-Round Loans		Difference
Variable	N	mean	N	mean	diff
FundingSuccess	571,735	0.069	170,539	0.726	-0.657***
Delinquent	39,378	0.085	123,774	0.021	0.063***
BidTime (h)	39,378	1.554	123,774	0.449	1.105***
CreditGrade	571,735	1.267	170,539	4.404	-3.137***
Age	571,723	32.528	170,535	36.887	-4.359***
EduLevel	504,022	1.824	166,241	1.955	-0.131***
JobIncomeLevel	423,602	3.954	161,449	4.373	-0.419***
JobLength	401,246	2.318	159,204	1.788	0.530***
Single	553,966	0.570	169,475	0.362	0.208***
Top20Province	401,074	0.873	159,100	0.885	-0.012***
HasAsset	571,735	0.356	170,539	0.549	-0.193***
HasLoan	571,735	0.125	170,539	0.393	-0.179***
NPriorLoan_Applied	571,735	0.796	170,539	0.393	0.403***
Loan_Amount (k)	571,735	57.708	170,539	66.152	-8.444***
Loan_Rate	571,735	13.269	170,539	12.589	0.680***
Loan_Premium	571,559	7.549	170,462	6.797	0.751***
Loan_Duration (month)	571,735	15.627	170,539	24.600	-8.973***

Panel C: Univariate Test by Loan Luckiness

	Lucky Loans		Non-Lucky Loans		Difference
Variable	N	mean	N	mean	diff
FundingSuccess	49,573	0.609	692,701	0.192	0.417***
Delinquent	30,205	0.022	132,947	0.040	-0.018***
BidTime (h)	30,205	0.503	132,947	0.764	-0.261***
CreditGrade	49,573	3.832	692,701	1.856	1.976***
Age	49,573	36.272	692,685	33.333	2.940***
EduLevel	48,004	1.920	622,259	1.852	0.068***
JobIncomeLevel	46,280	4.370	547,771	4.042	0.328***
JobLength	45,365	1.814	515,085	2.199	-0.384***
Single	49,207	0.384	674,234	0.531	-0.147***
Top20Province	45,314	0.878	514,860	0.876	0.002
HasAsset	49,573	0.569	692,701	0.388	0.181***
HasLoan	49,573	0.310	692,701	0.155	0.154***
NPriorLoan_Applied	49,573	0.536	692,701	0.715	-0.179***
Loan_Amount (k)	49,573	63.241	692,701	59.391	3.850***
Loan_Rate	49,573	12.792	692,701	13.136	-0.344***
Loan_Premium	49,549	7.006	692,472	7.403	-0.397***
Loan_Duration (month)	49,573	23.848	692,701	17.248	6.599***

Table 6: Determinants of Borrowers' Preferences for Round Numbers and Lucky Numbers

This table presents the estimation result on the determinants of borrowers' heuristics used in setting loan amounts. The sample includes all the loan applications. The dependent variable in the first two columns is Heuristic, a dummy variable which equals 1 if the loan amount is either a round number or lucky number, and 0 otherwise. The dependent variable in column 3 and 5 is LoanRound, a dummy variable which equals 1 if the loan amount is a round number. The dependent variable in column 4 and 6 is LoanLucky, a dummy variable which equals 1 if the loan amount is a lucky number. Robust standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Refer to Appendix 1 for the definition of other control variables.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Heuristic	Heuristic	LoanRound	LoanLucky	LoanRound	LoanLucky
CreditGrade	-0.344***	-0.315***	-0.449***	0.191***	-0.410***	0.146***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Age		0.002***			0.004***	0.000
		(0.000)			(0.000)	(0.000)
Edulevel		-0.033***			-0.025***	-0.005
		(0.003)			(0.003)	(0.003)
JobIncomelevel		0.011***			0.023***	0.020***
		(0.002)			(0.002)	(0.002)
JobLength		-0.027***			0.008***	-0.029***
		(0.002)			(0.002)	(0.003)
Single		-0.023***			-0.052***	0.013**
		(0.005)			(0.005)	(0.006)
Top20Province		0.005			0.022***	-0.018**
		(0.007)			(0.007)	(0.008)
HasAsset		-0.050***			-0.140***	0.111***
		(0.005)			(0.006)	(0.007)
HasLoan		-0.010			-0.119***	0.046***
		(0.006)			(0.006)	(0.007)
NPriorLoan_Applied		0.004***			0.006***	0.005***
		(0.001)			(0.001)	(0.001)
logLoanAmount (k)		-0.083***			-0.073***	0.036***
		(0.003)			(0.003)	(0.003)
Loan_Premium		-0.002*			-0.008***	0.010***
		(0.001)			(0.001)	(0.001)
Loan_Duration (month)		-0.011***			-0.024***	0.011***
		(0.000)			(0.000)	(0.000)
Constant	2.975***	3.188***	3.190***	-2.693***	3.386***	-2.864***
	(0.152)	(0.153)	(0.161)	(0.137)	(0.159)	(0.135)
Year Qtr FE	YES	YES	YES		YES	
Observations	742,292	556,980	742,274		556,980	
Pseudo R-squared	0.274	0.287				
Wald Chi2 (ρ=0)			1,683.63***		698.74***	

Table 7: Substitution between the Round-Number Heuristic and the Lucky-Number Heuristic

This table estimates the substitution effect between the round-number heuristic and the lucky-number heuristic using Probit regressions. The dependent variables include LoanRound and LoanLucky, which indicate whether the loan amount is round or lucky, respectively. PriorRoundLoan% is defined as the percentage of round-number loans applied for by the borrower previously, using loan amount as the weight. PriorLuckyLoan% is defined as the percentage of lucky-number loans applied for by the borrower previously, using loan amount as the weight. Robust standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Refer to Appendix 1 for the definition of other control variables.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	LoanRound	LoanLucky	LoanRound	LoanLucky	LoanRound	LoanLucky
LoanRound		-0.195***				
		(0.008)				
LoanLucky	-0.234***					
	(0.008)					
PriorRoundLoan%				-0.226***	1.399***	-0.209***
				(0.016)	(0.012)	(0.017)
PriorLuckyLoan%			-0.172***		-0.095***	1.563***
			(0.019)		(0.021)	(0.018)
CreditGrade	-0.405***	0.121***	-0.238***	0.091***	-0.183***	0.070***
	(0.001)	(0.002)	(0.004)	(0.005)	(0.005)	(0.006)
Age	0.004***	0.001	0.004***	0.001	0.004***	-0.000
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Edulevel	-0.025***	-0.006	-0.045***	0.016**	-0.042***	0.017***
	(0.003)	(0.003)	(0.005)	(0.006)	(0.005)	(0.007)
JobIncomelevel	0.023***	0.021***	-0.016***	0.025***	-0.009**	0.019***
	(0.002)	(0.002)	(0.004)	(0.005)	(0.004)	(0.005)
JobLength	0.006**	-0.028***	-0.018***	0.023***	-0.030***	0.017***
	(0.002)	(0.003)	(0.004)	(0.005)	(0.004)	(0.006)
Single	-0.052***	0.010*	-0.006	-0.013	-0.002	-0.014
	(0.005)	(0.006)	(0.008)	(0.011)	(0.009)	(0.012)
Top20Province	0.021***	-0.017**	0.022**	-0.005	0.010	-0.002
	(0.007)	(0.008)	(0.011)	(0.014)	(0.012)	(0.015)
HasAsset	-0.136***	0.106***	-0.022**	0.045***	-0.019*	0.035***
	(0.006)	(0.007)	(0.009)	(0.012)	(0.010)	(0.013)
HasLoan	-0.117***	0.041***	-0.059***	-0.006	-0.042***	0.005
	(0.006)	(0.007)	(0.010)	(0.014)	(0.011)	(0.014)
NPriorLoan_Applied	0.007***	0.006***	0.006***	-0.002*	0.006***	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
logLoanAmount (k)	-0.073***	0.033***	-0.102***	0.007	-0.072***	-0.001
	(0.003)	(0.003)	(0.004)	(0.005)	(0.004)	(0.005)
Loan_Premium	-0.008***	0.010***	-0.001	-0.006***	0.000	-0.004*
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Loan_Duration (month)	-0.023***	0.010***	-0.006***	0.005***	-0.004***	0.004***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Constant	3.363***	-2.601***	2.458***	-2.068***	0.872***	-2.059***
	(0.157)	(0.134)	(0.160)	(0.179)	(0.152)	(0.188)
Year Qtr FE	YES	YES	YES	YES	YES	YES
Observations	555,980	555,980	189,212	189,212	189,212	189,212
Pseudo R-squared	0.426	0.115	0.051	0.021	0.150	0.116

Table 8: Numerological Heuristics and Funding Outcomes

This table presents estimation of the impacts of the heuristics used in setting loan amounts on funding outcomes. The sample includes all loan applications. The dependent variable in Panel A is FundingSuccess, which equals 1 if the loan is funded and 0 otherwise. The dependent variable in Panel B is bidding time in hours. The two focal variables are LoanRound and LoanLucky, which indicate whether the loan amount is round or lucky, respectively. Robust standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Refer to Appendix 1 for the definition of other control variables.

Panel A: Numerological Heuristics and Funding Success

Dependent Variable: Funding Success	(1)	(2)	(3)	(4)	(5)	(6)
LoanRound	-2.330***	-2.274***			-2.311***	-2.255***
	(0.018)	(0.019)			(0.018)	(0.019)
LoanLucky			1.223***	1.190***	1.136***	1.107***
			(0.027)	(0.029)	(0.029)	(0.030)
CreditGrade	1.560***		1.668***		1.552***	
	(0.008)		(0.007)		(0.008)	
Age	0.036***	0.032***	0.033***	0.028***	0.036***	0.032***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Edulevel	0.236***	0.237***	0.257***	0.258***	0.238***	0.239***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
JobIncomelevel	0.416***	0.420***	0.383***	0.390***	0.413***	0.418***
	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)	(0.008)
JobLength	0.198***	0.240***	0.191***	0.247***	0.200***	0.241***
	(0.008)	(0.009)	(0.008)	(0.009)	(0.008)	(0.009)
Single	-0.177***	-0.180***	-0.153***	-0.161***	-0.176***	-0.178***
	(0.017)	(0.018)	(0.017)	(0.017)	(0.017)	(0.018)
Top20Province	0.075***	0.065***	0.058**	0.048**	0.071***	0.061**
	(0.024)	(0.024)	(0.023)	(0.023)	(0.024)	(0.024)
HasAsset	0.085***	0.118***	0.094***	0.122***	0.074***	0.109***
	(0.019)	(0.019)	(0.018)	(0.019)	(0.019)	(0.019)
HasLoan	0.112***	0.078***	0.161***	0.110***	0.115***	0.081***
	(0.022)	(0.022)	(0.021)	(0.021)	(0.022)	(0.022)
NPriorLoan_Applied	-0.064***	-0.011***	-0.067***	-0.010***	-0.065***	-0.012***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
logLoanAmount (k)	-0.923***	-0.884***	-0.812***	-0.767***	-0.933***	-0.893***
	(0.008)	(0.009)	(0.008)	(0.008)	(0.009)	(0.009)
Loan_Premium	-0.088***	-0.088***	-0.084***	-0.082***	-0.088***	-0.088***
	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)
Loan_Duration (month)	0.005***	0.001	0.015***	0.007***	0.004***	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	-5.335***	-3.113***	-7.990***	-5.408***	-5.354***	-3.139***
	(0.329)	(0.203)	(0.360)	(0.194)	(0.332)	(0.205)
Year Qtr FE	YES	YES	YES	YES	YES	YES
CreditGrade FE	NO	YES	NO	YES	NO	YES
Observations	555,980	555,980	555,980	555,980	555,980	555,980
Pseudo R-squared	0.805	0.816	0.784	0.798	0.808	0.818

Panel B: Numerological Heuristics and Funding Time

Dependent Variable: BidTime (h)	(1)	(2)	(3)	(4)	(5)	(6)
LoanRound	0.088***	0.080**			0.088***	0.080**
	(0.033)	(0.033)			(0.033)	(0.033)
LoanLucky			-0.080***	-0.084***	-0.080***	-0.084***
			(0.022)	(0.022)	(0.022)	(0.022)
CreditGrade	-0.333***		-0.337***		-0.334***	
	(0.024)		(0.024)		(0.024)	
Age	-0.002	-0.001	-0.002	-0.001	-0.002	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Edulevel	-0.060***	-0.071***	-0.059***	-0.071***	-0.060***	-0.072***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
JobIncomelevel	-0.102***	-0.103***	-0.100***	-0.101***	-0.102***	-0.103***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
JobLength	0.038**	0.011	0.036**	0.009	0.037**	0.009
	(0.018)	(0.016)	(0.018)	(0.016)	(0.018)	(0.016)
Single	-0.004	-0.005	-0.006	-0.006	-0.004	-0.004
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
Top20Province	0.134***	0.134***	0.134***	0.134***	0.133***	0.133***
	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)
HasAsset	-0.110***	-0.144***	-0.113***	-0.146***	-0.108***	-0.141***
	(0.033)	(0.032)	(0.033)	(0.032)	(0.033)	(0.032)
HasLoan	-0.205***	-0.214***	-0.202***	-0.211***	-0.204***	-0.213***
	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)
NPriorLoan_Applied	-0.063***	-0.055***	-0.063***	-0.055***	-0.063***	-0.055***
	(0.007)	(0.009)	(0.007)	(0.009)	(0.007)	(0.009)
logLoanAmount (k)	1.145***	1.152***	1.141***	1.149***	1.148***	1.156***
	(0.054)	(0.054)	(0.055)	(0.054)	(0.054)	(0.054)
Loan_Premium	-0.466***	-0.487***	-0.468***	-0.489***	-0.466***	-0.487***
	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)
Loan_Duration (month)	0.014***	0.018***	0.013***	0.017***	0.014***	0.018***
	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)
Constant	98.730***	98.327***	98.854***	98.433***	98.740***	98.335***
	(4.940)	(4.919)	(4.940)	(4.919)	(4.940)	(4.919)
Year Qtr FE	YES	YES	YES	YES	YES	YES
CreditGrade FE	NO	YES	NO	YES	NO	YES
Observations	162,436	162,436	162,436	162,436	162,436	162,436
Adj. R-squared	0.303	0.304	0.303	0.304	0.303	0.304

Table 9: Numerological Heuristics and Loan Performance

This table presents the Logit estimation of the impacts of the heuristics used in setting loan amounts on loan performance. The sample includes all funded loans. The dependent variable is Delinquent, a dummy variable that equals 1 if the loan is not fully repaid or repaid with late payments and 0 otherwise. The two focal variables are LoanRound and LoanLucky, which indicate whether the loan amount is round or lucky, respectively. Robust standard errors are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Refer to Appendix 1 for the definition of other control variables.

Dependent Variable: Delinquent	(1)	(2)	(3)	(4)	(5)	(6)
LoanRound	0.039	0.026			0.040	0.026
	(0.037)	(0.037)			(0.037)	(0.038)
LoanLucky			-0.080	-0.059	-0.081	-0.059
			(0.051)	(0.052)	(0.051)	(0.052)
CreditGrade	-1.468***		-1.467***		-1.466***	
	(0.022)		(0.022)		(0.022)	
Age	0.024***	0.027***	0.024***	0.027***	0.024***	0.027***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Edulevel	-0.349***	-0.353***	-0.351***	-0.354***	-0.350***	-0.353***
	(0.021)	(0.022)	(0.021)	(0.022)	(0.021)	(0.022)
JobIncomelevel	0.108***	0.105***	0.110***	0.107***	0.108***	0.106***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
JobLength	0.060***	0.021	0.060***	0.020	0.060***	0.020
	(0.018)	(0.019)	(0.018)	(0.019)	(0.018)	(0.019)
Single	0.087**	0.096**	0.087**	0.096**	0.087**	0.096**
	(0.038)	(0.039)	(0.038)	(0.039)	(0.038)	(0.039)
Top20Province	-0.059	-0.051	-0.057	-0.050	-0.059	-0.051
	(0.050)	(0.051)	(0.050)	(0.051)	(0.050)	(0.051)
HasAsset	0.002	-0.009	0.002	-0.009	0.002	-0.009
	(0.041)	(0.042)	(0.041)	(0.042)	(0.041)	(0.042)
HasLoan	-0.363***	-0.332***	-0.363***	-0.332***	-0.363***	-0.332***
	(0.043)	(0.044)	(0.043)	(0.044)	(0.043)	(0.044)
NPriorLoan_Applied	0.059***	0.027***	0.059***	0.027***	0.059***	0.027***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
logLoanAmount (k)	0.129***	0.113***	0.121***	0.108***	0.127***	0.112***
	(0.029)	(0.027)	(0.028)	(0.027)	(0.029)	(0.027)
Loan_Premium	0.074***	0.075***	0.074***	0.075***	0.074***	0.075***
	(0.011)	(0.010)	(0.011)	(0.010)	(0.011)	(0.010)
Loan_Duration (month)	0.035***	0.036***	0.035***	0.036***	0.035***	0.036***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Constant	-1.347**	-2.974***	-1.308**	-2.945***	-1.339**	-2.966***
	(0.566)	(0.510)	(0.565)	(0.510)	(0.565)	(0.511)
Year Qtr FE	YES	YES	YES	YES	YES	YES
CreditGrade FE	NO	YES	NO	YES	NO	YES
Observations	162,436	162,436	162,436	162,436	162,436	162,436
Pseudo R-squared	0.543	0.558	0.543	0.558	0.543	0.558

Table 10: Numerological Heuristics, Lender's Activeness, and Risk Preference

This table presents the relationships between lender's activeness, risk preference, and the heuristics used in setting the bid amount. The sample includes all bidding records. Panel A reports the bivariate Probit estimation of the effect of lenders' laziness on the heuristics used in bid amounts. The dependent variable in columns 1 and 3 is RoundBid, a dummy variable indicating whether the bid amount is a round number, and the dependent variable in columns 2 and 4 is LuckyBid, a dummy variable indicating whether the bid amount is a lucky number. The focal variable is Lazy, a dummy variable that equals 1 if a bidder invests the same amount for all bids and 0 otherwise. Panel B reports the OLS regression result on the effect of heuristics on credit grade and bid amount. The dependent variable in column 1 is the credit grade of the loan on which the bid is placed, and the dependent variable in column 2 is the logarithm of the bid amount. Robust standard errors clustered at lender level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Refer to Appendix 1 for the definition of other control variables.

Panel A: Lenders' Activeness and Numerological Heuristics in Bid Amounts

	(1)	(2)	(3)	(4)
Dependent Variable	RoundBid	LuckyBid	RoundBid	LuckyBid
Lazy	0.881***	-0.691***	0.623***	-0.689***
	(0.027)	(0.053)	(0.025)	(0.065)
Porior_Return			-0.004***	0.001
			(0.001)	(0.001)
LogPriorBids			-0.054***	0.062***
			(0.002)	(0.002)
PriorRoundBid%			1.242***	-0.115***
			(0.005)	(0.007)
PriorLuckyBid%			0.372***	1.653***
			(0.027)	(0.026)
WA_CreditGrade			-0.045***	-0.009***
			(0.003)	(0.003)
logBidAmt			-0.738***	0.475***
			(0.005)	(0.005)
CreditGrade			0.035***	-0.047***
			(0.002)	(0.002)
Constant	1.133***	-2.059***	0.719***	-2.218***
	(0.073)	(0.114)	(0.068)	(0.126)
Year Qtr FE	YES		YES	
Cluster SE	Lender		Lender	
Observations	7,330,957		7,257,604	
Wald Chi2 (ρ=0)	21977.40***		9004.46***	

Panel B: Lender's Risk Preference and Numerological Heuristics in Bid Amounts

	(1)	(2)
Dependent Variable	CreditGrade	logBidAmt
RoundBid	0.041***	-0.346***
	(0.002)	(0.002)
LuckyBid	-0.071***	0.344***
	(0.004)	(0.004)
LogPriorBids	0.013***	-0.145***
	(0.002)	(0.001)
PriorRoundBid%	0.050***	-0.034***
	(0.007)	(0.007)
PriorLuckyBid%	-0.126***	-0.071***
	(0.026)	(0.022)
WA_CreditGrade	0.262***	0.021***
	(0.006)	(0.002)
logBidAmt	-0.001	
	(0.002)	
CreditGrade		-0.000
		(0.001)
Constant	2.257***	0.418***
	(0.081)	(0.059)
Lender FE	YES	YES
Year Qtr FE	YES	YES
Cluster SE	Lender	Lender
Observations	7,385,248	7,385,248
Adj. R-squared	0.359	0.401

Table 11: Robustness Test: Using Loans and Bids Involving Human Bids Only

This table presents the robustness test of the main results in Tables 6-10. Panels A, B, and C present estimations of the determinants of heuristics used by borrowers, the relationship between heuristics, and the impact on loan performance using the subsample of loans involving human bids only (excluding auto-bids). Panels D and E present the estimation of lender's laziness on the use of heuristics and the risk preference implications using the subsample of bidding records involving human bids only. Dependent variables and focal independent variables are defined as in Tables 6-10. Robust standard errors are reported in parentheses in Panels A, B, and C. Panels D and E present standard errors clustered at lender level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Refer to Appendix 1 for the definition of other control variables.

Panel A: Determinants of Borrower Preferences on Round Numbers and Lucky Numbers

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	LoanRound	LoanLucky	LoanRound	LoanLucky	LoanLucky	LoanLucky
CreditGrade	-0.392***	0.164***	-0.370***	0.144***	-0.372***	0.138***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Borrower Characteristics	NO		YES		YES	
Loan Characteristics	NO		NO		YES	
Year Qtr FE	YES		YES		YES	
Observations	631,079		445,163		445,016	
Wald Chi2 (ρ=0)	1152.74***		825.78***		670.03***	

Panel B: Substitution between the Round-Number Heuristic and the Lucky-Number Heuristic

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	LoanRound	LoanLucky	LoanRound	LoanLucky	LoanRound	LoanLucky
LoanRound		-0.237***				
		(0.009)				
LoanLucky	-0.280***					
	(0.010)					
PriorRoundLoan%				-0.218***	1.400***	-0.200***
				(0.017)	(0.012)	(0.018)
PriorLuckyLoan%			-0.163***		-0.087***	1.599***
			(0.020)		(0.021)	(0.018)
Borrower Characteristics	YES	YES	YES	YES	YES	YES
Loan Characteristics	YES	YES	YES	YES	YES	YES
Year Qtr FE	YES	YES	YES	YES	YES	YES
Observations	445,016	445,016	187,711	187,711	187,711	187,711
Pseudo R-squared	0.197	0.054	0.039	0.018	0.138	0.117

Panel C: Numerological Heuristics, Funding Success, and Loan Performance

	(1)	(2)	(3)	(4)
	Excluding Loans Receiving Auto Bids		Purely Human-Funded Loans	
Dependent Variable	FundingSuccess		Delinquent	
LoanRound	-2.312***	-2.282***	0.016	0.001
	(0.018)	(0.019)	(0.037)	(0.038)
LoanLucky	1.136***	1.109***	-0.077	-0.067
	(0.029)	(0.031)	(0.052)	(0.054)
Borrower Characteristics	YES	YES	YES	YES
Loan Characteristics	YES	YES	YES	YES
Year Qtr FE	YES	YES	YES	YES
CreditGrade FE	NO	YES	NO	YES
Observations	445,016	445,016	51,472	51,472
Pseudo R-squared	0.611	0.631	0.392	0.410

Panel D: Lender's Activeness and Numerological Heuristics in Bid Amounts

	(1)	(2)	(3)	(4)
Dependent Variable	RoundBid	LuckyBid	RoundBid	LuckyBid
Lazy	0.883***	-0.496***	1.457***	-1.705***
	(0.033)	(0.029)	(0.073)	(0.263)
Lender Side Controls	YES		YES	
Year Qtr FE	YES		YES	
Cluster SE	Lender		Lender	
Observations	1,627,009		1,494,424	
Wald Chi2 (ρ=0)	8816.72***		4401.90***	

Panel E: Lender's Risk Preference and Numerological Heuristics in Bid Amounts

	(1)	(2)
Dependent Variable	CreditGrade	logBidAmt
RoundBid	0.013***	-0.174***
	(0.005)	(0.003)
LuckyBid	-0.030***	0.272***
	(0.010)	(0.004)
Lender Side Controls	YES	YES
Lender FE	YES	YES
Year Qtr FE	YES	YES
Cluster SE	Lender	Lender
Observations	1,543,319	1,543,319
Adj. R-squared	0.269	0.505

Table 12: Robustness Test: Financial Constraint and the Minimum-amount Heuristic

This table reports the robustness tests of the determinants and risk preference implications of heuristics used in bid amounts. The sample in Panel A includes those bids from investors whose cumulative investment amount exceeds 800 in the past 3 months. The sample in Panel B is the subsample excluding all bids in the minimum allowed amount of RMB 50. Within each panel, Columns 1 and 2 report Bivariate Probit model results, in which the model settings are identical to those in Table 10 Panel A. Columns 3 and 4 estimate the OLS model used in Table 10 Panel B. Standard errors clustered at lender level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Refer to Appendix 1 for the definition of other control variables.

Panel A: Using the Subsample of Bids Submitted by Unconstrained Investors

	(1)	(2)	(3)	(4)
Dependent Variable	RoundBid	LuckyBid	CreditGrade	logBidAmt
Lazy	0.612***	-0.707***		
	(0.030)	(0.073)		
RoundBid			0.032***	-0.355***
			(0.002)	(0.002)
LuckyBid			-0.068***	0.346***
			(0.004)	(0.004)
Lender Side Controls	YES		YES	YES
Year Qtr FE	YES		YES	YES
Lender FE	No		YES	YES
Cluster SE	Lender		Lender	Lender
Observations	5,892,943		5,984,635	5,984,635
Wald Chi2 (ρ=0)	7198.02***		-	-
Adj. R-squared	-		0.345	0.396

Panel B: Using the Subsample That Excludes Bids in the Minimum-bid Amount

	(1)	(2)	(3)	(4)
Dependent Variable	RoundBid	LuckyBid	CreditGrade	logBidAmt
Lazy	0.724***	-0.833***		
	(0.025)	(0.070)		
RoundBid			0.038***	-0.344***
			(0.002)	(0.002)
LuckyBid			-0.070***	0.339***
			(0.004)	(0.004)
Lender Side Controls	YES		YES	YES
Year Qtr FE	YES		YES	YES
Lender FE	No		YES	YES
Cluster SE	Lender		Lender	Lender
Observations	7,140,812		7,257,279	7,257,279
Wald Chi2 (ρ=0)	9,326.72***			
Adj. R-squared			0.354	0.380

Appendix 1: Variables Definition

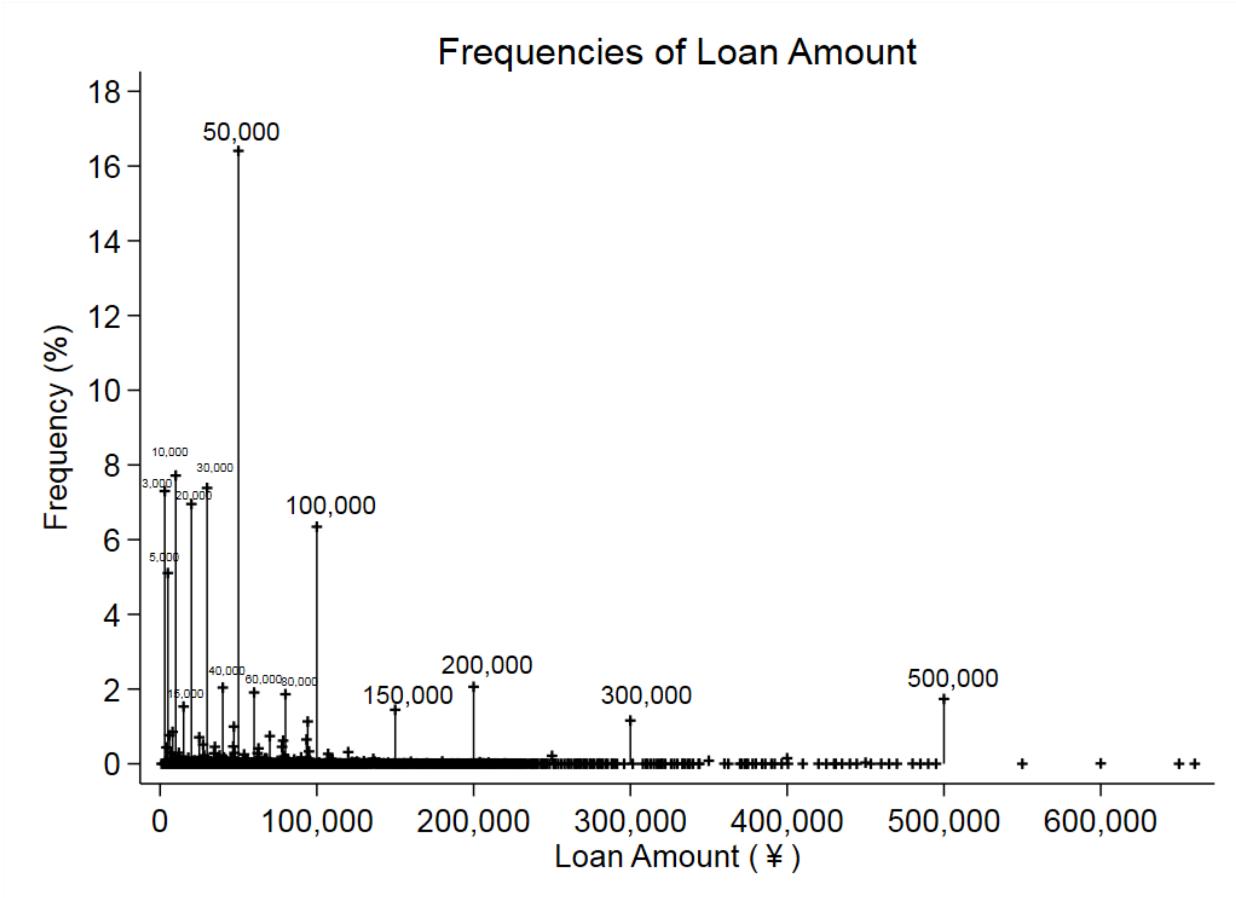
Variables	Definition
Loan-level Heuristic Measures	
LoanLucky	A dummy variable that equals 1 if the loan amount has 8 but does not have 4, and 0 otherwise.
LoanRound	A dummy variable that equals 1 if the loan amount has only one nonzero number at the leftmost digit, and 0 otherwise.
Heuristic	A dummy variable that equals 1 if the loan amount is either a lucky number or round number or both, and 0 otherwise.
PriorLuckyLoan%	The percentage of lucky loan applications in the past (before the current bid) of each bidder, weighted against bid amount.
PriorRoundLoan%	The percentage of round loan applications in the past (before the current bid) of each bidder, weighted against bid amount.
Bid-level Heuristic Measures	
LuckyBid	A dummy variable that equals 1 if the bid amount has 8 but does not have 4, and 0 otherwise.
RoundBid	A dummy variable that equals 1 if the bid amount has only one nonzero number at the leftmost digit, and 0 otherwise.
BidtoLucky	A dummy variable that equals 1 if the bid is placed on a loan whose amount has 8 but does not have 4, and 0 otherwise.
BidtoRound	A dummy variable that equals 1 if the bid is placed on a loan whose amount has only one nonzero number at the highest digit, and 0 otherwise.
PriorLuckyBid%	The percentage of lucky bids in the past (before the current bid) of each bidder, weighted against bid amount.
PriorRoundBid%	The percentage of round bids in the past (before the current bid) of each bidder, weighted against bid amount.
PriorBidtoLucky%	The percentage of bids in the past (before the current bid) that are placed on the lucky loans of each bidder, weighted against bid amount.
PriorBidtoRound%	The percentage of bids in the past (before the current bid) that are placed on the round loans of each bidder, weighted against bid amount.
Delinquent_Bid	Dummy variable that equals 1 if the bid is placed on a delinquent loan, and 0 otherwise.
Borrower Characteristics	
CreditGrade	Credit grade assigned by the platform, including seven grades AA, A, B, C, D, E, and HR. AA equals 7; A equals 6; B equals 5; C equals 4; D equals 3; E equals 2; and HR equals 1.
Age	The age of each borrower.
EduLevel	Education level. Equals 4 if the borrower's highest qualification is a master's degree or above; 3 if the borrower's highest qualification is a bachelor's degree; 2 if the borrower's highest qualification is post-tertiary; and 1 if the borrower's highest qualification is secondary or below.
JobIncomeLevel	Monthly income level. 7 means more than 50,000 RMB; 6 means between 20,000 and 50,000 RMB; 5 means between 10,000 and 20,000 RMB; 4 means between 5,000 and 10,000 RMB; 3 means between 2,000 and 5,000 RMB; 2 means between 1,000 and 2,000 RMB; and 1 means less than 1,000 RMB.
JobLength	Employment length. 4 means more than 5 years; 3 means between 3 and 5 years; 2 means between 1 and 3 years; and 1 means less than 1 year.
Single	Dummy variable that equals 1 if the borrower is single, and 0 otherwise.
Top20Province	Dummy variable that equals 1 if the borrower is from one of the top-20 provinces by GDP level, and 0 otherwise.
HasAsset	Dummy variable that equals 1 if the borrower owns a house or a car, and 0 otherwise.
HasLoan	Dummy variable that equals 1 if the borrower has a car loan or a mortgage loan, and 0 otherwise.

NPriorLoan_Applied	Number of prior loans applied for by each borrower.
Loan Characteristics	
Loan_Amount (k)	Requested loan amount in thousand RMB of each loan.
Loan_Rate	Interest rate of each loan.
Loan_Premium	Premium of each loan. Measured by the difference between the loan interest rate and the People's Bank of China's (POBC's) benchmark interest rate of the same duration.
Loan_Duration (month)	Duration in months of each loan.
BidTime (h)	Number of hours it takes for a listing to be fully funded.
FundingSuccess	Dummy variable that equals 1 if a listing is fully funded, and 0 otherwise.
Delinquent	Dummy variable that equals 1 if the loan is not fully repaid or repaid with late payments, and 0 otherwise.
Portfolio Characteristics	
Lazy	Dummy variable that equals 1 if the lender invests a fixed amount for all bids, and 0 otherwise.
Porior_Return	The average internal rate of return of past bids (before the current bid) of each bidder weighted against bid amount.
LogPriorBids	The logarithm of the number of past bids made by each lender before the current bid.

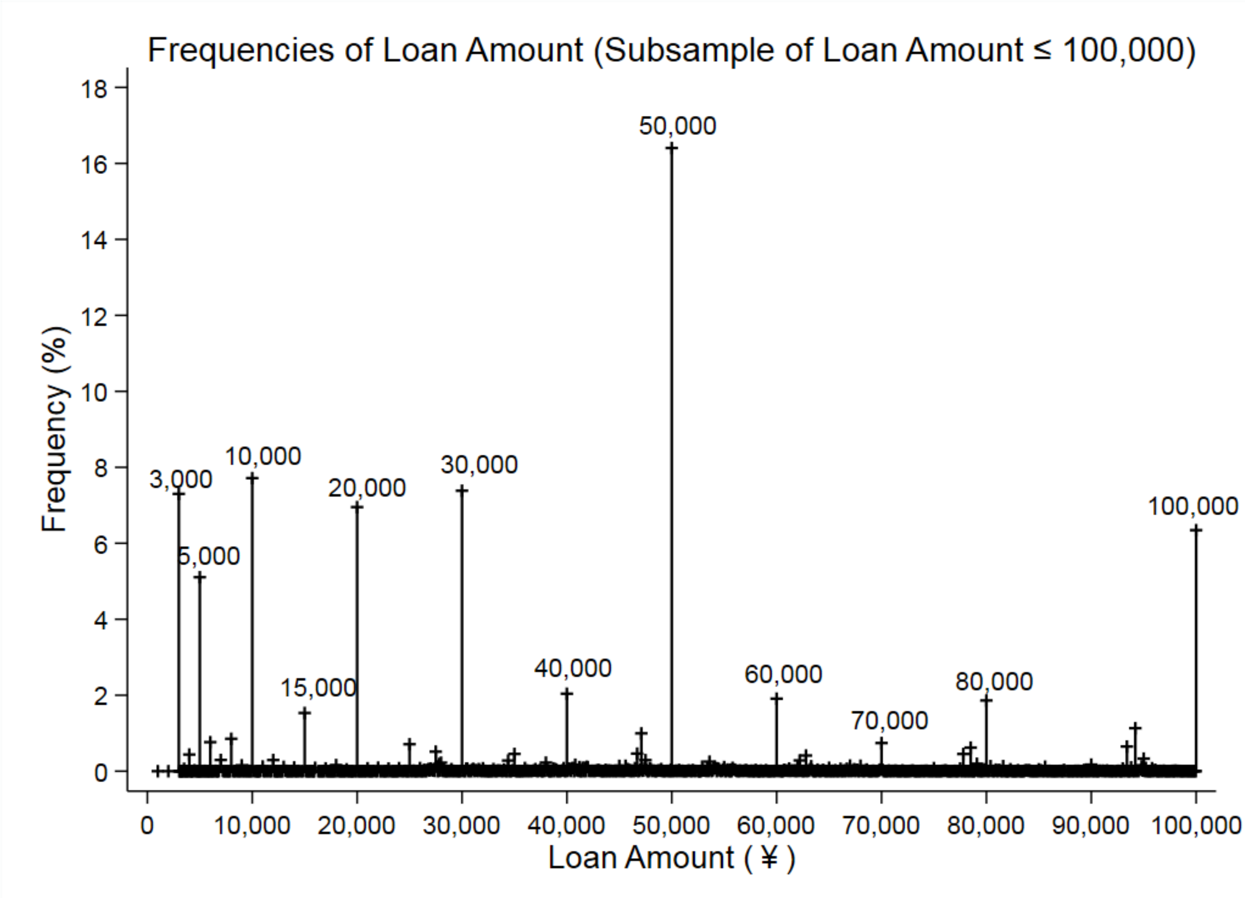
Online Appendix 1: Distribution of Loan Amounts and Bid Amounts

Panels A and C present the frequencies of loan amounts and bid amounts in the full sample, and Panels B and D present the frequencies of loan amounts and bid amounts in the subsample of loan amounts no more than RMB 100,000 and bid amounts no more than RMB 5,000, respectively.

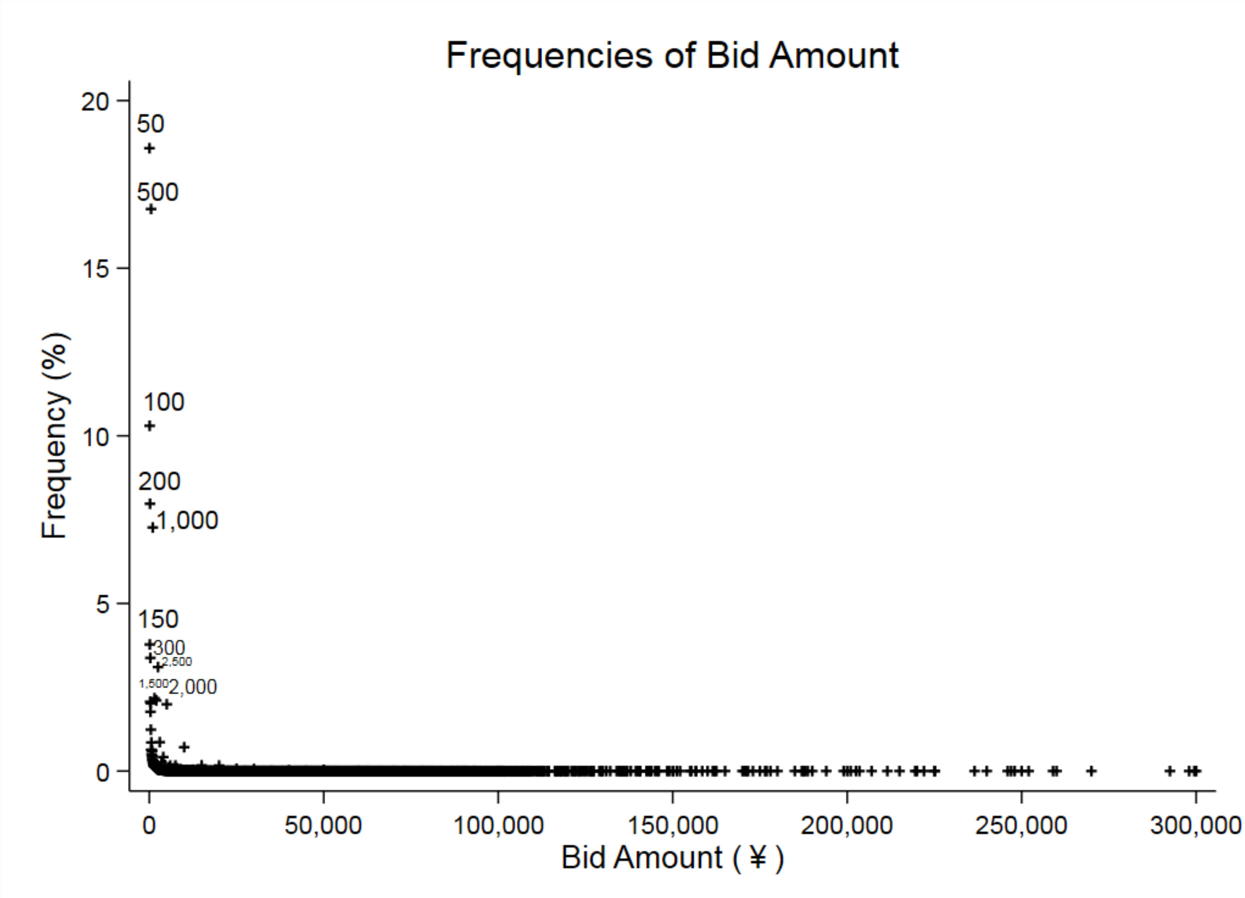
Panel A: Loan Amounts



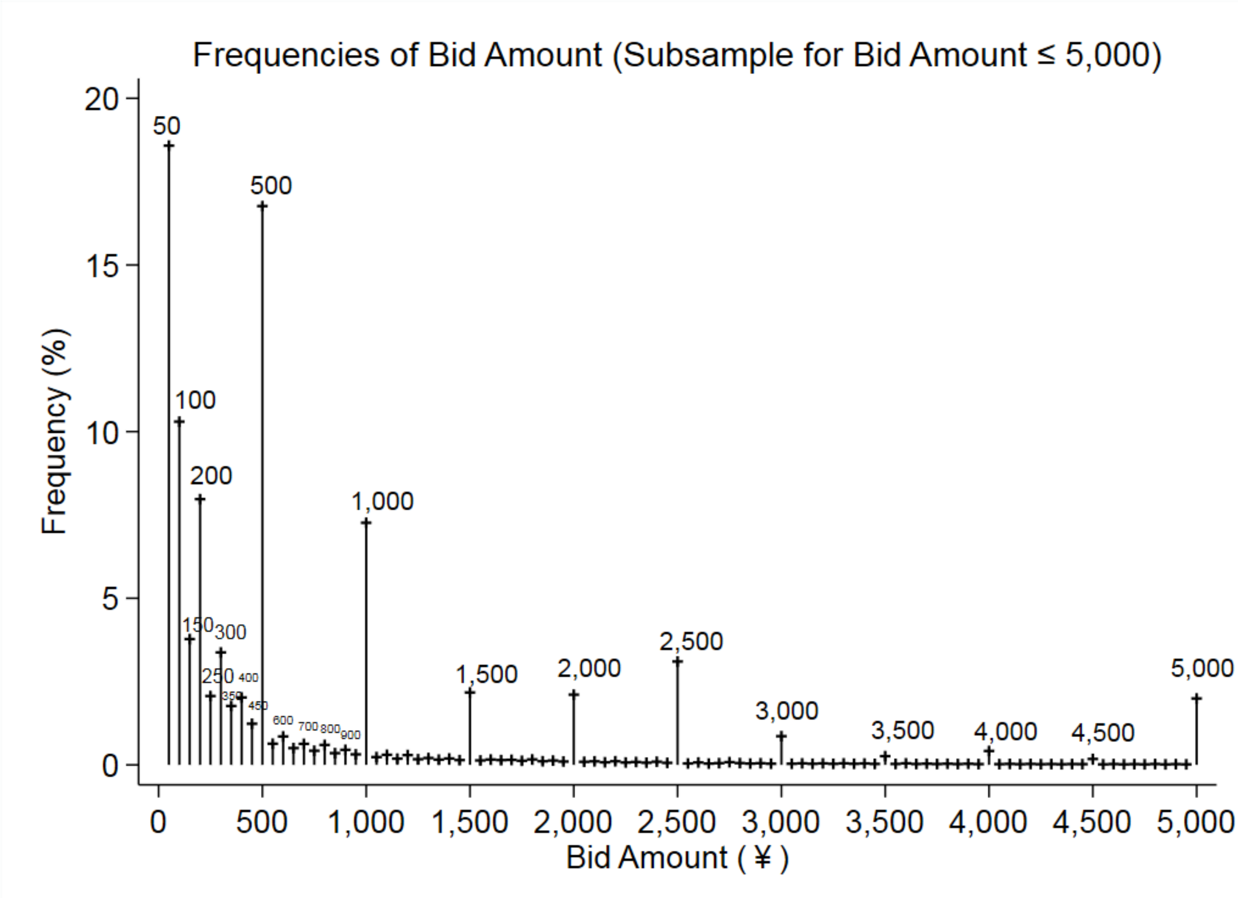
Panel B: Loan Amounts ≤ 100,000



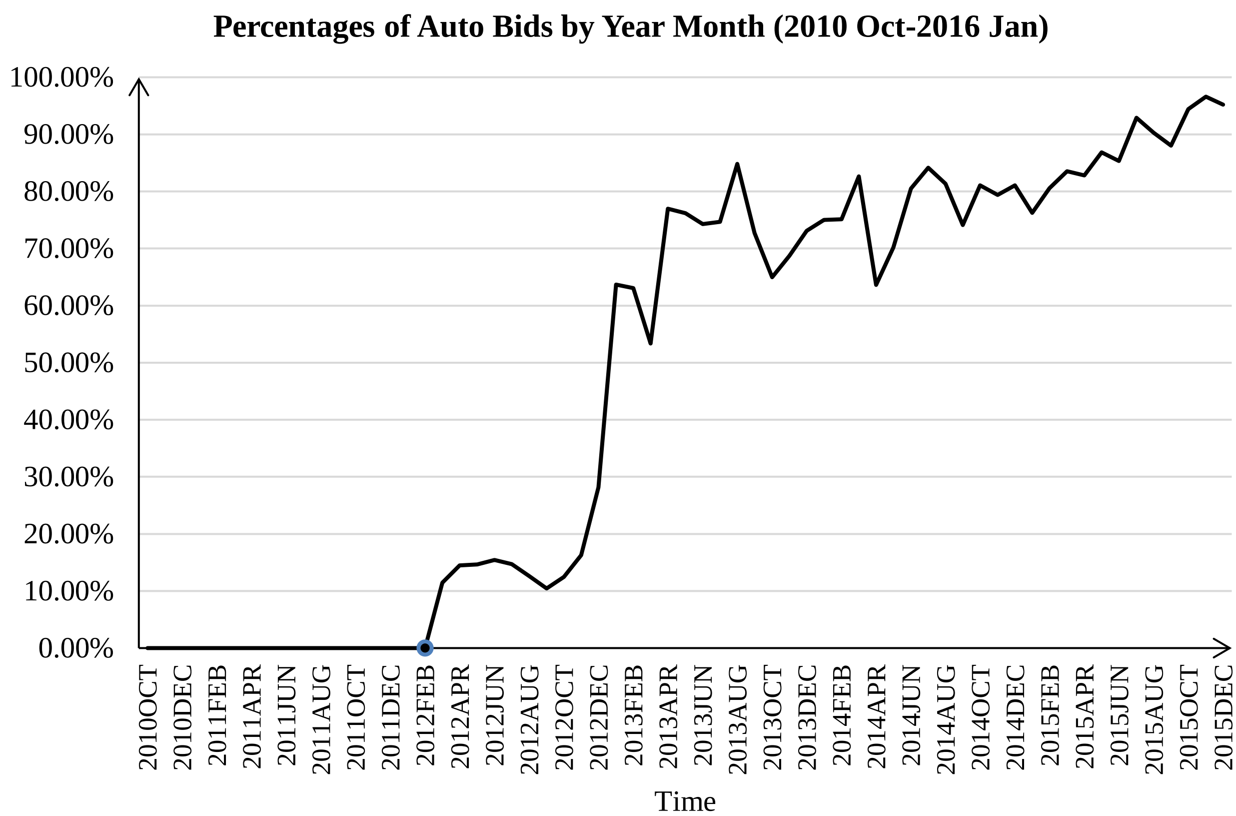
Panel C: Bid Amounts



Panel D: Bid Amounts ≤ 5,000



Online Appendix 2: Percentages of Auto Bids by Month
This figure describes the average percentage of auto bids in our sample over time.



Online Appendix 3: Numerological Heuristics and Investors' Responses

This table presents the Bivariate Probit estimation on the impact of investment experience on lenders' responses to the use of heuristics by borrowers. The sample includes all bids. The dependent variable in columns 1 and 3 is BidtoRound, which indicates whether the bid goes to a loan of a round amount, and the dependent variable in columns 2 and 4 is BidtoLucky, which indicates whether the bid goes to a loan of a lucky amount. PriorBidtoRound% is defined as the percentage of bids in the past (before the current bid) that are placed on the round loans of each bidder, using bid amount as the weight. PriorLuckyLoan% is defined as the percentage of bids in the past (before the current bid) that are placed on the lucky loans of each bidder, using bid amount as the weight. Robust standard errors are clustered at lender level and reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Refer to Appendix 1 for the definition of other control variables.

	(1)	(2)	(3)	(4)
Dependent Variable	BidtoRound	BidtoLucky	BidtoRound	BidtoLucky
LogPriorBids	-0.043***	0.017***	-0.037***	0.019***
	(0.000)	(0.000)	(0.002)	(0.001)
PriorBidtoRound%			1.144***	-0.178***
			(0.008)	(0.004)
PriorBidtoLucky%			-0.171***	0.369***
			(0.009)	(0.004)
Lazy			-0.056***	-0.048***
			(0.020)	(0.007)
WA_CreditGrade			0.036***	0.006***
			(0.003)	(0.001)
logBidAmt			-0.092***	-0.002*
			(0.003)	(0.001)
CreditGrade			-0.221***	0.074***
			(0.002)	(0.001)
Constant	1.228***	-1.637***	1.031***	-1.804***
	(0.053)	(0.067)	(0.056)	(0.056)
Year Qtr FE	YES		YES	
Cluster SE	Lender		Lender	
Observations	7,546,182		7,385,248	
Wald Chi2 (ρ=0)	3351.23***		1047.83***	