Are All Heuristics Created Equal? Evidence from P2P Investments

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June 19, 2020

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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 amongst them. Using detailed peer-to-peer (P2P) investment data 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. We document a substitution relationship between these two heuristics. 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. Lenders also apply heuristics in setting the bid amount, which potentially reveals 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 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 heuristics created equal? Are various heuristics independent from each other? Do they impose an identical impact on decision-making? What can we learn about people's characteristics from their choice of heuristics? In this paper, we answer the above questions by examining the heterogeneities of two important numerological heuristics, the round-number heuristic and the lucky-number heuristic, utilizing unique bidding-level, peer-to-peer lending data. Our research shows that people do not adopt heuristics randomly and that the use of various heuristics affects 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 the decision-making process (e.g., see Hirshleifer, 2001; Shiller 2003; Sewell, 2007; Bruce, 2010; and Hirshleifer, 2015). Evidence abounds that the heuristics induce biases in various personal and corporate decisions, 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), asset pricing (Hirshleifer, 2001), and so on.

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

In this study, we aim to 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, i.e., the round-number heuristic and the lucky-number heuristic, as these are common heuristics that platform participants adopt. Second, we check whether different heuristics are independent from each other when they are concurrently available. We check whether adopting one heuristic affects the likelihood of using the other at the same time. Third, we analyze how certain borrower's or lender's characteristics and preferences affect his/her choice of heuristics. Fourth, we study the implications on funding outcomes, as well as repayment and investment performance. In particular, we examine how borrowers' adoption of certain heuristics affects funding success and loan repayment performance, and whether lenders' use of certain heuristics is associated with suboptimal investment outcomes.

We explore the above questions using data from Renrendai (RRD), one of the largest peer-to-peer (P2P) Chinese lending platforms. P2P investment data provide an ideal laboratory for us to explore the research questions by offering two important advantages. First, participants in Chinese P2P lending platforms, both borrowers and investors, have limited experience and expertise, and they are especially prone to behavior biases. Consequently, we are able to observe a widespread application of heuristics and analyze the implications and potential biases to which they may lead. In our sample, 83.66% of borrowers and 77.97% of lenders use either the round-number heuristic or the lucky-number heuristic.

Second, our data include detailed information on borrower characteristics, the bidding process, and monthly loan repayment, allowing us to conduct a comprehensive analysis on 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, the detailed bid-level investment records enable us to investigate how investors adopt and respond to the two main types of heuristics. The lender-side analysis, together with the analysis on the funding success rate and loan performance, offers a complete understanding on the role of heuristics in the P2P lending process.

The two heuristics we examine, i.e., the round-number heuristic and the lucky-number heuristic, are prevalently used by platform participants, as seen from the overrepresentation of round and lucky numbers in the loan amounts and bidding amounts. For example, among 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 77.2% in loan amounts and 75.6% in bid amounts. This is in stark contrast with a hypothetical situation in which there is no adoption of a round-number heuristic; in this situation both the loan amount and the bid amount follow a uniform distribution, where 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, respectively. And for the lucky-number heuristic, we find 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, suggesting the active use of the lucky-number heuristic.

More importantly, we show that borrowers' choice of a certain type of heuristic is not random. In particular, we find that borrowers with better credit quality and a greater 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) which document Chinese firms intentionally use lucky IPO listing codes to cater to investors' lucky preference. In contrast, the round-number heuristic tends to be used by borrowers with worse credit ratings and lower asset level. The pattern is consistent with Lin and Pursiainen (2019) which show that inexperienced entrepreneurs prefer to set round campaign amounts in reward-based crowd funding, and have poorer funding performance. On average, a one-notch increase in credit grade[1] reduces the likelihood of the using round numbers in loan amounts by 10.42% and increases the probability of using lucky numbers in loan amounts by 14.39%.

The use of heuristics by borrowers are not independent either. We document a substitution effect between the two different heuristics; that is, when a borrower uses a certain heuristic in setting the loan amount, he/she is less likely to use the other one at the same time. Resorting to a round-number heuristic by a borrower reduces the probability of using a lucky-number heuristic by 19.78%, and having a lucky loan amount lowers the probability of using a round-number heuristic by 5.72%.

Next, we examine the implication of using these two heuristics in the loan amount on the bidding and funding process of each loan application. Specifically, we focus on two variables: the funding success rate and time to funding completion. Interestingly, we find that the use of the round-number heuristic and the lucky-number heuristic in loan amounts have opposite effects on the funding success rate. On the one hand, having a lucky-number loan amount in the loan application increases the funding success probability by around 24.66%. On the other hand, having a round-number loan amount reduces the funding success rate by 19.13%. Loans in the lucky amount take a shorter time to get fully funded: 0.08 hours less funding time than non-lucky loans,

[1] Renrendai assigns each borrower a credit grade. There are 7 different grades, namely AA, A, B, C, D, E and HR, where AA is the highest rating and HR is the lowest.

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 0.72 hours, it is 11.11% more time. The findings are robust to including borrower and loan characteristics as control variables.

In addition to the funding process, we also examine the implications of using different heuristics in the loan amount on loan performance. To our surprise, neither of these 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, the loan performance ex post appears similar. One potential 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 scrutiny 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.

And 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 loans are faced with relatively lax screening, as seen from the higher funding success rate and the shorter time to completion. The combination of the two effects could potentially explain the insignificant impact of heuristic adoption on loan performance, suggesting that the better credit quality of lucky-amount loans is offset by the lax screening.

On the lenders' side, 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. Our results show that lazy lenders who invest the same amount in all bids prefer using round numbers in setting the bid amount, whereas lenders that actively adjust their investment amount prefer lucky bid amounts. Lenders' choice of heuristics reveals their risk preference as well. We use two proxies to measure lenders' risk preference. The first proxy is the credit grade of the loan on which a bid is placed, which reflects the risk undertaken in investing. And the second proxy is the bid amount, which reflects a lender's diversification preference, as smaller bid amounts reflect higher degrees of diversification.

We find that lenders who make round bids are more risk-averse in general, as they invest in loans of higher credit rating. They also tend to invest smaller amount in each loan for better diversification. Lenders who make lucky bids, in contrast, invest in loans of lower credit quality and pay less attention to diversification. This pattern is consistent with Jiang et al. (2009), which show that people are more aggressive in taking risks when feeling lucky.

This paper makes the following important contributions. First of all, it makes 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. Further, 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 observe people adopt different heuristics in decision-making. Since they are preferred by individuals of different characteristics, with the help of our findings, we can infer an individual's qualities by the heuristics he or she uses. Our findings should have a wide application in real life. Besides the context of P2P loan application and investment, it could also be of use in situations like credit ratings and job interviews.

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 round-number heuristics in both the price and quantity of stock trading, we adopt a similar estimation methodology to examine individuals' choice of different heuristics. The model allows for the interrelationship between the use of heuristics of different kinds. Specifically, it recognizes the effect of using one heuristic on the use of others, thereby providing more accurate estimations.

Third, the paper adds to the burgeoning literature on P2P lending, focusing on lenders' and borrowers' behavioral biases. Different from well-developed financial markets, the P2P lending market is still at 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 very 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), and gambling (Demir et al., 2019), as well as biases due to perceptions of impact (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 the bid level analysis are presented in Sections 5 and 6, respectively. Section 7 shows 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 has to 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 the documents provided by the borrowers. Applicants who are found to be using fake material are denied by the platform, while qualified applications are posted on the platform's website. Interested lenders then can browse the profiles and bids on the listings. The bid amount is also required to be multiples of 50 RMB. 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 limitation, the loan is materialized: the borrower receives the funds and has an obligation to make monthly repayment. Otherwise, the application fails, with the invested money 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 development financial market, where the participants are sophisticated, the users of P2P platform are inexperienced borrowers and retail investors who are prone to heuristics. In particular, when borrowers and lenders decide their borrowing and investment amount, respectively, they resort to numerological heuristics. As will show in the data description, we find an overrepresentation of round numbers and lucky numbers in both loan amount and bid amount, indicating the use of round-number heuristic and lucky-number heuristic.

The definition of round number various across researches. For example, Bhattacharya et al. (2012) and Kuo et al. (2014) identify round numbers focusing on the last two digits, and Lin and Pursiainen (2019) define round number as divisible by 1,000 or 500. For the platform we study, the loan amount and bid amount have to be multiples of RMB 50, such as 1,050, 2,000, etc., and 87.33% of the applied amounts are divisible by 1,000. It is also noteworthy that defining roundness 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 only one non-zero number at the leftmost digit as round.

The luckiness of numbers is culture specific. In most of the western countries, 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 I-ching). Simmons and Schindler (2003) document a disproportionately higher frequency of 8 in advertisement as compared to 4. Block and Kramer (2009) show an illogical result that Chinese consumers are willing to pay more for a package of 8 tennis balls than 10 in Taiwan. Following the literature, we measure lucky numbers as those having 8 and not having 4 in loan or bid amounts.[2]

3. Literature Review and Hypothesis Development

3.1 Round-Number Heuristic

Since the seminal work of Ginzberg (1936) which showed 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 on various occasions. For example, there is significant clustering in round numbers in the bank deposit rate (Khan et al.,

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

1999), the gold market (Ball et al., 1985), the real estate market (Palmon et al., 2004), credit card repayment (Keys and Wang, 2019), financial misreporting (Thomas, 1989; Jorgensen et al., 2014; Garmaise, 2015), analyst forecasts (Hirshleifer et al., 2019), IPOs (Kandel et al., 2001; Bradley et al., 2004), SEOs (Mola and Loughran, 2004), mergers and acquisitions (M&As) (Hukkanen and Keloharju, 2019), foreign exchange market (Bessembinder, 1999; Sopranzetti and Datar, 2002; Osler, 2003), and savings and loans (Khan et al., 1999).

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

Empirical evidence in finance suggests that the use of round-number heuristics is associated with inferior cognitive ability of individuals (Kuo et al., 2015; Gao et al., 2019). On borrower side, Lin and Pursiainen (2019) find that inexperienced entrepreneurs are more likely to socialite round amounts in reward-based crowdfunding, and the use of round goal amounts reduces campaign success rate. Along the same vein, we expect that lower quality borrowers prefer to use round numbers in setting loan amount and have inferior funding outcomes on P2P platforms.

The relationship between loan roundness and the ex post repayment is complicated. On the one hand, loans of round numbers are applied by borrowers of lower qualities, thus should have a worse performance. On the other hand, the lower funding success indicates tighter screening by lenders, which is associated with better repayment. The combination of these two forces leads to three possible situations, depending on the relative strength of borrower's quality disparity and lender's tightness in screening.

One 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 screening dominates the effect from credit quality, using a round number will be associated with lower delinquency rate. Third, it is also possible that screening may just cancel out the credit quality differences, and the use of round-number heuristic would have neutral influence on delinquency. We do not hold any priori expectation on the impact of round-number heuristic on loan repayment. Instead, we leave the answer to data.

On lender side, Kuo et al. (2014) show that inexperienced investors who use the round-number heuristic in trade-order submissions suffer significant losses. Interestingly, even sophisticated institutional investors are not immune from round-number heuristics. Using the institutional investors bids in IPO, Gao et al., (2019) also document that 62.07% of the bid price cluster at round numbers. The intensive use of round numbers is further pinned down to the cognitive restrictions of institutional investors. Our study examines how the cognitive quality revealed by the use of round-number heuristic affects the diversification strategy of investors. Specifically, if the lenders making round number bids are of lower cognitive ability and rely more on subjective feelings in decision making, they are expected to be more prone to naïve diversification strategies as suggested by Benartzi and Thaler (2001). That is, instead of deciding the investment amount to different projects based on cognition and analysis, they invest a fixed amount in all bids.

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

Hypothesis 1 (H1): Users of round-number heuristic are of lower cognitive quality.

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

Hypothesis 1B (H1B): Lenders who use round bid amount are more passive and 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) document lucky listing codes appear abnormally frequent in Chinses IPO market, and Bhattacharya et al. (2018) find from the trading data in Taiwan Futures Exchange that individual investors significantly submit more limited orders at 8 than 4.

The use of lucky number is associated with superstitious beliefs (Hirshleifer et al., 2018) and optimism (Darke and Freedman, 1997; Day and Maltby, 2003), which has a strong implication on risk-taking. For example, Fisman et al. (2020) show individuals buy more insurance when feeling unlucky, and when a chairman of a firm feels unlucky, the firm significantly reduces R&D. Jiang et al. (2009) provide experimental evidence that Asians hold superstitious belief put 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.

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 higher price for plate including Chinese lucky 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. Similar evidence in China and the US is found by Shum et al. (2014) and Fortin et al. (2014).

As a response, developers take homebuyers' lucky number preference into account in building design. Anecdotal evidence shows that real estate developer in Vancouver purposefully skip floor numbers including 4 and 13, the unlucky numbers in Chinses and western culture.[3] 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 the consumers.

Guryan and Kearney (2008) document a *lucky store effect*. A store recently sold lotteries 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 cater for investors' lucky number preference, which results in larger price run-ups and more active trading in secondary market. In the P2P platform, borrowers can intentionally set lucky loan numbers to cater for investor preference, and we expect these loans should have better funding performance.

The influence of lucky-number heuristic on loan performance is also subject to two contradicting forces, i.e., the higher credit quality of the applicants using lucky numbers and the lax screening by bidders. Similar as the case of round-number heuristic, if the credit quality difference plays a dominating role, then the use of lucky-number heuristic should imply lower delinquency rates; if the screening has a stronger impact, then lucky amount loans should have higher delinquencies; and if the screening tightness just offset the disparity in borrowers qualities, the use of lucky-number heuristic should be irrelevant to loan repayment performance.

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

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

[3] See this media report as an example: https://vancouversun.com/news/local-news/no-more-skipping-4-13-14-24-in-vancouver-floor-numbers/

Hypothesis 2B (H2B): Lenders who prefer lucky numbers in bid amount 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, the number of loans granted in the past, the number of overdue loans from this borrower in the past, etc. 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 into 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. The 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 start our analysis of borrowers' and lenders' use of heuristics by showing the presence of round numbers and lucky numbers in both loan amount and bid amount. Table 1 lists the top 10 frequent loan amounts and bid amounts, respectively. The number 50,000 is the most frequently used loan amount by borrowers, having a frequency of 131,200 (or 16.41% of the entire loan sample). The other loan amounts with top frequency are also round, indicating borrowers' prevalent use of the round-number heuristic in setting the loan amount. On the lender side, bid amounts are concentrated in round numbers as well: 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 Internet Appendix 1.

[INSERT TABLE 1 ABOUT HERE]

We provide further evidence on the extensive use of round-number heuristic in setting the loan amounts and bid amounts by comparing the "hypothetical" and observed occurrence rates of round numbers. As the borrowing and bidding amounts have to 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 same probabilities, and the leftmost digit cannot be 0.

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 10^3 level, as the minimum borrowing amount is RMB 1,000. And for the 10^6 level, we consider only the numbers below the maximum borrowing amount, RMB 3,000,000. Compared with the "hypothetical" percentage of round numbers in the above range is 0.05%, we find 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, as compared to the "hypothetical" percentage of 0.18%.

[INSERT TABLE 2 ABOUT HERE]

In Table B, we list out the frequency of lucky numbers in loan amounts and bid amounts and compare 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 in the next section. The prevalent use of round-number heuristics reduces use of lucky-number heuristics, resulted in the observed frequencies of lucky numbers in loan amounts and bid amounts being lower than hypothetical probabilities.

To examine the preference of lucky numbers, we also compare the relative frequency of lucky numbers with non-lucky ones. We find that lucky numbers have higher frequency than non-lucky ones, especially in loan amounts. Figure 2 Panel A illustrates the frequency of non-zero figures in loan amounts. As the platform requires that loan amounts have to be multiples of 50, the only non-zero number that the tens digit can take is 5, hence 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 the mathematical principle, Benford's law, which states that smaller numbers occur more frequently than larger ones (Benford, 1938).

Following Benford's law, the frequency of a number 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 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 look at the bid amount and find consistent albeit weak evidence of the use of lucky-number heuristic by lenders.

[INSERT FIGURE 2 ABOUT HERE]

Further, we show that round-number heuristic and lucky-number heuristic encompass most of the numerological choices made by borrowers and investors, highlighting the prevalence of the two heuristics. We find 77.02% of borrowers adopt the round-number heuristic and 6.68% adopt lucky-number heuristic in setting their borrowing amounts, as shown in Table 3 Panel A. 80.77% of borrowers resort to either one of the heuristics[4]. 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 assures the representativeness of our results.

[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 if the loan amount is a round number or lucky number, respectively. Round loans consist of 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

[4] There is 2.93% of the listings with loan amounts that are both round and lucky.

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. 40% of borrowers 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 interest rate and the benchmark rate of the same duration from 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, indicating if 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 IRR is simply the loan interest rate. In case of delinquency, we derive the internal rate of return (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, 75.6% of the bids are round and 1.7% are lucky, and 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 one if a borrower puts the same amount in each bid throughout his/her investment history, and zero otherwise. About 1.0% of the bidders take this shortcut and never adjust their investment amount.

4.4 Univariate Analysis

In Table 5 Panel A, we report the univariate test result on the difference in key loan and borrower characteristics between round loans and non-round loans. The number of observations, the means of the variables in each group, and the mean differences are presented along with t-test significance. Consistent with our hypothesis, the t-test results show that the use of a round number in the loan amount is associated with certain negative attributes of borrowers. Specially, those who borrow round number loan amounts, on average, have a worse credit rating, obtain a more junior education certificate, and earn lower income from employment. They are also less likely to possess such assets as a house and a car.

[INSERT TABLE 5 ABOUT HERE]

Round loans are also associated with a significantly lower funding success rate, with a difference of -65.7%. For successfully funded loans, round loans also need 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 the non-round ones 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 look at the differences between lucky and non-lucky loans. In Panel B, we find that borrowers who apply for lucky loans, on average, have a better credit profile, as indicated by a higher credit grade, education level, and income from employment. Lucky loans are also more likely to be fully funded, with a significant difference in the probability of 41.3 percentage points. We also find that lucky loans are associated with a shorter bidding time. In terms of the loan contracts, a lucky loan has a lower interest rate and a longer duration. As for loan performance, lucky loans are less likely to be delinquent by 2 percentage points.

5. Loan Level Analysis

5.1 How Borrowers Use Heuristics in Setting Loan Amounts

To understand how borrowers use numerological heuristics to set loan amounts, we examine the determinants on the occurrence of round numbers and lucky numbers in loan amounts. Bivariate probit models are used in Table 6 to estimate of the appearance of round and lucky loan amounts simultaneously, while incorporating 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 the correlation between error terms. Specifically, instead of assuming the 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 the lucky-number heuristic are not independent from each other. Resorting to one heuristic reduces the possibility of using the other one. Therefore, the separate estimations of two binary probit models may give biased results, as 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 if 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 into the full model. The regression result is 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. We find that while borrowers with higher credit grade are less likely to use round-number heuristic, they are more likely to use 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 the use of bivariate probit model. [5]

[5] Nevertheless, we find the findings remain robust to the separate estimation of two binary probit models. The results are not reported for brevity and are available upon request.

This finding is robust to the inclusion of other borrower characteristics and loan characteristics in Models 2 and 3, respectively. Quantitatively, a one-notch increase in credit grade is associated with a 10.42% lower likelihood of using a round loan amount and a 14.39% higher likelihood of using a lucky number.[6] 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, as the title of the paper goes, heuristics are not created equal and the use of heuristics reveals individuals' attributes.

We further investigate the relationship between the use of round-number heuristic and lucky-number heuristic, and estimate the extent of the substitution effect quantitatively using probit regression. In the first column of Table 7, the dependent variable is LoanRound, and 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 a 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, he/she is 5.72% less likely to use a round number. Similarly, the probability of applying for a lucky-number loan is decreased by 19.78% when an individual uses a round-number heuristic.[7]

The above estimation may be subject to endogeneity issues, as 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. WA_LoanRound) and lucky (i.e. WA_LoanLucky) loans applied by the borrower in the past, where the weight of each application is the loan amount. Sample size decreases as these proxies are only applicable to repeat borrowers. The finding that the use of one heuristic reduces the probabilities of using the other one 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,

[6] We first convert the coefficients into changes in odds ratios of -33.57% (=$1-e^{-0.409}$) and 15.72% (=1-$e^{0.146}$). Next, the probabilities of using round numbers and lucky numbers of 77.0% and 6.7% in the full sample indicate the original odds of using round numbers and lucky numbers are 3.3478 and 0.07, respectively. Third, we derive the new odds ratios with a one-notch increase in credit grade as 3.3478*(1-33.57%)=2.223 and 0.0718*(1+15.72%)=0.0831. Fourth, we translate the new odds ratios into probabilities of 68.97% and 7.66%. Lastly, we compare the new probabilities with the original funding probabilities (i.e. 77.0% and 6.7%) to get the 10.42% decrease and 14.39% increase in probabilities of using round numbers and lucky numbers, respectively.
[7] We convert the regression coefficients into changes in probabilities using the same methodology as in footnote 6.

the use of lucky numbers in the past increases the probability of using lucky numbers in the next application, but is negatively related to use of round numbers.

The substitution relationship is driven by the disparities in cognitive limitations of different borrowers. Specifically, borrowers with inferior cognitive abilities tend to use round numbers more often, as they are easier to process, whereas cognitively more capable individuals use lucky numbers to cater to investors' lucky preference. The dual-system theory in cognitive psychology[8] suggests that people may not even realize the use of certain heuristics in some fast and intuitive decision-making (Gigerenzer and Gaissmaier, 2011). The substitution between round-number heuristic and lucky-number heuristic reflects borrowers' unconscious choice affected by cognitive abilities[9].

[INSERT TABLE 7 ABOUT HERE]

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

We further investigate the impact of the choice of heuristics by relating them to funding success. Table 8 Panel A reports the results of the logit regressions where 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, indicating if the loan amount is round or lucky, respectively. Borrower characteristics, such as age, education level, job income level, job length, residential province, homeownership, etc., and loan characteristics, including loan premium, loan amount, and loan duration, are also included as control variables. Year-quarter fixed effects are added in all specifications. A discrete variable, CreditGrade, which take 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 it with credit rating fixed effects. Specifications (1) to (4) examine the influence of our focal variables, LoanRound and LoanLucky,

[8] The dual-system theory distinguishes between two cognitive processes: one is fast, automatic, and unconscious, while the other system is slow, deliberative, and conscious (Evans, 2008). Or as Kahneman (2011) describes as fasting thinking and slow thinking.

[9] Another potential reason for the observed substitution between the two heuristics is the inherent incompatibility between the use of round numbers and lucky numbers. For example, consider a borrower who needs 2,599 RMB for a cell phone. As loan amount has to be in multiple of 50, the borrower can set 2600, which does not use either of the two heuristics. Or he or she can either apply for 2,800 driven by a lucky-number heuristic, or apply for 3,000, using a round-number heuristic. The chance is slim, however, to set a borrowing amount that is consistent with both heuristics, e.g. 8,000, as it is likely to deviate too much from the original point. However, the incompatibility cannot to explain the substitution effects observed in the last four columns, where prior choice of round numbers and lucky numbers are used. Thus, the mutual incompatibility is not able to rule out the behavior explanation emphasized in this paper.

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, where both heuristic dummies and two fixed effects are included, we observe that round loans have 19.13 percentage points lower funding success and lucky loan amounts have 24.66 percentage points greater funding likelihood.[10]

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.

Besides the funding success rate, we also examine the effect 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 a longer time to get fully funded, and vice versa for lucky loans.

Table 8 Panel B reports the OLS regression results on the effect of loan roundness and luckiness on bidding time, where the funded loans subsample is used. The first two columns present the result on round amounts, the next two columns on lucky amounts, and the last two specifications include both of our 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 amounts increases the funding time by 0.08 hours, the use of lucky loan amounts reduces the funding time by a similar magnitude.

[10] We first convert the coefficients into changes in odds ratios of -89.5% (=$1 - e^{-2.254}$) and 202.2% (=$e^{1.106}$-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+202.2%)=0.8749. Fourth, we translate the new odds ratios into funding probabilities of 2.87% and 46.66%. Lastly, we compare the new probabilities with the original funding probability (i.e. 22.0%) to get the 19.13 percentage points decrease and the 24.66 percentage points increase in funding probabilities.

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

Earlier 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 seen from 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 hypothesis development part, and we formally check which above 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 key explanatory variables of interest are the two heuristic measures: LoanRound and LoanLucky. The dependent variable is Delinquent, a dummy variable which equals 1 if there is a late payment associated with the loan, and 0 otherwise.

We find weak evidence that a lucky loan amount is associated with lower delinquency rates, as the negative coefficient of LoanLucky is borderline significant. LoanLucky loses significance, however, when credit grade fixed effect is controlled. Although all the estimated coefficients for the round-number heuristics are positive, and the coefficients for the lucky-number heuristic are negative, most of them are statistically insignificant. The outcomes are in line with the scenario that the disparity in credit quality of borrowers using different heuristics is just offset by the tightness in screening.

[INSERT TABLE 9 ABOUT HERE]

We also notice that larger loan amount, 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). Besides, superior borrowers' credit quality, such as better credit grade and advanced 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 behaviors in response to borrowers' use of round numbers and lucky numbers, respectively, in the loan amount. We test if lenders make more sophisticated responses as they accumulate more experience on the platform. In particular, we examine if the 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 Internet Appendix 3, we perform a bivariate probit regression, where the dependent variables are BidtoLucky and BidtoRound, indicating 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 strong screening on round loans and are less likely to invest in them as they gain more experience.

And as lenders accumulate more experience, they prefer lucky loans. A 1% increase in the prior number of bids reduces the likelihood of investing in a round loan by 2.91% and increases the likelihood of investing in a lucky loan by 1.49%.[11] The findings confirm that investors learn from their 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). Besides, 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 timestamp 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, 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). As an active lender would formulate a bid amount specific to each loan request, which are less likely to constant across all loans invested, we measure a lender's laziness by a dummy variable, Lazy, which 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 naïve diversification strategy and the inferior cognitive ability revealed by round number use.

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

Table 10 reports the regression result. We find that lazy investors prefer to use round numbers in bid amounts rather than lucky numbers, as shown in Panel A. Compared to investors who actively adjust their investment quantity across loans, lazy investors are 12.9% more likely to place a round bid and 49.3% less likely to place a lucky bid.[12] In Panel A Model 1, we only include our focal variable, 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. Besides, we include the average prior portfolio return measured as the weighted average IRR from all the previous bids made by each lender, which reflects their prior investment performance.

The average prior portfolio return exhibits a negative coefficient when RoundBid is used as the dependent variable, implying that lenders using a round bid amount have worse investment performance. The relationship between laziness, worse investment performance and the use of round-number heuristic in setting bid amounts is again consistent with the evidence from loan amount analysis, where round-number heuristic is associated with inferior borrower quality.

[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 use 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.

Besides lenders' laziness, we are also interested in the relationship between a lender's use of heuristics and his/her 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 reflects a lender's diversification across loans.[13] Our focal variables are RoundBid and LuckyBid, indicating 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.

[12] We convert the regression coefficients into changes in probabilities using the same methodology as in footnote 6.
[13] In unreported regressions, we also measure a lender's diversification by the Herfindahl-Hirschman Index (HHI) of the previous bids and find consistent outcomes. The results are available upon request.

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, as the bid amount is 34.6% less. Lucky bids, in contrast, are associated with more aggressive risk-taking by the investors, as the loans on which they bid are of lower credit ratings. Besides, the bid amount is 34.4% larger, which may potentially lead to more concentrated portfolios. The aggressive risk taking associated with lucky bid amount is consistent with the literature that users of lucky-number heuristic tend to be over-optimistic (Darke and Freedman, 1997; Day and Maltby, 2003), or hold superstitious beliefs (Hirshleifer et al., 2018).

We also examine how lenders' choice of heuristics affects their investment performance, which is measured by the investment IRR, as well as a Delinquent_Bid dummy that indicates whether the bid goes to a delinquent loan. Similar to the analysis on loan amount, results in Internet Appendix 4 show no impact of lender's use of heuristics in setting bid amount on their investment performance.

A possible explanation is that while the investors using lucky numbers are more active in adjusting investment amounts, as shown in Table 10, they also take excess risks without much diversification. And for round number heuristics, those lenders that use round bids adopt naïve diversification strategies but control the risk exposure by investing in loans with higher credit quality (See Table10). The active adjustment of investment amount and excess risk-taking potentially counterbalance each other and result in a limited impact on the overall investment performance.

7. Robustness Checks

7.1 Removing Auto Bids

The RRD started to provide auto bidding service to investors and manage investors' funds through an algorithm-based auto investment since February 2012, and the proportion of auto bids keeps increasing. Internet Appendix 2 presents the percentages of auto bids across time. As only humans are subjective to heuristics, including auto bids in our sample may potentially weaken our result.

We argue that although auto bids are executed by machines, the algorithms are still designed by humans who are subject to heuristics. So, the influence of auto bids on our analysis may not be a serious concern. Even if auto bids were to be different from traditional human bids, they should be less affected by the heuristics, thus 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 a subsample of human bids only. Table 11 Panel A reports the result from the baseline bivariate probit model estimation used in Table 6. We again find that the 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. And the coefficients of our focal variables remain highly 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 effects 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 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 very limited 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 round numbers in bid amounts is associated with stronger risk aversion and better diversification and that lenders who make lucky bids are more aggressive in risk-taking and have more concentrated portfolios.

[INSERT TABLES 11 ABOUT HERE]

Overall, we estimate all the previous models using a subsample of funded loans with human-bid 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 the findings from the full sample are not driven by auto bids and that our findings are robust.

7.2 Financial Constraints

Another potential concern is that the use of lucky-number heuristic is influenced by investors' financial constraints. According to platform rules, the bid amount must be in multiples of 50 RMB. As a result, the smallest lucky number that an investor can place is 800, which is considerably large, given the median bid amount of 450, though the mean is 1,191, greater than 800. In unreported regressions, we define the lucky number as having an 8 or a 6 but no 4, which further reduces the smallest lucky bid amount to 600. The results are very similar to the results in Table 10, indicating that the influence of a lucky bid is not likely to be driven by financial constraints.

More formally, we rule out the effect of financial constraints using subsample of unconstrained lenders. Lenders whose cumulative investment amount in the past three months is larger than 800 (i.e. the smallest lucky amount available to lenders) are considered unconstrained.[14]

Table 12 model 1 presents the results on the determinants of heuristic choice by the unconstrained lenders. 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 model 2 and 3 that a round bid amount is associated 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, the results using the unconstrained subsample are very similar to those in the models using full sample. The unconstrained lenders are capable of making lucky bids if they wish to do so. Therefore, the nonconflicting results alleviate the concern about the impact of financial constraints.

[INSERT TABLE 12 ABOUT HERE]

8. Conclusion

Heuristics play an important role in decision making. A large strand of 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

[14] We also try another stricter criterion and define the unconstrained lenders as making a cumulative investment amount in the past 1 week exceeding 800. The results are consistent and omitted for brevity.

heterogeneities among two main types of numerological heuristics, i.e., the round-number heuristic and the lucky-number heuristic.

First, we find that these two heuristics are not independent from each other. A borrower's application of the round-number heuristic reduces the probability of using the lucky-number heuristic by 19.78%, and having a lucky loan amount lowers the probability of using a round-number heuristic by 5.72%. Around 80.77% of the borrowers and 76.67% of the lenders resort to at least one of the two heuristics in setting the borrowing and bidding amounts.

Second, we find that these two heuristics are adopted by borrowers and lenders of different characteristics. While borrowers with higher credit quality are more likely to use lucky numbers in loan amounts to attract investors, borrowers with lower credit quality use the round-number heuristic more often, as 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 those funded loans, lucky loans also take a shorter time to get fully funded, whereas round loans need a longer time to get fully funded. In terms of loan performance, we do not find that these 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 the funded loans is not influenced by the heuristics used by borrowers.

Third, we find that the selection of heuristics in setting the bid amount also reveals the investor characteristics. Active lenders who adjust bid amounts across loans are more likely to make lucky bids and use fewer round bids, which proofs the relationship between limited cognitive ability associated with round-number heuristic and the adoption of naïve diversification strategy. The implications for investors' risk preference are different as well. When bidding in lucky numbers, lenders are more aggressive in taking risks, and the use of round numbers in bid amounts is associated with more conservative risk-taking and better diversification. This pattern is consistent with the psychology theory that the use of lucky numbers is associated with optimism beliefs and excess risk taking.

To the best of our knowledge, this is the first paper that reveals the concurrent application and interplay of multiple heuristics. We document 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 is informative of his/her credit and risk profiles. The findings in this study could potentially be further applied to other similar frameworks to address information asymmetry problems. Apart from the loan screening scenario this paper studies, the framework could also be applied to situations like credit ratings and job interviews, among others.

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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.

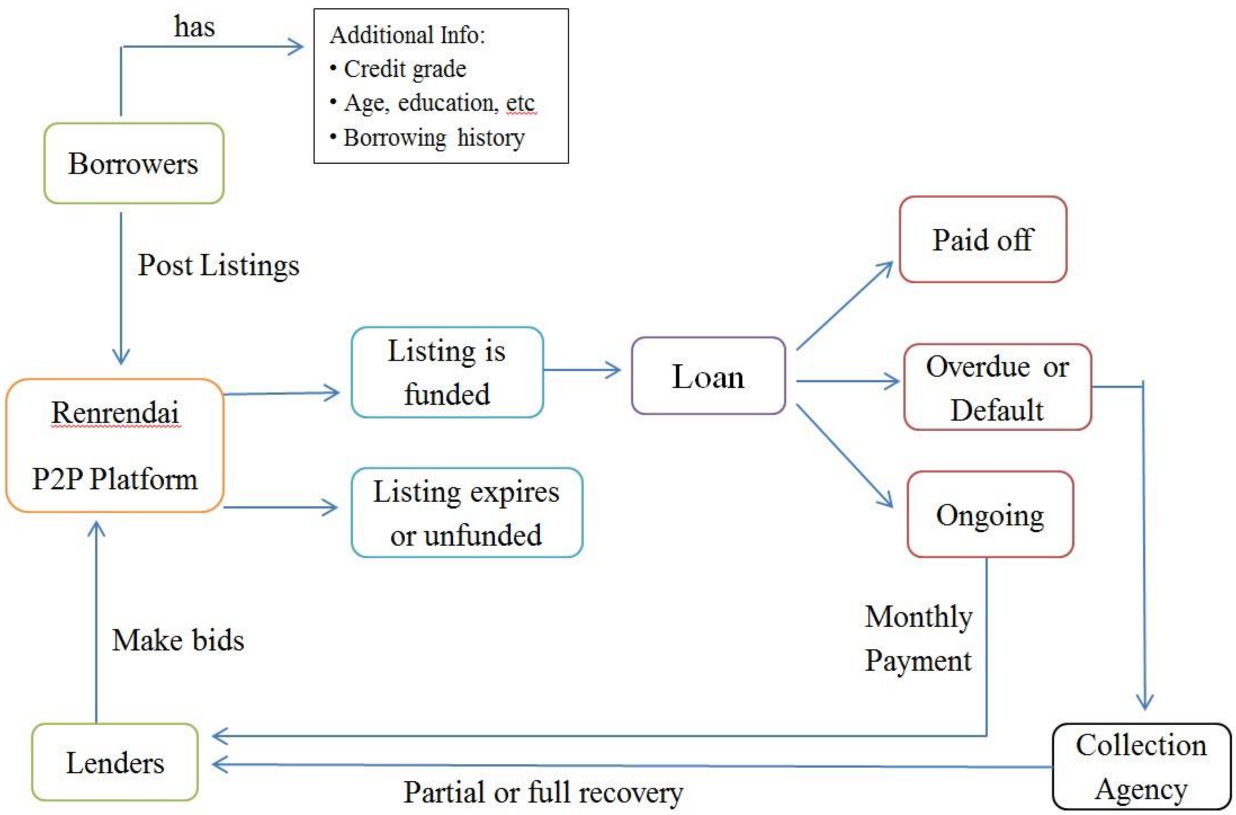
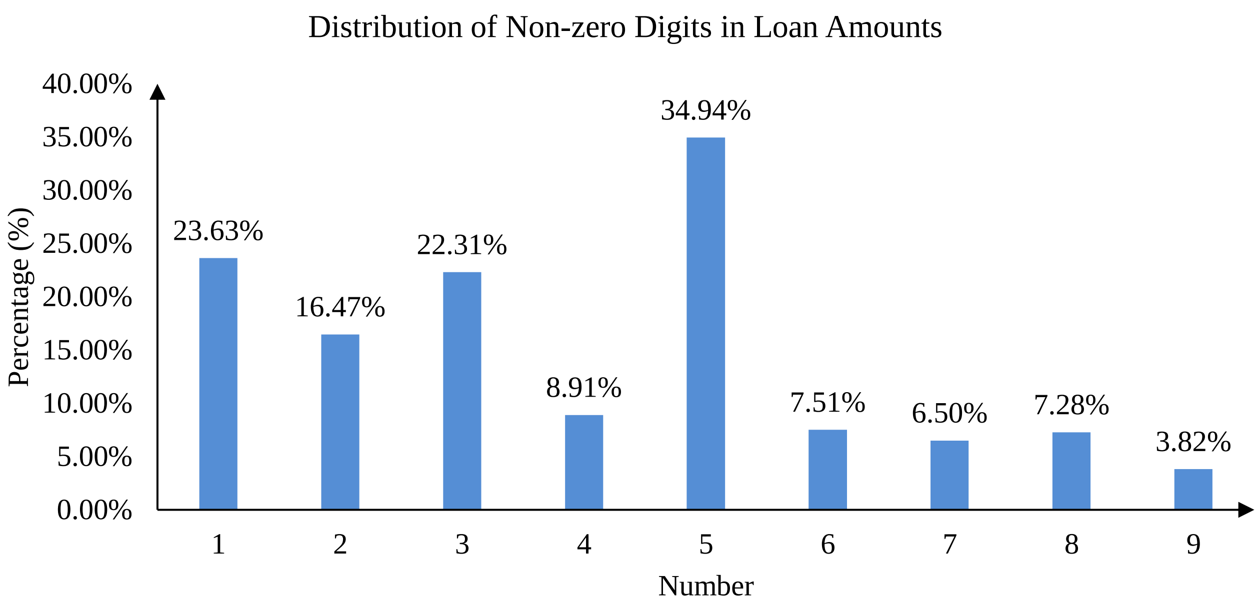


Figure 2: Distribution of Numbers in Loan and Bid Amounts
This figure shows the percentage of non-zero digits in loan amounts and bid amounts in Panel A and Panel B, respectively.

Panel A: Percentages of All Non-zero Digits in Loan Amounts



Panel B: Percentages of First Non-zero Digits in Bid Amounts

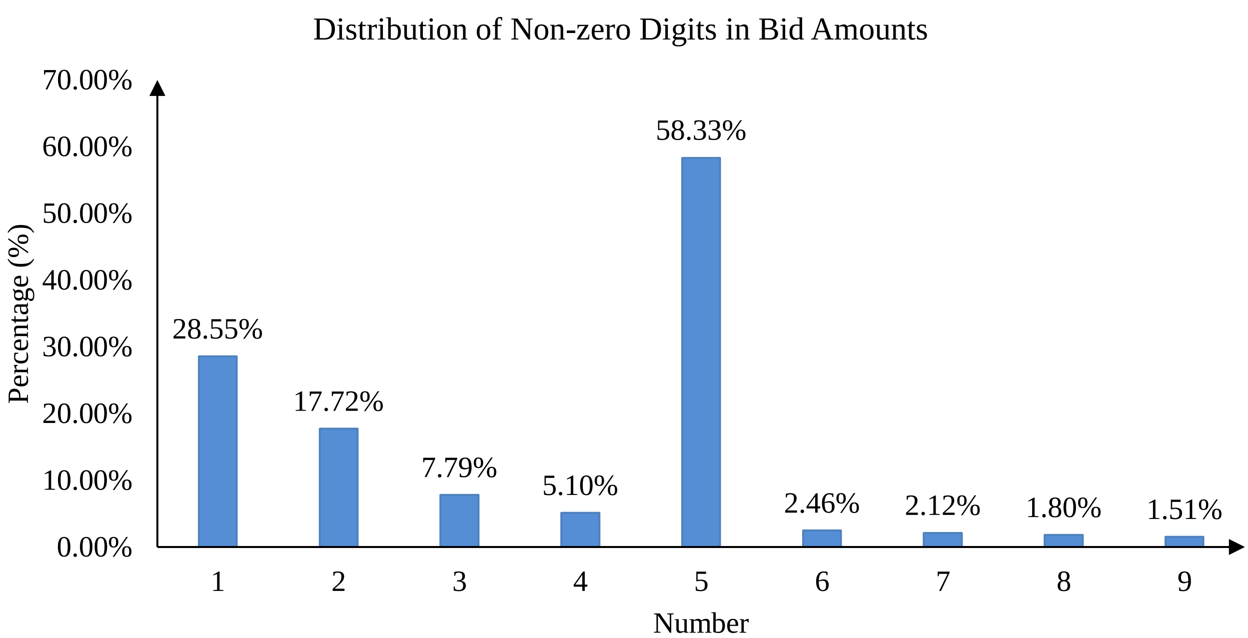


Table 1: Loan Amounts and Bid Frequencies

This table presents the count and percentage of the top ten 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	50000	131220	16.41	50	1402123	18.58
2	10000	61719	7.72	500	1265260	16.77
3	30000	59058	7.38	100	777220	10.30
4	3000	58393	7.30	200	601717	7.97
5	20000	55615	6.95	1000	548296	7.27
6	100000	50748	6.34	150	284928	3.78
7	5000	40843	5.11	300	254698	3.38
8	200000	16490	2.06	2500	234131	3.10
9	40000	16317	2.04	1500	163973	2.17
10	60000	15274	1.91	2000	159060	2.11
Total		**505677**	**63.22**		**5691406**	**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. Panel A presents the percentages of round numbers, and Panel B reports the percentages of lucky numbers. ***Round amount*** is defined as having only one non-zero number at the leftmost digit, and ***Lucky amount*** is defined as having an 8 but no 4.

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

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

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

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

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[15]
10^4	360,411	72.27	0.50
10^5	91,583	75.05	0.05
10^6	462	94.48	0.0075[16]
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	0.025[17]
Overall	5,704,739	75.60	0.175

[15] For example, the 10^3 group contains 9 round numbers, including 1,000, 2,000, …, and 9,000. And the total number of possible loan amounts is 180 = ((9950-1000)/50+1). Thus the hypothetical probability equals 5% = 9/180.

[16] The maximum loan amount in our sample is 3,000,000 RMB, so we only consider the values between 1,000,000 and 3,000,000.

[17] The maximum bid amount in our sample is 1,200,000 RMB, so we only consider values between 1,000,000 and 1,200,000.

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

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

This table describes the use of round-number heuristic and the lucky-number heuristic in the choice of loan and bid amounts. Every amount is classified into 4 different 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 loan application sample, and Panel B uses the funded subsample. Panel C uses bid-level data and presents the lender and bid characteristics. The definition of variables is presented in Appendix 1.

Panel A: Borrower and Loan Characteristics (Full Sample with both Funded and Unfunded Loans)

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	670,294	1.857	0.780	1	2	2	1	4
JobIncomeLevel	594,206	4.068	1.218	3	4	5	1	7
JobLength	560,552	2.168	1.039	1	2	3	1	4
Single	723,459	0.521	0.500	0	1	1	0	1
Top20Province	560,663	0.562	0.496	0	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	0.704	2.250	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: Funded 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	163,144	1.987	0.742	1	2	2	1	4
JobIncomeLevel	163,145	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	162,563	0.554	0.497	0	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	0.403	3.202	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 and Loan-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
WA_RoundBid	7,385,250	0.689	0.303	0.478	0.780	0.963	0	1
WA_LuckyBid	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 the roundness of the loan amount, where round loans are those that have only one non-zero figure at the leftmost digit. For example, 1,000 is a round loan and 1,200 is not a round loan. Panel B partitions the loan application sample by the luckiness of the loan amount, where 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. As Delinquent and BidTime are only observable among 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. The definitions of all variables are presented in Appendix 1.

Panel A: 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	504,034	1.824	166,242	1.955	-0.131***
JobIncomeLevel	423,725	3.954	161,463	4.373	-0.419***
JobLength	401,324	2.318	159,210	1.788	0.529***
Single	553,966	0.570	169,475	0.362	0.208***
Top20Province	401,494	0.562	159,152	0.563	-0.001
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	0.807	170,539	0.358	0.450***
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 B: 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	48,005	1.920	622,271	1.852	0.068***
JobIncomeLevel	46,287	4.370	547,901	4.042	0.328***
JobLength	45,367	1.814	515,167	2.199	-0.384***
Single	49,207	0.384	674,234	0.531	-0.147***
Top20Province	45,333	0.557	515,313	0.563	-0.006**
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	0.518	692,701	0.717	-0.199***
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 determinants of borrowers' choice of the round-number heuristic and the lucky-number heuristic. The dependent variables are LoanRound and LoanLucky, which indicate if the loan amount is a round number or a lucky number. We start from a simple specification that includes only the borrower's credit grade, along with year-quarter fixed effects, in Model 1. Other borrower characteristics and loan contract terms are further introduced into Models 2 and 3, respectively. Estimated coefficients are reported, along with heteroskedasticity robust standard errors in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The definitions of all variables are presented in Appendix 1.

	(1)		(2)		(3)	
Dependent Variable	LoanRound	LoanLucky	LoanRound	LoanLucky	LoanRound	LoanLucky
CreditGrade	-0.449***	0.191***	-0.435***	0.163***	-0.409***	0.146***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Age			0.002***	0.001***	0.004***	0.000
			(0.000)	(0.000)	(0.000)	(0.000)
Edulevel			-0.032***	0.002	-0.025***	-0.004
			(0.003)	(0.003)	(0.003)	(0.003)
JobIncomelevel			0.023***	0.015***	0.023***	0.020***
			(0.002)	(0.002)	(0.002)	(0.002)
JobLength			0.010***	-0.031***	0.007***	-0.029***
			(0.002)	(0.003)	(0.002)	(0.003)
Single			-0.047***	0.013**	-0.053***	0.013**
			(0.005)	(0.006)	(0.005)	(0.006)
Top20Province			-0.007	-0.007	-0.004	-0.009*
			(0.005)	(0.005)	(0.005)	(0.005)
HasAsset			-0.172***	0.133***	-0.142***	0.113***
			(0.005)	(0.006)	(0.006)	(0.007)
HasLoan			-0.178***	0.090***	-0.119***	0.046***
			(0.006)	(0.007)	(0.006)	(0.007)
NPriorLoan_Applied			0.023***	0.001	0.013***	0.005***
			(0.001)	(0.001)	(0.001)	(0.001)
logLoanAmount (k)					-0.073***	0.036***
					(0.003)	(0.003)
Loan_Premium					-0.009***	0.010***
					(0.001)	(0.001)
Loan_Duration (month)					-0.024***	0.011***
					(0.000)	(0.000)
Constant	3.190***	-2.693***	3.173***	-2.734***	3.362***	-2.891***
	(0.161)	(0.137)	(0.165)	(0.138)	(0.156)	(0.135)
Year Qtr FE	YES		YES		YES	
Observations	742,274		556,740		556,538	
Wald Chi2 (ρ =0)	1683.63***		1202.67***		702.031***	

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

This table presents the relationship between the round-number heuristic and the lucky-number heuristic. The dependent variables are LoanRound and LoanLucky, which indicate if the loan amount is round or lucky, respectively. WA_LoanRound and WA_LoanLuck are the weighted percentages of round-number loans and lucky-number loans applied by the borrower previously, where the loan amount is used as the weight. Probit regression coefficients are reported, along with heteroskedasticity robust standard errors in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The definitions of all variables are presented in Appendix 1.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	LoanRound	LoanLucky	LoanRound	LoanLucky	LoanRound	LoanLucky
LoanRound		-0.196***				
		(0.008)				
LoanLucky	-0.234***					
	(0.008)					
WA_LoanRound				-0.226***	1.400***	-0.209***
				(0.016)	(0.012)	(0.017)
WA_LoanLucky			-0.172***		-0.095***	1.564***
			(0.019)		(0.021)	(0.018)
CreditGrade	-0.404***	0.121***	-0.237***	0.089***	-0.182***	0.069***
	(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	-0.026***	-0.005	-0.046***	0.015**	-0.043***	0.017**
	(0.003)	(0.003)	(0.005)	(0.006)	(0.005)	(0.007)
JobIncomelevel	0.024***	0.021***	-0.015***	0.025***	-0.008**	0.019***
	(0.002)	(0.002)	(0.004)	(0.005)	(0.004)	(0.005)
JobLength	0.005**	-0.028***	-0.019***	0.023***	-0.030***	0.017***
	(0.002)	(0.003)	(0.004)	(0.005)	(0.004)	(0.006)
Single	-0.052***	0.010*	-0.007	-0.013	-0.002	-0.013
	(0.005)	(0.006)	(0.008)	(0.011)	(0.009)	(0.012)
Top20Province	-0.004	-0.010*	0.005	0.007	0.008	0.006
	(0.005)	(0.005)	(0.008)	(0.010)	(0.008)	(0.011)
HasAsset	-0.138***	0.107***	-0.023**	0.045***	-0.019**	0.034***
	(0.006)	(0.007)	(0.009)	(0.012)	(0.010)	(0.013)
HasLoan	-0.116***	0.041***	-0.059***	-0.005	-0.042***	0.006
	(0.006)	(0.007)	(0.010)	(0.014)	(0.011)	(0.014)
NPriorLoan_Applied	0.013***	0.006***	0.008***	-0.001	0.007***	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
logLoanAmount (k)	-0.072***	0.033***	-0.103***	0.007	-0.073***	-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	3.338***	-2.627***	2.448***	-2.077***	0.850***	-2.068***
	(0.154)	(0.134)	(0.159)	(0.179)	(0.151)	(0.188)
Yr Qr FE	YES	YES	YES	YES	YES	YES
Observations	556,538	556,538	189,424	189,424	189,424	189,424
R-squared	0.425	0.115	0.051	0.020	0.150	0.117

Table 8: Numerological Heuristics and Funding Outcomes

This table presents the influence of heuristics on funding outcomes. Panel A focuses on funding success and reports the Logit regression results. The dependent variable is FundingSuccess, which equals 1 if the loan is funded, and 0 otherwise. Panel B focuses on funding time of the fully funded subsample, and reports the OLS regression results. The dependent variable is bidding time in hours. The two focal variables are LoanRound and LoanLucky, which indicate if the loan amount is round or lucky, respectively. Estimated coefficients are reported, along with heteroskedasticity robust standard errors in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The definitions of all variables are presented in Appendix 1.

Panel A: Numerological Heuristics and Funding Success

Dependent Variable: FundingSuccess	(1)	(2)	(3)	(4)	(5)	(6)
LoanRound	-2.324***	-2.274***			-2.305***	-2.254***
	(0.018)	(0.019)			(0.018)	(0.019)
LoanLucky			1.219***	1.189***	1.132***	1.106***
			(0.027)	(0.029)	(0.029)	(0.030)
CreditGrade	1.560***		1.670***		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	0.242***	0.242***	0.264***	0.263***	0.245***	0.245***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
JobIncomelevel	0.411***	0.418***	0.378***	0.388***	0.408***	0.416***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)
JobLength	0.197***	0.241***	0.191***	0.248***	0.199***	0.242***
	(0.008)	(0.009)	(0.008)	(0.009)	(0.008)	(0.009)
Single	-0.178***	-0.181***	-0.154***	-0.162***	-0.177***	-0.179***
	(0.017)	(0.018)	(0.017)	(0.017)	(0.017)	(0.018)
Top20Province	-0.172***	-0.157***	-0.173***	-0.158***	-0.171***	-0.156***
	(0.016)	(0.016)	(0.015)	(0.016)	(0.016)	(0.016)
HasAsset	0.088***	0.124***	0.100***	0.130***	0.077***	0.116***
	(0.019)	(0.019)	(0.018)	(0.019)	(0.019)	(0.019)
HasLoan	0.113***	0.077***	0.160***	0.108***	0.116***	0.081***
	(0.022)	(0.022)	(0.021)	(0.021)	(0.022)	(0.022)
NPriorLoan_Applied	-0.058***	-0.010***	-0.067***	-0.013***	-0.058***	-0.011***
	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
logLoanAmount (k)	-0.918***	-0.884***	-0.807***	-0.767***	-0.927***	-0.892***
	(0.008)	(0.009)	(0.008)	(0.008)	(0.009)	(0.009)
Loan_Premium	-0.088***	-0.088***	-0.084***	-0.083***	-0.088***	-0.088***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)
Loan_Duration (month)	0.005***	0.001	0.014***	0.007***	0.004***	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	-5.061***	-2.925***	-7.708***	-5.237***	-5.081***	-2.954***
	(0.320)	(0.198)	(0.348)	(0.191)	(0.323)	(0.200)
Year Qtr FE	YES	YES	YES	YES	YES	YES
CreditGrade FE	NO	YES	NO	YES	NO	YES
Observations	556,538	556,538	556,538	556,538	556,538	556,538
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	0.092***	0.084**			0.092***	0.084**
	(0.033)	(0.033)			(0.033)	(0.033)
LoanLucky			-0.080***	-0.084***	-0.079***	-0.083***
			(0.022)	(0.022)	(0.022)	(0.022)
CreditGrade	-0.327***		-0.331***		-0.328***	
	(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	-0.057***	-0.070***	-0.057***	-0.069***	-0.058***	-0.070***
	(0.018)	(0.017)	(0.018)	(0.017)	(0.018)	(0.017)
JobIncomelevel	-0.099***	-0.100***	-0.096***	-0.098***	-0.099***	-0.100***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
JobLength	0.038**	0.009	0.036**	0.007	0.036**	0.007
	(0.018)	(0.016)	(0.018)	(0.016)	(0.018)	(0.016)
Single	-0.010	-0.011	-0.012	-0.012	-0.010	-0.011
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
Top20Province	-0.028	-0.033	-0.030	-0.035	-0.029	-0.034
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
HasAsset	-0.106***	-0.142***	-0.109***	-0.145***	-0.103***	-0.140***
	(0.033)	(0.032)	(0.033)	(0.032)	(0.033)	(0.032)
HasLoan	-0.207***	-0.217***	-0.204***	-0.214***	-0.206***	-0.216***
	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)
NPriorLoan_Applied	-0.081***	-0.075***	-0.081***	-0.075***	-0.081***	-0.075***
	(0.009)	(0.011)	(0.009)	(0.011)	(0.009)	(0.011)
logLoanAmount (k)	1.132***	1.142***	1.128***	1.139***	1.136***	1.146***
	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)
Loan_Premium	-0.473***	-0.492***	-0.475***	-0.494***	-0.474***	-0.492***
	(0.044)	(0.045)	(0.044)	(0.044)	(0.044)	(0.045)
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	99.263***	98.778***	99.394***	98.890***	99.272***	98.786***
	(4.927)	(4.908)	(4.927)	(4.908)	(4.927)	(4.909)
Year Qtr FE	YES	YES	YES	YES	YES	YES
CreditGrade FE	NO	YES	NO	YES	NO	YES
Observations	162,460	162,460	162,460	162,460	162,460	162,460
Adj. R-squared	0.303	0.304	0.303	0.304	0.303	0.304

Table 9: Numerological Heuristics and Loan Performance

This table exhibits the logit regression results of loan performance, with the dependent variable being 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 if the loan amount is round or lucky, respectively. Estimated coefficients are reported, along with heteroskedasticity robust standard errors in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The definitions of all variables are presented in Appendix 1.

Dependent Variable: Delinquent	(1)	(2)	(3)	(4)	(5)	(6)
LoanRound	0.032	0.016			0.032	0.016
	(0.037)	(0.038)			(0.037)	(0.038)
LoanLucky			-0.083*	-0.060	-0.083*	-0.060
			(0.050)	(0.052)	(0.050)	(0.052)
CreditGrade	-1.473***		-1.473***		-1.472***	
	(0.022)		(0.022)		(0.023)	
Age	0.023***	0.027***	0.024***	0.027***	0.023***	0.027***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Edulevel	-0.342***	-0.348***	-0.343***	-0.349***	-0.343***	-0.349***
	(0.021)	(0.022)	(0.021)	(0.022)	(0.021)	(0.022)
JobIncomelevel	0.112***	0.110***	0.114***	0.111***	0.112***	0.111***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
JobLength	0.050***	0.011	0.049***	0.011	0.049***	0.011
	(0.018)	(0.019)	(0.018)	(0.019)	(0.018)	(0.019)
Single	0.082**	0.088**	0.081**	0.087**	0.082**	0.088**
	(0.037)	(0.039)	(0.037)	(0.039)	(0.037)	(0.039)
Top20Province	0.114***	0.105***	0.113***	0.105***	0.113***	0.105***
	(0.033)	(0.034)	(0.033)	(0.034)	(0.033)	(0.034)
HasAsset	0.022	0.004	0.022	0.003	0.022	0.004
	(0.041)	(0.042)	(0.041)	(0.042)	(0.041)	(0.042)
HasLoan	-0.366***	-0.337***	-0.366***	-0.337***	-0.366***	-0.337***
	(0.043)	(0.044)	(0.043)	(0.044)	(0.043)	(0.044)
NPriorLoan_Applied	-0.011	-0.019**	-0.011	-0.019**	-0.011	-0.019**
	(0.010)	(0.009)	(0.010)	(0.009)	(0.010)	(0.009)
logLoanAmount (k)	0.103***	0.086***	0.096***	0.082***	0.101***	0.085***
	(0.029)	(0.027)	(0.028)	(0.027)	(0.029)	(0.027)
Loan_Premium	0.067***	0.071***	0.067***	0.071***	0.067***	0.071***
	(0.011)	(0.010)	(0.011)	(0.010)	(0.011)	(0.010)
Loan_Duration (month)	0.035***	0.036***	0.034***	0.036***	0.035***	0.036***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Constant	-1.227**	-2.909***	-1.192**	-2.887***	-1.219**	-2.901***
	(0.569)	(0.503)	(0.569)	(0.503)	(0.569)	(0.503)
Year Qtr FE	YES	YES	YES	YES	YES	YES
CreditGrade FE	NO	YES	NO	YES	NO	YES
Observations	162,460	162,460	162,460	162,460	162,460	162,460
Pseudo R-squared	0.542	0.558	0.542	0.558	0.542	0.558

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

This table presents the relationships among lender's activeness, risk preference, and the heuristics used in setting the bid amount. Panel A uses a bivariate probit model. The dependent variables are RoundBid, which indicates if the bid amount is a round number, and LuckyBid, which indicates if the bid amount is a lucky number. The focal variable is Lazy, a dummy variable, which equals 1 in a bidder invests the same amount for all bids, and 0 otherwise. Panel B reports the OLS regression outcomes, where the dependent variables are the credit grade of the loan on which the bid is placed, and the logarithm of the bid amount. Estimated coefficients are reported, along with standard errors clustered at lender level in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The definitions of all variables are presented in Appendix 1.

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

	(1)		(2)	
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)
WA_RoundBid			1.242***	-0.115***
			(0.005)	(0.007)
WA_LuckyBid			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)
WA_RoundBid	0.050***	-0.034***
	(0.007)	(0.007)
WA_LuckyBid	-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: Subsample of Purely Human-Funded Loans and Human Bids

This table presents the robustness test of the main results. Panels A, B, and C investigate the determinants of heuristics used by borrowers, the relationship between heuristics, and the impact on loan performance using the purely human-funded subsample. Panels D and E use the human-bid subsample to study lender's activeness and use of heuristics and the risk preference implications. Estimated coefficients are reported, along with standard errors in parentheses. Heteroskedasticity robust standard errors are used in Panel A, B and C, Panel D and E cluster the standard errors at lender level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The definitions of all variables are presented in Appendix 1.

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

	(1)		(2)		(3)	
Dependent Variable	LoanRound	LoanLucky	LoanRound	LoanLucky	LoanLucky	LoanLucky
CreditGrade	-0.392***	0.164***	-0.369***	0.144***	-0.372***	0.139***
	(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		445,722		445,574	
Wald Chi2 (ρ =0)	1152.74***		828.42***		671.81***	

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)					
WA_LoanRound				-0.221***	1.395***	-0.203***
				(0.017)	(0.012)	(0.018)
WA_LoanLucky			-0.165***		-0.089***	1.603***
			(0.020)		(0.021)	(0.018)
Borrower Characteristics	YES	YES	YES	YES	YES	YES
Loan Characteristics	YES	YES	YES	YES	YES	YES
Yr Qr FE	YES	YES	YES	YES	YES	YES
Observations	445,574	445,574	187,497	187,497	187,497	187,497
R-squared	0.197	0.054	0.037	0.017	0.135	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	-2.308***	-2.282***	0.009	0.000
	(0.018)	(0.019)	(0.037)	(0.038)
LoanLucky	1.133***	1.108***	-0.079	-0.068
	(0.029)	(0.031)	(0.051)	(0.053)
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	445,574	445,574	51,496	51,496
Pseudo R-squared	0.611	0.631	0.389	0.410

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

	(1)		(2)	
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: Subsamples of Unconstrained Investors

This table reports the determinants and risk preference implications of heuristics used in bid amounts. Bidding records from bidders who have accumulative investment amount exceeded 800 in the past 3 months are used. Model 1 reports the bivariate probit model results, the model settings are identical to those in Table 10 Panel A. Model 2 and 3 estimate the OLS models used in Table 10 Panel B. Estimated coefficients are reported, along with standard errors clustered at lender level in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The definitions of all variables are presented in Appendix 1.

	(1)		(2)	(3)
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

Appendix 1: Variable Definitions

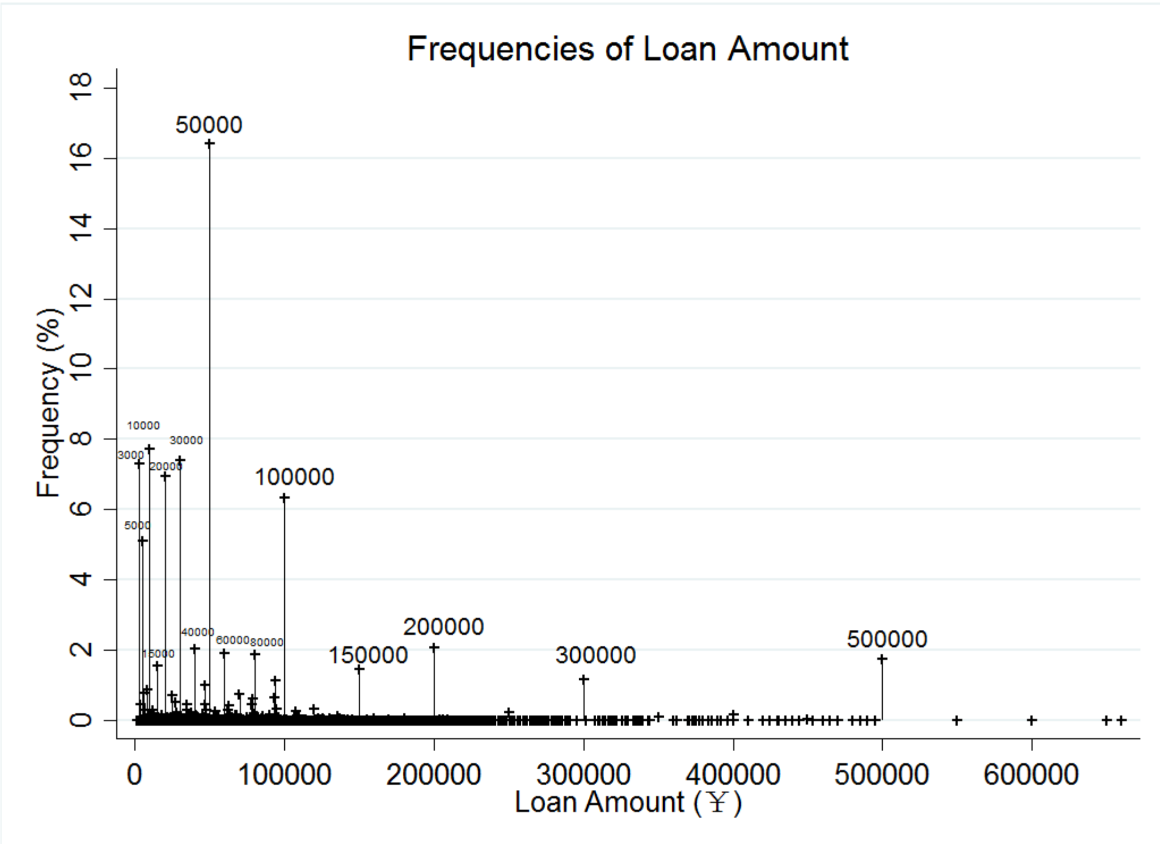
Variable	Definition
Loan-Level Heuristic Measures	
LoanLucky	A dummy variable that equals 1 if the loan amount has 8 but does not have 4, and 0 otherwise.
LoanRound	A dummy variable that equals 1 if the loan amount has only one non-zero number at the leftmost digit, and 0 otherwise.
WA_LoanLucky	The percentage of lucky loan applications in the past (before the current bid) of each bidder, weighted against bid amount.
WA_LoanRound	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 non-zero 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 non-zero number at the highest digit, and 0 otherwise.
WA_LuckyBid	The percentage of lucky bids in the past (before the current bid) of each bidder, weighted against bid amount.
WA_RoundBid	The percentage of round bids in the past (before the current bid) of each bidder, weighted against bid amount.
WA_BidtoLucky	The percentage of bids in the past (before the current bid) that are placed on lucky loans of each bidder, weighted against bid amount.
WA_BidtoRound	The percentage of bids in the past (before the current bid) that are placed on 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 applied loans of 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.

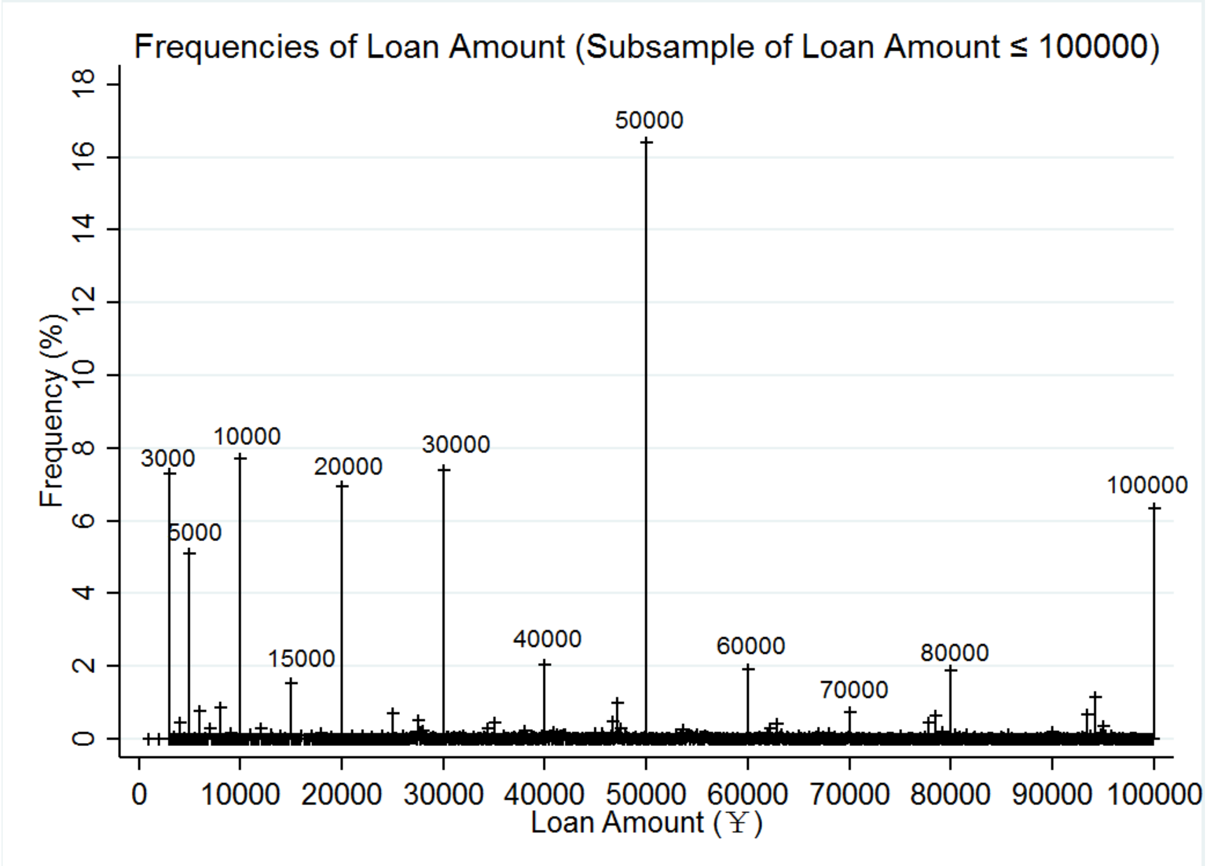
Internet Appendix 1: Distribution of Loan Amounts and Bid Amounts

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

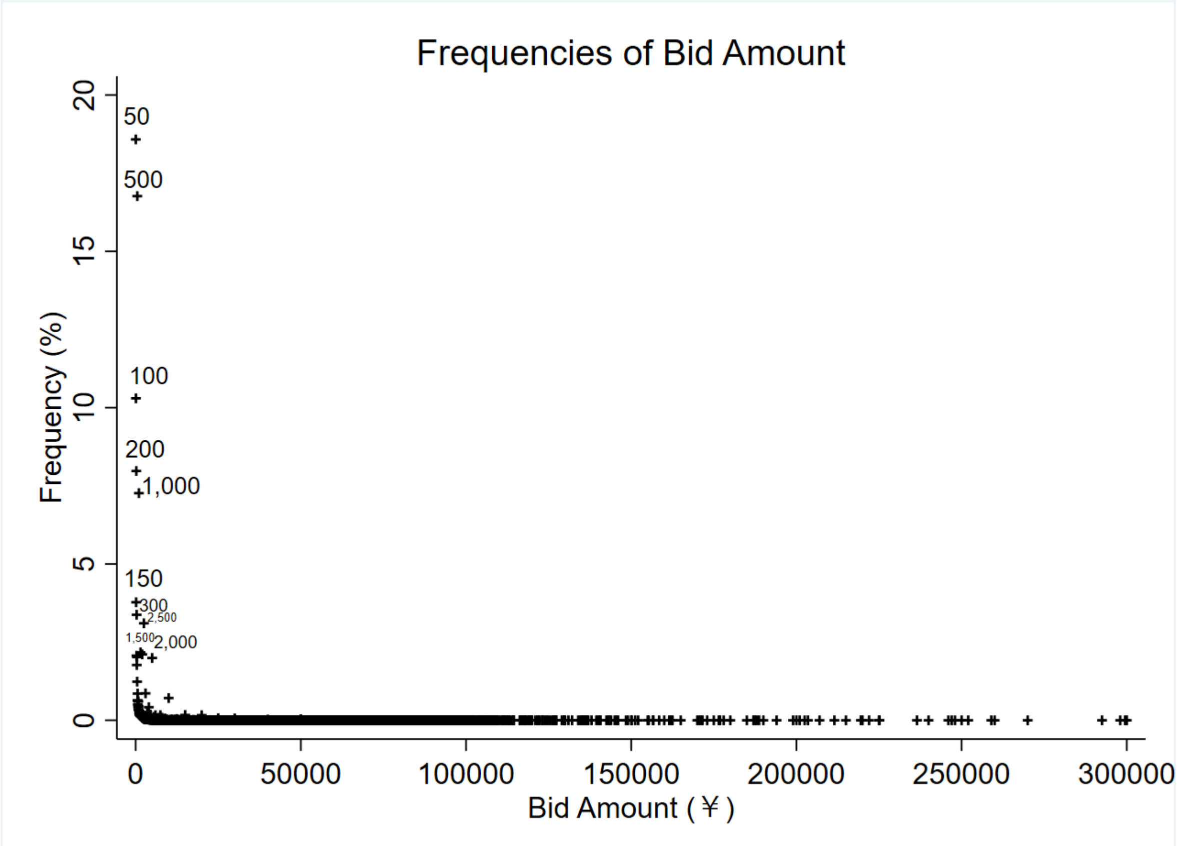
Panel A: Loan Amounts



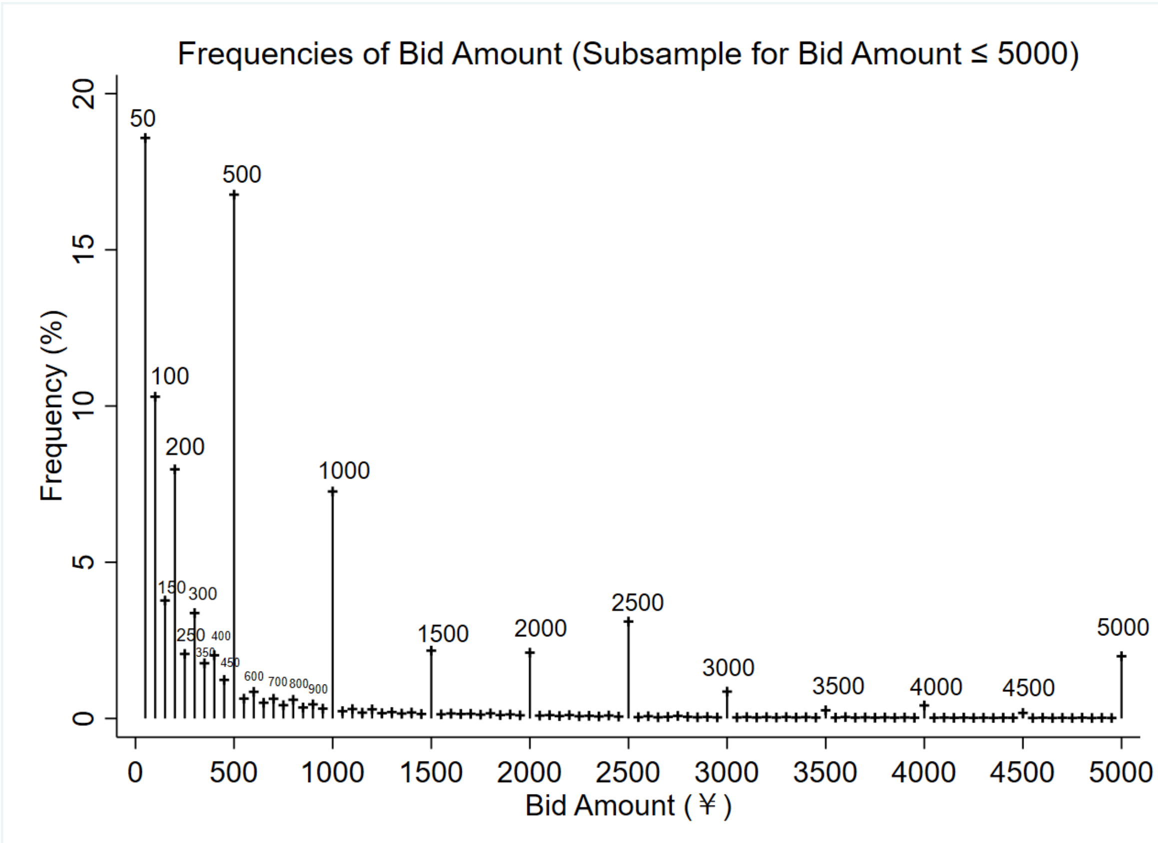
Panel B: Loan Amounts ⩽ 100,000



Panel C: Bid Amounts

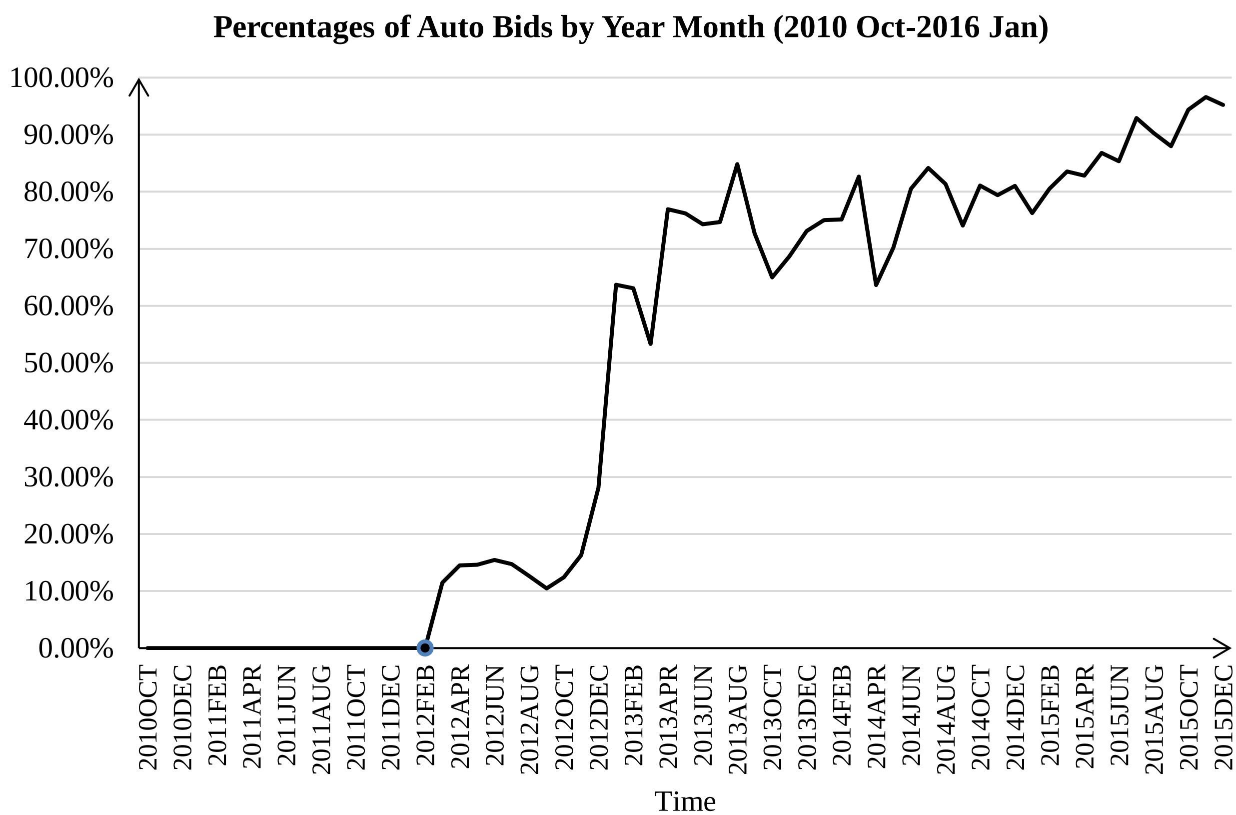


Panel D: Bid Amounts ⩽ 5,000



Internet Appendix 2: Percentages of Auto Bids by Month

This figure describes the average percentage of auto bids in our sample over time.



Internet Appendix 3: Numerological Heuristics and Investors' Responses

This table presents the impacts of investment experience on lenders' responses to the use of heuristics by borrowers. Bivariate Probit models are used. The dependent variables are BidtoRound, which indicates if the bid goes to a loan of a round amount, and BidtoLucky, which indicates if the bid goes to a loan of a lucky amount. Estimated coefficients are reported, along with standard errors clustered at lender level in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The definitions of all variables are presented in Appendix 1.

	(1)		(2)	
Dependent Variable	BidtoRound	BidtoLucky	BidtoRound	BidtoLucky
LogPriorBids	-0.043***	0.017***	-0.037***	0.019***
	(0.000)	(0.000)	(0.002)	(0.001)
WA_BidtoRound			1.144***	-0.178***
			(0.008)	(0.004)
WA_BidtoLucky			-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***	

Internet Appendix 4: Lenders' Numerological Heuristics and Investment Performance

This table reports the relationship between the use of numerological heuristics by lenders and their investment performance. The first three columns measure investment performance by the internal rate of returns of the bid, and the last three columns measure investment performance by Delinquent_Bid, a dummy variable that equals 1 if the bid goes to a delinquent loan, and 0 otherwise. OLS regressions are used in this table, and the two focal variables are RoundBid and LuckyBid, which indicate if the bid amount is round or lucky, respectively. Estimated coefficients are reported, along with standard errors clustered at lender level in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The definitions of all variables are presented in Appendix 1.

	(A) IRR			(B) Delinquent_Bid		
	(1)	(2)	(3)	(4)	(5)	(6)
RoundBid	-0.011		-0.011	0.000		0.000
	(0.007)		(0.007)	(0.000)		(0.000)
LuckyBid		-0.007	-0.010		0.000	0.000
		(0.024)	(0.024)		(0.000)	(0.000)
CreditGrade	3.921***	3.921***	3.921***	-0.073***	-0.073***	-0.073***
	(0.021)	(0.021)	(0.021)	(0.000)	(0.000)	(0.000)
Age	-0.009***	-0.009***	-0.009***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Edulevel	0.371***	0.371***	0.371***	-0.005***	-0.005***	-0.005***
	(0.007)	(0.007)	(0.007)	(0.000)	(0.000)	(0.000)
JobIncomelevel	-0.142***	-0.142***	-0.142***	0.001***	0.001***	0.001***
	(0.004)	(0.004)	(0.004)	(0.000)	(0.000)	(0.000)
JobLength	0.063***	0.063***	0.063***	-0.001***	-0.001***	-0.001***
	(0.006)	(0.006)	(0.006)	(0.000)	(0.000)	(0.000)
Single	0.083***	0.083***	0.083***	-0.001***	-0.001***	-0.001***
	(0.006)	(0.006)	(0.006)	(0.000)	(0.000)	(0.000)
Top20Province	-0.100***	-0.100***	-0.100***	0.001***	0.001***	0.001***
	(0.005)	(0.005)	(0.005)	(0.000)	(0.000)	(0.000)
HasAsset	0.341***	0.341***	0.341***	-0.005***	-0.005***	-0.005***
	(0.010)	(0.010)	(0.010)	(0.000)	(0.000)	(0.000)
HasLoan	0.473***	0.473***	0.473***	-0.007***	-0.007***	-0.007***
	(0.011)	(0.011)	(0.011)	(0.000)	(0.000)	(0.000)
NPriorLoan_Applied	-0.018***	-0.018***	-0.018***	0.000**	0.000**	0.000**
	(0.004)	(0.004)	(0.004)	(0.000)	(0.000)	(0.000)
logLoanAmount (k)	-0.557***	-0.557***	-0.557***	0.011***	0.011***	0.011***
	(0.011)	(0.011)	(0.011)	(0.000)	(0.000)	(0.000)
Loan_Premium	1.045***	1.045***	1.045***	-0.004***	-0.004***	-0.004***
	(0.017)	(0.017)	(0.017)	(0.000)	(0.000)	(0.000)
Loan_Duration (month)	-0.073***	-0.073***	-0.073***	0.001***	0.001***	0.001***
	(0.002)	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)
Constant	-11.768***	-11.779***	-11.768***	0.382***	0.383***	0.382***
	(0.612)	(0.613)	(0.612)	(0.012)	(0.012)	(0.012)
Year Qtr FE	YES	YES	YES	YES	YES	YES
Lender FE	YES	YES	YES	YES	YES	YES
Cluster SE	Lender	Lender	Lender	Lender	Lender	Lender
Observations	7,523,012	7,523,010	7,523,010	7,523,012	7,523,010	7,523,010
Adj. R-squared	0.219	0.235	0.219	0.295	0.310	0.295