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Numerological Heuristics and Credit Risk in Peer-to-Peer Lending

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Abstract. Heuristics are mental shortcuts that have ubiquitous influences on decision making. We investigate whether and how different heuristics have distinct effects in the context of peer-to-peer (P2P) lending. Drawing on theories on the roles that heuristics play in decision making, we conjecture that when borrowers use different heuristics based on distinct motives to set their loan amounts, their funding success and repayment performance also differ. Using detailed P2P lending data from a Chinese P2P lending platform, we examine two important numerological heuristics, the round-number heuristic and the lucky-number heuristic, which are observable in over 80% of the submitted loan amounts. We find that round-number loans are less likely to get funded and exhibit poor repayment performance after being funded, whereas lucky-number loans exhibit the opposite pattern. These findings, which we attribute to the different motives behind the borrowers' heuristic choices, challenge the conventional understanding that generally treats all heuristics as behavioral biases. Our results are robust to various identification strategies, including coarsened exact matching and instrumental variable estimation. Our paper sheds new light on the heterogeneity of heuristics and their distinctive implications for the credit market.

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Keywords: credit risk • numerological heuristics • round-number heuristic • lucky-number heuristic • information asymmetry • P2P lending

1. Introduction

Decision makers use heuristics to reduce cognitive load and find satisfactory solutions quickly. However, as a result, heuristics create biases (Kahneman et al. 1982, Gilovich et al. 2002, Brynjolfsson et al. 2021, Lu et al. 2022). These influences of heuristic usage differ by individuals as they adopt different heuristics and reach different decisions, even for similar problems. We investigate the heterogeneous implications of individuals' adopting heuristics of different kinds.

In peer-to-peer (P2P) lending, borrowers post loan applications for the lender crowd to fund on the platform. Borrowers specify funding requirements, such as the loan amount and interest rate, and disclose their credit-related information. To determine the appropriate loan amount, a borrower needs to evaluate his or her credit demand (Lin and Pursiainen 2021) and repayment ability (Abraham et al. 2022) and estimate the borrowing cost (DeFusco and Paciorek 2017). Given the estimation complexity and uncertainty involved in devising an exact loan amount, borrowers often rely on numerological heuristics to simplify the decision-making process. We find that over 80% of loan requests in our peer-to-peer lending data exhibit two common numerological heuristics, that is, either the round-number heuristic or the lucky-number heuristic. We use this setting to investigate whether and how the use of different heuristics in setting loan amounts affects the funding success and loan repayment for each loan request.

Heuristics are mental shortcuts in decision making (Kahneman et al. 1982) that rest on simplification rather than extensive algorithmic processing (Gilovich et al. 2002). People use different kinds of heuristics at various stages of proactive design theorizing, with the problem-structuring heuristics serving as "rules of thumb that provide a plausible aid in structuring the problem at hand" and artifact design heuristics assisting in "searching for a satisficing artifact design" (Gregory and Muntermann 2014, pp. 640). Similar to their framework, we consider heuristics that serve rules of thumb and heuristics that help in satisficing decision making. However, rather than focus on their interactive roles in the theorization process as in Gregory and Muntermann (2014), we study their heterogeneous implications for decision making. We conceptualize two main types of heuristics based on the adopters' motives. First, decision makers use heuristics as rules of the thumb to save cognitive resources and reduce mental burden. We classify these heuristics as *cognition-conserving heuristics*, which simplify human decision making by aiding the search for satisficing decisions (Gigerenzer and Gaissmaier 2011). Second, aware of their counterparties' heuristic preferences, decision makers use certain heuristics to cater to those preferences and enhance their own performance. We conceptualize these heuristics as *catering heuristics*, based on the rationale that people use them to cater to their clients' preferences.

Under this conceptualization, the round-number heuristic is a type of *cognition-conserving heuristic*. Round numbers are cognitively more accessible (Rosch 1975) and easier to process than sharp numbers (Thomas et al. 2010). They also come to mind more easily and thus often serve as cognitive reference points (Schindler and Kirby 1997). People disproportionally use round numbers more often as mental shortcuts to reduce cognitive burden. In contrast, we classify the lucky-number heuristic as a *catering heuristic*. Consumers and investors often display superstitious preferences for lucky numbers (Bhattacharya et al. 2018), assess lucky products more positively (Kramer and Block 2008), and are willing to pay higher prices for them (Wong et al. 2019, He et al. 2020). Thus, in the marketplace, people can reach a better deal by catering to the counterparty's superstitious preferences, with more sophisticated market participants deliberately using lucky numbers to take advantage of superstitious consumers and investors (Simmons and Schindler 2003, Hirshleifer et al. 2018).

In the context of P2P lending, we identify borrowers' adoption of the round-number heuristic and the lucky-number heuristic as the usage of round numbers and lucky numbers in the loan amount, respectively. Although setting a round-number loan amount is mentally less demanding, the decision is less accurate than cognitive-based decisions that use nonround numbers (Wadhwa and Zhang 2015). Thus, the use of a *cognition-conserving heuristic* indicates that the borrower has traded accuracy for effort saving (Shah and Oppenheimer 2008) and have chosen to allocate limited mental resources to the borrowing process. Accordingly, we expect lenders are less likely to invest in applications with round loan amounts, leading to lower funding success rates. Other things being equal, we also expect borrowers who allocate inadequate cognitive resources to the decision-making process to be associated with worse loan repayment performance, as measured by higher delinquency rates.

In contrast, as the presence of lucky numbers in a loan amount makes the loan application more appealing to superstitious lenders, we expect the lucky-number heuristic to be associated with a better funding success rate. In addition, by including lucky numbers in their loan amounts to appeal to superstitious lenders, these borrowers use the *catering heuristic* to intentionally enhance the likelihood of their funding success. We expect these borrowers to be more sophisticated and hypothesize that the use of lucky-number heuristic predicts better repayment performance.

We empirically examine the above hypotheses using data from a leading P2P lending platform in China. P2P lending is a typical kind of debt-based crowdfunding, where lenders bid on and jointly fund loan applications from borrowers (Jiang et al. 2022). An application gets funded if the total bids received match the requested amount by the end of the bidding period; otherwise, the application will be cancelled. Borrowers of funded loans make monthly repayments to the lenders.

Our data include highly granular bid-level and loan-level information on the platform's funding activities and loan repayment performance. At the loan level, the platform discloses loan and borrower characteristics. We determine if a borrower uses the round-number heuristic or the lucky-number heuristic by whether the loan amount is a round or lucky number, respectively. At the bid level, we have access to detailed bidding records for each application, which enables us to identify the funding outcomes and measure the funding time for each loan application. Our data set also includes detailed monthly loan repayment records for funded loans, allowing us to identify all delinquent events and their timestamps. We define a *round* number as having only one nonzero number for the leftmost digit and zeros for all other digits and a *lucky* number as having the lucky number eight but not having the unlucky number four in the loan amount.

Our empirical analysis shows that the use of the round-number and lucky-number heuristics has distinct influences on funding outcomes and repayment performance. Compared with benchmark loans that are neither round nor lucky, round-number (lucky-number) loans are 6.83 percentage points less likely (12.21 percentage points more likely) to get funded, after controlling for other borrower and loan characteristics. Next, we examine the effects of different heuristics on loan performance. Other things being equal, the delinquency rate is 2.79 percentage points higher (6.45 percentage points lower) for round-number (lucky-number) loans, compared with loans in neither round nor lucky amounts. We use coarsened exact matching (CEM) and instrumental variable regressions to establish causality, and the findings are also robust to alternative definitions of the heuristics and specifications.

This paper makes two contributions to the literature. First, we examine the heterogeneity of the round-number and lucky-number heuristics and demonstrate their distinct implications for the funding success rate and loan performance in P2P lending. We conceptualize the heuristics that reduce mental burden as *cognition-conserving heuristics* and those that improve decision outcomes by catering to the counterparties' preferences as *catering heuristics.* Our findings show that the use of the *cognition-conserving* round-number heuristic in setting loan amounts lowers the funding success rate and leads to higher delinquency rates in P2P lending, whereas using the *catering* lucky-number heuristic yields the opposite in terms of funding and repayment performance. Our findings challenge the conventional wisdom that treats all kinds of heuristics as identical forms of behavioral bias.

Second, we add to the burgeoning literature on P2P lending by focusing on the borrowers' use of heuristics. Crowdfunding, P2P lending in particular, has experienced rapid growth in the past decade (Hildebrand et al. 2017, Kim et al. 2022). Households and entrepreneurs both use these platforms for fundraising (Roma et al. 2018, Burtch and Chan 2019). Research shows that the behavior of individuals can be affected by factors such as cultural and geographic similarity (Burtch et al. 2014), prosocial behavior (Hong et al. 2018, Du et al. 2020), campaign quality (Geva et al. 2019), soft and nonstandard information (Duarte et al. 2012, Iyer et al. 2016), investor experience (Kim and Viswanathan 2019), friendship (Lin et al. 2013, Liu et al. 2015), social influence and altruism (Zhang and Zhu 2011, Burtch et al. 2013), the pricing mechanism (Wei and Lin 2017), and level of wealth (Paravisini et al. 2017), among others. This paper takes a unique perspective by focusing on P2P borrowers' choice of heuristics. We show that the round-number heuristic resembles a type of behavioral bias whereby borrowers reduce the cognitive burden at the cost of the decision accuracy, and this leads to inferior outcomes. In contrast, the use of the lucky-number heuristic boosts funding success and helps achieve satisficing outcomes by catering to the lucky number preferences of the lenders.

2. Literature Review and Hypothesis Development

2.1. Heuristics and P2P Lending

Stemming from cognitive psychology, the concept of heuristics refers to the processes whereby individuals seek to reduce complex tasks to simpler judgmental operations (Tversky and Kahneman 1974, Choi et al. 2018) and thus process information with less effort (Polites and Karahanna 2012, 2013). Heuristics are widely used in decision making in various scenarios, such as healthcare (KC 2020), privacy protection (Dinev et al. 2015), information security (Bahreini et al. 2022), and gambling (Ma et al. 2014). Extensive research has shown that heuristics introduce bias into various personal and corporate decisions (Shiller 2003, Hirshleifer 2015, Lu et al. 2022), such as borrowing and saving (Benartzi and Thaler 2007), corporate operations (Luan et al. 2019), stock investments (Kaustia et al. 2008, Hendershott et al. 2021), diversification strategies (Benartzi and Thaler 2001), and asset pricing (Hirshleifer 2001).

Heuristics also affect the borrowing and lending process in the P2P lending market. Research has documented empirical evidence of behavioral biases, such as herding (Zhang and Liu 2012, Liu et al. 2015, Sun et al. 2019), home bias (Lin and Viswanathan 2016), and gambling (Demir et al. 2021). We focus on borrowers' use of heuristics when faced with the complicated task of setting a loan amount. Before submitting the required loan amount in a P2P loan application, the borrower first needs to estimate his or her credit demand and repayment capacity (Abraham et al. 2022). Another associated consideration is the loan interest rate. As larger loans are generally riskier and are associated with higher interest rates (DeFusco and Paciorek 2017), borrowers may need to offer higher interest rates if they request a larger loan amount. Given the complexity of the estimation task and various uncertainties in forecasting future credit demand, taking all the relevant factors into consideration and devising an optimal loan amount requires considerable cognitive resources. Some borrowers use numerological heuristics to simplify this process. Lin and Pursiainen (2021) document an overrepresentation of round campaign amounts in a similar setting of equity-based crowdfunding.

The literature describes heuristics in various ways. Focusing on proactive design theorization, Gregory and Muntermann (2014) propose two categories of heuristics that allow easier problem structing and that facilitate the searching for satisficing decisions. Similar to their framework, we separate heuristics into those that reduce the mental burden and those that help the adopters make decisions that achieve satisfactory outcomes.

A large strand of the literature defines heuristics as plausible forms of "rules of thumb" or "mental shortcuts" used in problem solving (see Robey and Taggart 1982, Liu et al. 2019, among others). Although the use of heuristics can reduce the mental burden involved in decision making, it can also lead to biased decisions (Tversky and Kahneman 1974, Dinev et al. 2015). This definition highlights the manner in which heuristics involve a trade-off between decision accuracy and cognitive effort (Payne et al. 1993, Shah and Oppenheimer 2008) and thus implies that the use of heuristics can lead to suboptimal outcomes. We conceptualize heuristics that reduce mental burden as *cognition-conserving heuristics*.

Another strand of the literature, following Simon (1955), defines heuristics as methods for finding satisfactory solutions that might not be optimal (see Rowe 1987 and Papi 2012, among others). Some of these heuristics, which we conceptualize as *catering-heuristics*, facilitate satisficing decisions by catering to the preferences of counterparties. Although these heuristics are unlikely to help the decision maker find the optimal choice, they improve the solution to a satisfactory level. In line with this, psychologists have defined heuristics as "a strategy that ignores part of the information, intending to make decisions more quickly, frugally, and/or accurately than more complex methods" (Gigerenzer and Gaissmaier 2011, p. 454). Here, the words "quickly" and "frugally" refer to the abovementioned *cognition-conserving heuristics*, whereas "accurately" refers to the *catering-heuristics* that improve decision outcomes.

2.2. The Round-Number Heuristic

Round numbers often serve as reference points in decision making (Rosch 1975). Pope and Simonsohn (2011) show that professional athletes, SAT examination takers, and participants in a laboratory experiment exhibit a stronger desire to improve their performance when their evaluations are just below a round number. Moreover, round numbers are cognitively more accessible than nonround ones (Schindler and Kirby 1997). According to Hukkanen and Keloharju (2019, p. 293), "people are hardwired to communicate with round numbers." Thomas et al. (2010) show that round numbers require less cognitive effort to process than nonround numbers, making the round-number heuristic a *cognition-conserving heuristic*.

The cognitive accessibility of round numbers allows decision makers to make subjective judgments more frugally, thus saving cognitive effort (Tversky and Kahneman 1974). However, compared with cognitive-based decision making using sharp (i.e., nonround) numbers, the use of round numbers is associated with more feeling-based decision making (Wadhwa and Zhang 2015). Consequently, we expect the use of round numbers may lead to suboptimal decisions. This suggests that in using the round-number heuristic, decision makers sacrifice accuracy for convenience.

Sophisticated investors may be able to tell the credit quality of borrowers from the heuristics used in setting the loan amounts. In particular, they may interpret the use of the round-number heuristic as a sign the borrower is facing cognitive constraints and has taken a mental shortcut to reduce his or her mental burden. Knowing a borrower may have traded accuracy for convenience, we expect sophisticated investors may be less likely to invest in loans with round amounts, leading to lower funding success associated with round loan amounts. We formulate our first hypothesis as follows.

Hypothesis A1. *Other things being equal, loans with round amounts have lower funding success rates than loans with nonround amounts.*

The use of the round-number heuristic leads to inferior outcomes in various contexts. Keys and Wang (2019) show that credit card users tend to round up their payments from the minimum payment to multiples of US$25, which deviates from their optimal repayment schemes. Using Taiwan Futures Exchange data, Kuo et al. (2015) find that investors who submit round number orders suffer greater losses on the stock market. Similarly, using 100 million stock trading records from NASDAQ, Bhattacharya et al. (2012) show that investors who use round prices as reference points have negative abnormal trading returns of US$813 million per year.

In P2P lending, borrowers use the round-number heuristic to conserve their cognitive resources. Compared with borrowers who make more careful decisions, we expect those who resort to mental shortcuts (i.e., the round-number heuristic) are more likely to experience difficulties in financial budgeting or make negligent mistakes when repaying the loan, leading to a higher likelihood of delinquency. We summarize this hypothesis below.

Hypothesis A2. *Other things being equal, round-amount loans are more likely to be delinquent than nonround amount loans.*

2.3. The Lucky-Number Heuristic

Some investors and consumers are superstitious and have a preference for lucky numbers. Bhattacharya et al. (2018) show that individual investors on the Taiwan Futures Exchange submit significantly more limit orders that contain the number eight than the number four. Some superstitious investors and consumers are willing to pay a premium for lucky numbers. For instance, Wong et al. (2019) find that Chinese motorists in Malaysia pay a higher price for plates that include the lucky number eight. Block and Kramer (2009) show that Chinese consumers pay more for a packet of 8 tennis balls than one with 10. Drawing on evidence from the Singapore housing market, He et al. (2020) show that housing prices are inflated when the addresses contain lucky numbers. Shum et al. (2014) and Fortin et al. (2014) find similar evidence using Chinese and U.S. housing data, respectively.

In P2P lending, lenders with superstitious beliefs tend to favor lucky amount loans. Other things being equal, superstitious lenders are thereby more likely to invest in these loans, thus improving the funding success of round amount loans. We propose the following hypothesis.

Hypothesis B1. *Other things being equal, loans with lucky amounts are more likely to get funded than loans with nonlucky amounts.*

Some sophisticated borrowers deliberately use lucky amounts to increase their likelihood of funding success. Research documents the intentional use of lucky numbers in many different settings. Simmons and Schindler (2003) find that advertisements in China include the number eight with a disproportionately higher frequency and avoid the number four. Hirshleifer et al. (2018) show that Chinese initial public offering firms intentionally include lucky numbers in their listing codes to appeal to investor preferences and find that this indeed generates better stock performance in terms of larger price run-ups and more active trading on the secondary market.

In contrast to the round-number heuristic, which reduces a borrower's cognitive burden, the lucky-number heuristic enhances a borrower's likelihood of funding success by attracting more lenders, especially those with the lucky-number preference. Rather than reducing the mental burden, borrowers who set lucky-number loan amounts make more effort to understand the preferences of the lenders and make their loans more attractive to boost their funding success rate. Accordingly, we conjecture that setting a lucky-number loan amount demonstrates the borrower's intellectual sophistication and suggests they allocate more cognitive resources to the borrowing and budgeting process (relative to users who do not use the lucky-number heuristic), which positively predicts the loan repayment performance. Thus, we propose the following hypothesis.

Hypothesis B2. *Other things being equal, loans with lucky amounts have lower delinquency rates than loans with nonlucky amounts.*

We summarize the framework of the borrower's choice of heuristics under different motives in Figure 1.[1]

3. Method and Setting

3.1. The P2P Platform

Our research context is one of the largest P2P lending platforms in China. Established in 2010, by January 2016 the platform had facilitated RMB13.53 trillion (US$2 trillion) of P2P loans. Before posting a loan application, a borrower needs to first register on the platform and provide detailed information, such as gender, age, education level, and job income level. Based on the submitted information, the platform assigns a credit grade for each borrower ranging from AA, A, B, C, D, E, to HR (i.e., high risk).

A registered borrower can then post a loan request on the platform by submitting the desired loan amount, interest rate offered, loan duration, etc. The loan amount must be in multiples of RMB50 (about US$7.62). The minimum loan amount is RMB1,000 (US$150) and the maximum is RMB3 million (US$0.45 million) in our sample. Lenders observe the borrower characteristics and loan contract terms and decide whether to bid on a loan listing.

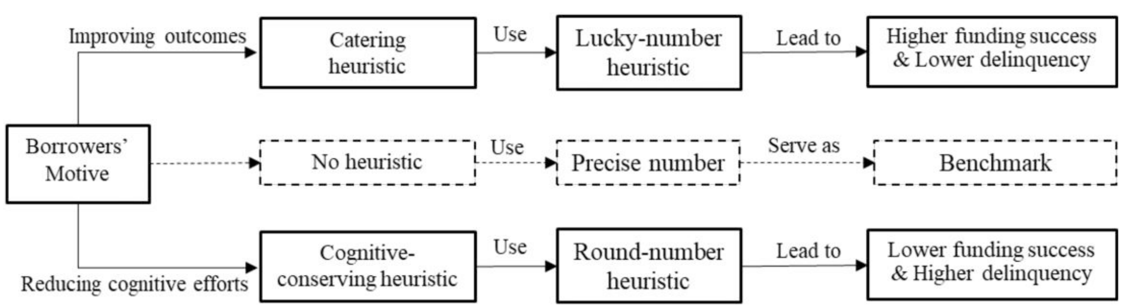
Loan applications have limited funding time. Funding succeeds if the cumulative bidding amount reaches the requested amount before the listing expires and fails otherwise. Borrowers of funded loans receive the funds and are obliged to make monthly repayments thereafter. There are three possible statuses for funded loans. We classify a loan as *paid off* if it is closed and fully repaid on time; as *ongoing* if it is still at the repayment stage; and as *delinquent* if it has overdue or default record(s). Internet Appendix 1 illustrates the borrowing and funding process.

The information environment of P2P lending is similar to that of eBay, investigated by Backus et al. (2019), where sellers post goods online for buyers to select. However, on eBay, the prices are auction based, whereas the interest rates in P2P lending are predetermined before the funding process, thus precluding price negotiation. Thus, the practice of using round numbers to obtain a higher deal likelihood rather than the optimal deal price observed among eBay sellers does not exist among P2P borrowers.

3.2. Data Description

We begin with all loan applications from the October 11, 2010 to January 14, 2016 period. Excluding observations with missing borrower and loan characteristics, we obtain a sample of 611,079 loans, which we use to study the funding success. The total number of funded loans is 219,236. We exclude 57,529 ongoing loans with censored repayment performance and use the remaining sample of 161,707 funded loans to examine the loan delinquency. For the robustness test,

Figure 1. Framework of Borrowers' Heuristic Choices



we also use the 5,948,938 monthly repayment records from all 217,237 funded loans to study loan repayment performance.[2]

For each loan application, we collect the details on the borrower characteristics, loan characteristics, and bidding records. Borrower characteristics include age (*Age*), income level (*HighJobIncome*), work experience (*JobLength*), education level (*HighEdu*), marital status (*Single*), province of origin (fixed effect), whether a borrower owns any housing asset or a car (*HasAsset*), whether a borrower has an existing car loan or mortgage from a bank (*HasLoan*), credit history on the platform (*NpriorLoan_Applied*), and the total length of the descriptive text (*LogDescriptionLength*). The platform assigns a credit *grade* to each loan application on a seven-point scale.

Loan characteristics include loan annual interest rate (*Loan_Rate*), loan amount (*LogLoanAmount (k)*), and duration (*Loan_Duration (month)*). We also construct our focal variable on heuristic use from the loan amounts. Bhattacharya et al. (2012) and Kuo et al. (2015) identify round numbers by focusing on the last two digits, whereas Lin and Pursiainen (2021) define round numbers as numbers divisible by 1,000 or 500. The platform requires loan amounts to be in multiples of RMB50, and 87.33% of the loan amounts are divisible by 1,000 in our sample. Thus, we use a stricter criterion and recognize an amount as round if it has only one nonzero number for the leftmost digit and zeros for all other digits (*LoanRound*). As an illustration, 30,000 is round but 31,000 is not. For robustness, we also construct an alternative measure *LoanRound_Score,* which is a continuous variable in the range of $(0, 1)$, defined as the number of consecutive zeros from the rightmost digit divided by the total number of digits.

In Chinese culture, the number eight is considered lucky (the word sounds like "getting rich") and the number four is deemed unlucky (the word sounds similar to "death"). Following Bhattacharya et al. (2018), we designate lucky-number loan amounts as those containing eight but not four (*LoanLucky*). Similarly, we use a continuous measure, *LoanLucky_Score*, defined as the frequency count of eight divided by the total number of digits.

To examine the influence of heuristics on the funding and repayment performance, we first partition the loan sample by whether the loan amount is a round number or not. The funding success rate for round-number loans is 73.79 percentage points lower than for nonrounded loans ($p < 0.001$).[3] For the funded loans, round-number loans take on average 1.05 hours longer ($p < 0.001$) to get funded, and the delinquency rate is 6.37 percentage points higher ($p < 0.001$). We also partition the loan sample into lucky-number and nonlucky-number loans. Lucky-number loans are 42.12 percentage points more likely to be fully funded ($p < 0.001$).[4] Conditional on being fully funded, lucky-number loans also require 0.19 hours ($p < 0.001$) less bidding time and have a 1.80 percentage point ($p < 0.001$) lower delinquency rate.

In Internet Appendix 2, we separate the loan applications into four groups based on whether the loan amounts are round or lucky and provide more detailed evidence on the effects of heuristics usage. We find that loans with lucky and nonround loan amounts have the highest funding success rate of 94.68% and the lowest delinquency rate of 1.16%. These loans are followed by nonround and nonlucky amount loans with an average funding success rate of 81.22% and a delinquency rate of 2.36%. For round and lucky amount loans, only 27.51% of applications are funded and the delinquency rate is 7.36%. Loans with round and nonlucky amounts are the worst performers, with only 9.11% of applications being fully funded and an average delinquency rate of 8.65%. In the unreported t-test difference test, the group differences in mean funding success and delinquency are all significant at the 0.001 level. This pattern is in line with our conjecture that the use of round numbers is associated with lower funding success and higher delinquency, whereas lucky numbers have the opposite effect.

We report the definitions and summary statistics of our main variables in Table 1. Our focal variables are *LoanRound* and *LoanLucky*, which indicate whether a loan amount is a round or lucky number, respectively. We find that round-number and lucky-number loans account for 64.85% and 9.45% of all loan applications, respectively. The average borrower is 34.67 years of age; 65.89% of borrowers have a high school degree or above; 62.57% earn over RMB5,000 per month; 54.49% own assets, such as cars or houses; 25.27% have car loans or house mortgages from traditional financial intermediaries. The average loan duration is 20.10 months. The maximum loan amount is RMB3 million, whereas the minimum is RMB1,000, with the mean being RMB62,150. Financing costs on the platform are high, with the average interest rate being 13.13%. For the funded loan sample, the average funding time is 0.65 hours and the delinquency rate is 3.66%.[5]

4. Results

4.1. The Use of Heuristics in P2P Lending

We first establish the overrepresentation of round numbers and lucky numbers in the loan amounts and report the top 10 most frequent loan amounts in Internet Appendix 3. All of the top 10 loan amounts are round, and 50,000 is the most frequently used loan amount, indicating borrowers' prevalent use of the round-number heuristic in setting the loan amounts.

We also plot the frequency percentages of nonzero digits in loan amounts in Internet Appendix 4, panel A.

Table 1. Variable Definition and Summary Statistics

Variable	Definition	Mean	SD	Min	Max
CreditGrade	Credit grade assigned by the platform, including seven grades AA, A, B, C, D, E, and HR: AA equals seven; A equals six; B equals five; C equals four; D equals three; E equals two; and HR equals one.	2.6555	2.3171	1	7
DescriptionLength (byte)	The length of the descriptive text in byte for each loan	18.8849	10.6489	0	60
HighEdu	A dummy variable equals one if the borrower has high school degree or above and zero otherwise.	0.6589	0.4741	0	1
HighJobIncome	A dummy variable equals one if the monthly job income of the borrower is more than 5,000 RMB and zero otherwise.	0.6257	0.4839	0	1
JobLength	The working experience level of each borrower: four means more than five years; three means between three and five years; two means between one and three years; and one means less than one year.	2.0939	1.0541	1	4
HasAsset	A dummy variable equals one if the borrower owns a house or a car and zero otherwise.	0.5449	0.4980	0	1
HasLoan	A dummy variable equals one if the borrower has car loan(s) or mortgage loan(s) from traditional financial intermediaries and zero otherwise.	0.2527	0.4346	0	1
Age	The borrower's age	34.6701	7.8231	18	89
Single	A dummy variable equals one if the borrower is single and zero otherwise.	0.4314	0.4953	0	1
NPriorLoan_Applied[a]	Number of prior loans applied for by each borrower	0.7179	1.5129	0	11
LoanRound	A dummy variable equals one if the loan amount has only one nonzero number at the leftmost digit and zero otherwise.	0.6485	0.4775	0	1
LoanLucky	A dummy variable equals one if the loan amount has eight but does not have four and zero otherwise.	0.0945	0.2925	0	1
Avg_LoanRound	The percentage of round amounts among all prior loan listings submitted by a group of similar borrowers; we require borrowers within the same group to have identical credit grade, job income level, working experience, education level, asset ownership, car or mortgage loan, and location.	0.6552	0.3958	0	1
Avg_LoanLucky	The percentage of lucky amounts among prior loan listings submitted by a group of similar borrowers; we require borrowers within the same group to have identical credit grade, job income level, working experience, education level, asset ownership, car or mortgage loan, and location.	0.0936	0.1059	0	1
LoanRound_Score	Round score calculated as the total number of consecutive zeros from the rightmost digit divided by total digit places for each loan	0.6799	0.1696	0.1667	0.8571
LoanLucky_Score	Lucky score calculated as the total number of eights divided by total number of digits for each loan	0.0223	0.0656	0	0.6
Loan_Amount (k)	Requested loan amount in thousand RMB of each loan	62.1496	82.8101	1	3,000
Loan_Rate	Annual interest rate of each loan	13.1291	2.6981	3	24.4
Loan_Duration (month)	Duration in months of each loan	20.0973	11.0163	1	48
FundingSuccess	A dummy variable equals one if a listing is fully funded and zero otherwise.	0.3588	0.4796	0	1
Delinquent[b]	A dummy variable equals one if the loan is not fully repaid or repaid with late payments and zero otherwise.	0.0366	0.1879	0	1
BidTime (hour)[c]	Number of hours it takes for a listing to be fully funded.	0.6453	4.8451	0.0003	167.5106

Note. SD, standard deviation.
[a]We trim the top 0.5% of *NPriorLoan_Applied* to eliminate the influence of extreme values.
[b]*Delinquent* is only available for funded loans with repayment records.
[c]*BidTime (hour)* is only available for funded loans.

The number five is the most common nonzero number, accounting for 35.46% of the usage; this is because the loan amounts must be multiples of RMB50. We observe a decrease in frequency as the number increases, consistent with the mathematical principle of Benford's law, which states that small numbers occur more frequently than large numbers in the leading digit (Benford 1938). Accordingly, we compare the frequency of a number with that of its neighbors (excluding five) to offer a cleaner assessment of the frequency of lucky and unlucky numbers. The lucky number eight appears more frequently than seven and nine, whereas the unlucky number four does not appear as often as three.[6] The above differences are statistically significant at the 0.001 level, which reflects borrowers' active use of the lucky-number heuristic in setting loan amounts.

4.2. Heuristics and Funding Outcomes

Table 2 reports the ordinary least squares (OLS) and probit estimation results on funding success, where the dependent variable equals one if the loan is funded and zero otherwise. The focal explanatory variables are *LoanRound* and *LoanLucky*, which indicate whether the loan amounts are in round or lucky numbers, respectively. The model controls for borrower and loan characteristics, year-quarter fixed effects, and borrower province fixed effects in all specifications. Specifications (1), (4), and (2), (5) examine the influence of our focal variables, *LoanRound* and *LoanLucky* separately, along with other controls as introduced above; specifications (3) and (6) include *LoanRound* and *LoanLucky* simultaneously.

Our results show that the coefficients for the round-amount loan indicator are negative and statistically significant in all specifications, implying that round-amount loans have lower funding success rates than non-round-amount loans in general. The coefficients of the lucky-amount loan indicator are significant and positive, implying that lucky-amount loans are more likely

Table 2. Numerological Heuristics and Funding Outcomes

Dependent variable: *Funding Success*	(1)	(2)	(3)	(4)	(5)	(6)
	OLS			Probit		
LoanRound	−0.1124***		−0.1113***	−1.1078***		−1.1006***
	(0.0148)		(0.0146)	(0.0778)		(0.0773)
LoanLucky		0.0345***	0.0296***		0.5530***	0.5275***
		(0.0031)	(0.0031)		(0.0260)	(0.0313)
CreditGrade	0.1776***	0.1915***	0.1770***	0.8402***	0.9071***	0.8345***
	(0.0031)	(0.0017)	(0.0031)	(0.0233)	(0.0251)	(0.0230)
LogDescriptionLength	0.0106***	0.0105***	0.0107***	0.1196***	0.1083***	0.1170***
	(0.0026)	(0.0023)	(0.0026)	(0.0296)	(0.0280)	(0.0301)
HighEdu	0.0146***	0.0151***	0.0146***	0.1839***	0.1967***	0.1848***
	(0.0021)	(0.0022)	(0.0021)	(0.0218)	(0.0240)	(0.0226)
HighJobIncome	0.0195***	0.0195***	0.0190***	0.2854***	0.2646***	0.2793***
	(0.0019)	(0.0018)	(0.0020)	(0.0221)	(0.0190)	(0.0226)
JobLength	0.0109***	0.0101***	0.0111***	0.0977***	0.0931***	0.0986***
	(0.0023)	(0.0019)	(0.0023)	(0.0216)	(0.0188)	(0.0215)
HasAsset	0.0070**	0.0096***	0.0066**	0.0815**	0.0873***	0.0774**
	(0.0020)	(0.0013)	(0.0020)	(0.0278)	(0.0240)	(0.0284)
HasLoan	0.0090***	0.0119***	0.0088***	0.0858**	0.1092***	0.0877**
	(0.0018)	(0.0023)	(0.0018)	(0.0317)	(0.0330)	(0.0323)
LogAge	0.0415***	0.0399***	0.0417***	0.7858***	0.7078***	0.7832***
	(0.0044)	(0.0051)	(0.0044)	(0.0612)	(0.0658)	(0.0623)
Single	−0.0071***	−0.0061***	−0.0072***	−0.0767***	−0.0637***	−0.0762***
	(0.0012)	(0.0010)	(0.0012)	(0.0116)	(0.0107)	(0.0115)
NpriorLoan_Applied	−0.0016	−0.0018	−0.0016	−0.0315*	−0.0368*	−0.0332*
	(0.0014)	(0.0014)	(0.0014)	(0.0157)	(0.0155)	(0.0160)
LogLoanAmount (k)	−0.0294***	−0.0288***	−0.0294***	−0.4038***	−0.3634***	−0.4068***
	(0.0036)	(0.0033)	(0.0036)	(0.0414)	(0.0352)	(0.0414)
Loan_Rate	−0.0038**	−0.0036**	−0.0038**	−0.0473**	−0.0450**	−0.0470**
	(0.0010)	(0.0010)	(0.0010)	(0.0160)	(0.0157)	(0.0161)
Loan_Duration (month)	−0.0007*	−0.0001	−0.0007**	0.0010	0.0063**	0.0008
	(0.0003)	(0.0002)	(0.0003)	(0.0025)	(0.0024)	(0.0025)
Constant	−0.1888***	−0.3232***	−0.1891***	−4.6042***	−5.6363***	−4.5875***
	(0.0323)	(0.0243)	(0.0317)	(0.3652)	(0.3182)	(0.3666)
Year Qtr FE	YES	YES	YES	YES	YES	YES
Borrower Province FE	YES	YES	YES	YES	YES	YES
Clustered SE	Year Qtr	Year Qtr	Year Qtr	Year Qtr	Year Qtr	Year Qtr
Observations	611,079	611,079	611,079	611,079	611,079	611,079
Adj. R^2	0.8683	0.8636	0.8686			
Pseudo R^2				0.8371	0.8207	0.8388

Notes. Clustered standard errors in parentheses. FE, fixed effects; Qtr, quarter; SE, standard errors.
$^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

to be funded than loans with nonlucky amounts. In specifications (3) and (6), which include both heuristic dummies, the benchmark group includes loans with nonround and nonlucky amounts. We find that compared with borrowers who use neither of these two heuristics, using the round-number heuristic decreases the funding odds by 66.73% (= $\exp(-1.1006) - 1$) and adopting the lucky-number heuristic raises the funding odds by 69.47% (= $\exp(0.5275) - 1$). The coefficients on the other control variables also make intuitive sense. Borrowers' positive attributes, such as higher credit grade, education level, income, longer working experience, and greater asset base, are also associated with a higher funding success rate. Listings that require larger amounts are less likely to be funded. The loan interest rate, considered as a comprehensive measure of loan riskiness (Karlan and Zinman 2009), is negatively related to funding success.

4.3. Heuristics and Loan Performance

In Table 3, we examine how the use of heuristics in setting loan amounts affects loan performance. The main explanatory variables of interest are the two heuristic measures: *LoanRound* and *LoanLucky*. The specifications also control for a comprehensive set of loan and borrower characteristics. The table reports the OLS regression results in the first three columns and the probit results in the last three specifications. The dependent variable is *Delinquent*, a dummy variable that equals one if there is any late payment associated with the loan and zero otherwise. Loan repayment performance is only observable among loans that are funded and

Table 3. Numerological Heuristics and Loan Performance

Dependent variable: *Delinquent*	(1)	(2)	(3)	(4)	(5)	(6)
		OLS			Probit	
LoanRound	0.0045^		0.0045^	0.0625*		0.0628*
	(0.0024)		(0.0024)	(0.0274)		(0.0276)
LoanLucky		−0.0062***	−0.0062***		−0.0660^	−0.0665^
		(0.0010)	(0.0010)		(0.0377)	(0.0382)
CreditGrade	−0.0702***	−0.0704***	−0.0703***	−0.6717***	−0.6725***	−0.6708***
	(0.0034)	(0.0034)	(0.0033)	(0.0586)	(0.0582)	(0.0587)
LogDescriptionLength	0.0012	0.0012	0.0012	0.0691**	0.0697**	0.0694**
	(0.0014)	(0.0014)	(0.0014)	(0.0218)	(0.0215)	(0.0216)
HighEdu	−0.0126***	−0.0126***	−0.0127***	−0.2363***	−0.2395***	−0.2376***
	(0.0018)	(0.0018)	(0.0019)	(0.0249)	(0.0252)	(0.0253)
HighJobIncome	0.0029	0.0030	0.0029	0.0706	0.0732	0.0719
	(0.0031)	(0.0032)	(0.0031)	(0.0450)	(0.0446)	(0.0446)
JobLength	−0.0024	−0.0025	−0.0025	0.0143	0.0132	0.0139
	(0.0017)	(0.0017)	(0.0017)	(0.0199)	(0.0199)	(0.0198)
HasAsset	−0.0085**	−0.0085**	−0.0083**	−0.0558	−0.0557	−0.0555
	(0.0028)	(0.0029)	(0.0028)	(0.0450)	(0.0448)	(0.0448)
HasLoan	−0.0195***	−0.0194***	−0.0195***	−0.2038***	−0.2032***	−0.2039***
	(0.0027)	(0.0027)	(0.0027)	(0.0344)	(0.0343)	(0.0345)
LogAge	0.0170**	0.0172**	0.0169**	0.4323***	0.4364***	0.4326***
	(0.0045)	(0.0046)	(0.0045)	(0.1099)	(0.1090)	(0.1096)
Single	−0.0012	−0.0013	−0.0012	0.0425*	0.0413*	0.0421*
	(0.0010)	(0.0010)	(0.0010)	(0.0167)	(0.0167)	(0.0166)
NpriorLoan_Applied	0.0037^	0.0038^	0.0037^	0.0492***	0.0491***	0.0491***
	(0.0019)	(0.0019)	(0.0018)	(0.0091)	(0.0092)	(0.0091)
LogLoanAmount (k)	0.0145***	0.0144***	0.0147***	0.1256***	0.1176***	0.1242***
	(0.0027)	(0.0026)	(0.0026)	(0.0289)	(0.0287)	(0.0291)
Loan_Rate	0.0033	0.0032	0.0033	0.0359***	0.0360***	0.0356***
	(0.0024)	(0.0024)	(0.0024)	(0.0105)	(0.0105)	(0.0104)
Loan_Duration (month)	0.0015**	0.0015**	0.0015**	0.0174***	0.0169***	0.0174***
	(0.0005)	(0.0004)	(0.0005)	(0.0050)	(0.0050)	(0.0050)
Constant	0.2410***	0.2480***	0.2423***	−2.0588***	−2.0003***	−2.0547***
	(0.0285)	(0.0300)	(0.0286)	(0.2709)	(0.2727)	(0.2697)
Year Qtr FE	YES	YES	YES	YES	YES	YES
Borrower province FE	YES	YES	YES	YES	YES	YES
Clustered SE	Year Qtr	Year Qtr	Year Qtr	Year Qtr	Year Qtr	Year Qtr
Observations	161,707	161,707	161,707	161,702	161,702	161,702
Adj. R^2	0.2781	0.2782	0.2782			
Pseudo R^2				0.5419	0.5418	0.5420

Notes. Clustered standard errors in parentheses. FE, fixed effects; Qtr, quarter; SE, standard errors.
$\hat{}p < 0.1$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

closed, so the sample only includes loans that are either fully paid off (*delinquent = 0*) or delinquent (*delinquent = 1*). We exclude all ongoing loans with censored repayment records from the sample.

The coefficients of *LoanRound* (*LoanLucky*) are significant and positive (negative) across all specifications, indicating that setting round-number (lucky-number) loan amounts is associated with worse (better) loan repayment performance. In specifications (3) and (6), we include both *LoanRound* and *LoanLucky* and use loans with neither round-number nor lucky-number amounts as the benchmark. Other things being equal, the use of the round-number heuristic is associated with a 6.48% (= $\exp(0.0628) - 1$) higher delinquency probability and the lucky-number heuristic with a 6.43% (= $\exp(-0.0665) - 1$) lower delinquency probability.

We also find that the loans of borrowers with higher credit grades, higher education levels, and more assets are less likely to be delinquent. These results are consistent with our expectation that higher borrower quality is associated with lower delinquency rates. In the probit regressions, the loan interest rate has significant and positive coefficients, consistent with the rationale that riskier loans offer higher interest rates as risk compensation.

Overall, the results in Table 3 suggest that borrowers' choice of heuristics in setting loan amounts also predicts loan performance. Taken together, the findings in Tables 2 and 3 demonstrate that borrowers' choice of heuristics has differential effects on their funding and repayment outcomes.

5. Robustness Analysis

5.1. Identification

5.1.1. Coarsened Exact Matching. A potential issue with our results is that the effect of heuristics usage on funding and loan performance could suffer from self-selection bias, as the heuristics usage could be correlated with individual characteristics. Although we include a very rich set of borrower and loan features, the estimated coefficients of the round-number and lucky-number heuristics may still be affected by systematic variations in borrower characteristics.

We use the CEM approach to address this endogeneity issue (Iacus et al. 2012). We first perform one-to-one matching between the round-amount loans and non-round-amount loans based on all borrower characteristics. For the discrete variables, we require the matching pairs to have identical values. We also follow Scott's rule and coarsen each continuous variable and obtain 151,850 strata. We match each round-amount loan with a nonround loan within the same stratum and exclude the round-amount loans without matching pairs within the same stratum, which gives us a matched sample of 106,082 observations from 53,041 matching pairs. Similarly, we perform the same CEM steps to match the lucky-amount and non-lucky-amount loans one by one and obtain a sample of 101,880 observations from 50,940 pairs. Last, to examine both heuristics simultaneously, we match round-amount loans and lucky-amount loans with loans that are neither round nor lucky, which generates a sample of 167,616 observations from 83,808 pairs.

Internet Appendix 5 panel A presents the results of the mean difference t-test. The first, middle, and last three columns report the differences in borrower characteristics between the round and nonround loans, between lucky and nonlucky loans in the following three columns, and between heuristics and nonheuristics loans. In the above three subsamples, the characteristics do no differ significantly across the groups, thereby indicating that the borrower characteristic variables are well balanced in the matched subsamples. In unreported results, we use the L1 distance to measure the differences in distribution between the treated and control loans. The indicator decreases from 0.7687, 0.6221, and 0.7171 to 0 in all three subsamples, thus demonstrating that the CEM approach substantially reduces the imbalance in the data.

The first column of Table 4 presents the regression results on the effect of *LoanRound* on funding success. We use the matched sample where each round-amount loan is matched to a nonround amount loan. The second specification in column (2) examines the effects of the lucky-number heuristic on funding success, using the matched sample where each lucky-amount loan is matched to a nonlucky amount loan. The third specification in column (3) examines the simultaneous effects of the two heuristics on funding success. We use the matched sample where each round or lucky amount loan is matched to a loan that is neither round nor lucky. Across all specifications, *LoanRound* has significant and negative coefficients, whereas *LoanLucky* shows significant and positive coefficients.

Columns (4)–(6) present the results for loan repayment performance using funded loans, and accordingly only funded loans are included in the matching steps. We follow the same procedure in matching round-amount (lucky-amount) loans with nonround (nonlucky) loans. The mean difference t-test results in panel B of Internet Appendix 5 show that all variables are balanced between the treated and control groups. Results using the matched subsample are also consistent with the baseline models. Specifically, the use of the round-number heuristic in setting loan amounts increases the likelihood of delinquency whereas the use of the lucky-number heuristic has the opposite effect.

In the matched subsample regressions, loans within each pair are from borrowers with similar credit quality and other characteristics. After eliminating the influence of borrower characteristics, we still observe

Table 4. Matched Sample Regressions

Dependent variable	(1)	(2) *Funding Success*	(3)	(4)	(5) *Delinquent*	(6)
LoanRound	−0.0914***		−0.0768***	0.0040*		0.0024*
	(0.0020)		(0.0017)	(0.0016)		(0.0012)
LoanLucky		0.0224***	0.0033***		−0.0015*	−0.0023***
		(0.0010)	(0.0007)		(0.0006)	(0.0005)
Borrower characteristics	YES	YES	YES	YES	YES	YES
Loan characteristics	YES	YES	YES	YES	YES	YES
Year Qtr FE	YES	YES	YES	YES	YES	YES
Borrower province FE	YES	YES	YES	YES	YES	YES
Clustered SE	Year Qtr	Year Qtr	Year Qtr	Year Qtr	Year Qtr	Year Qtr
Observations	106,082	101,880	167,616	41,254	51,334	81,456
Adj. R^2	0.8166	0.9028	0.8735	0.3520	0.3128	0.3210

Notes. Clustered standard errors in parentheses. FE, fixed effects; Qtr, quarter; SE, standard errors.
$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

robust and consistent results, indicating that variations in borrowers' attributes do not drive the opposite effects of the round-number heuristic and the lucky-number heuristic. Still, we fully acknowledge that CEM only addresses the selection issue on observable borrower characteristics. The unobservable borrower features could be possible confounding factors. Specifically, borrowers that use various heuristics may vary in several unobservable dimensions, leading to differential effects on funding success and delinquency. We use the instrumental variable approach to address these endogeneity issues associated with potentially omitted variables and to establish causality.

5.1.2. Instrumental Variable. Research on P2P lending reveals the possible sources of omitted borrower features. For example, Gao et al. (2023) extract the readability, emotion, and deception measures from P2P borrowers' descriptive texts and show that they have significant effects on funding success and repayment performance. Yan and Pena-Marin (2017) find that the use of precise numbers signals confidence, believability, and reasonability, which is relevant both to borrowers' use of the round-number heuristic and funding outcomes.[7] Jiang et al. (2020) show that crowdfunders' behavior is influenced by both on-platform and off-platform information. Therefore, endogeneity could also arise from off-platform factors related to borrowers' choice of heuristics. Borrowers occupied by other off-platform decision tasks are also more likely to use round numbers in their loan amounts (Hirshleifer et al. 2019).

To address the endogeneity concern, we use an instrumental variable regression motivated by Kuo et al. (2015). Their focal variable is each investor's use of the round-number heuristic in an order submission, and they construct the instrumental variable as the percentage of round-number orders in all previous orders submitted by the same investor. The underlying assumption is that individuals who frequently used round (or lucky) numbers in the past would habitually use similar heuristics in future decision tasks. Along the same line, we construct two instrumental variables for *LoanRound* and *LoanLucky* based on the percentage of round-number or lucky-number loans among the prior loan listings submitted by a group of similar borrowers. Note that our setting is slightly different from Kuo et al. (2015) in that a large proportion of their sample are repeat investors, whereas the majority of borrowers in our sample only have one loan application record. Hence our instrumental variable is constructed based on a group of similar borrowers instead of a single borrower, as elaborated below.

We partition the entire sample of 598,294 unique borrowers into different groups by several credit quality related borrower characteristics. Specifically, within each group, we require all borrowers to have exactly the same credit grade, education level, income level, work experience, asset ownership, and loan status, and to come from the same province.[8] After assigning each borrower to a group, we then calculate the percentages of round-number and lucky-number loans among the prior loan listings submitted by borrowers from the same group to obtain *Avg_LoanRound* and *Avg_LoanLucky*. We use these figures as the instrumental variables for *LoanRound* and *LoanLucky*.

The functioning of the instrumental variables hinges on the relevance and exogeneity conditions. First, the relevance condition requires that the past heuristic usage of a group of borrowers with similar credit status is able to predict a specific borrower's heuristic adoption within the group. We argue that borrowers with shared characteristics usually have similar motives for using particular heuristics. For example, cognitively challenged borrowers are more likely to use heuristics that reduce their mental burden in decision making, whereas experienced and sophisticated borrowers are more likely to use heuristics to improve their decision outcomes by catering to lenders' preferences. Therefore, we expect the prior use of heuristics by similar borrowers should predict a borrower's current choice of heuristics. Empirically, Kuo et al. (2015) provide investor-side evidence of the persistence of round-number heuristic usage in order submission, which also supports the relevance requirement.

Second, the exogeneity of instrumental variables requires *Avg_LoanRound* and *Avg_LoanLucky* to have no independent effects on the funding outcomes and repayment performance. Lenders make investment decisions based on the loan and borrower characteristics, and borrowers' repayment outcomes are determined by the loan contract terms and their own attributes. It is reasonable to assume that the prior use of heuristics by other similar borrowers does not have any direct effects on the funding and repayment of a specific borrower. Besides, our instrumental variables are independent from other potential omitted variables. The loan description text, borrower confidence, or whether a borrower is busy when making a loan application are unlikely to be correlated with prior heuristic usage of other borrowers in the same group, which allows clear identification of the effect of heuristics usage.

Table 5 reports the instrumental variable regression results. The first and last three specifications examine funding success and repayment performance, respectively. Specifications (1), (2), (4), and (5) report the first-stage regression outcomes. *Avg_LoanRound* and *Avg_LoanLucky* have significant and positive coefficients when the dependent variables are *LoanRound* and *LoanLucky*, respectively, consistent with our expectations. More formally, the first-stage regression F-values are greater than 10, and the second-stage Cragg–Donald statistics are much larger than the Stock and Yogo (2005) threshold, thus proving the correlation between our instrumental variables and the key explanatory variables. The second stage regression results in specifications (3) and (6) confirm our baseline findings that the use of the round-number-heuristic lowers the funding success rate and increases the delinquency rate, whereas the lucky-number-heuristic has the opposite effects.

5.2. Alternative Specifications and Measures

We conduct a series of additional tests to confirm the robustness of our findings. We first use Cox duration analysis to examine the loan performance, in addition to our OLS and probit analyses presented earlier. A loan is exposed to delinquency risk after origination and survives until one of the following three events occur: (1) the end of the sample period (i.e., censored), (2) late payment (i.e., delinquent), and (3) the end of loan maturity (i.e., paid off). For each funded loan, we define failure as late or no payment in a given month and use the monthly repayment records until one of the above three events occurs. The first three specifications of Table 6 present the standard Cox duration analysis outcomes. In our sample, a loan could have multiple late payment records. In the last three specifications, we follow Hu et al. (2019) and use the variance-corrected multiple failure Cox proportional hazard,

Table 5. Instrumental Variable Regressions

	(1)	(2)	(3)	(4)	(5)	(6)
	Funding outcomes			Repayment performance		
Dependent variable	1st Stage *LoanRound*	1st Stage *LoanLucky*	2nd Stage *Funding Success*	1st Stage *LoanRound*	1st Stage *LoanLucky*	2nd Stage *Delinquent*
LoanRound			−0.0683***			0.0279^
			(0.0191)			(0.0143)
LoanLucky			0.1221**			−0.0645*
			(0.0435)			(0.0302)
Avg_LoanRound	0.6686***	−0.0629**		0.6050***	−0.0289	
	(0.0563)	(0.0216)		(0.0650)	(0.0284)	
Avg_LoanLucky	−0.0254	0.4083***		0.0350	0.3593***	
	(0.0289)	(0.0540)		(0.0283)	(0.0503)	
Borrower characteristics		YES			YES	
Loan characteristics		YES			YES	
Year Qtr FE		YES			YES	
Borrower province FE		YES			YES	
Clustered SE		Year Qtr			Year Qtr	
Observations		605,854			159,428	
F-statistic (1st stage)	72.38	48.77		43.34	33.85	
Cragg–Donald F-statistic			2,376.710			672.475
10% Maximal IV size			19.93			7.03

Notes. Clustered standard errors in parentheses. FE, fixed effects; Qtr, quarter; SE, standard errors.
^$p < 0.1$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

Table 6. Cox Proportional Hazard Regressions

Dependent variable: *Delinquency Hazard*	(1)	(2)	(3)	(4)	(5)	(6)
	Single failure Cox			Multiple failure Cox		
LoanRound	0.0961***		0.0924***	0.04961*		0.0473*
	(0.0272)		(0.0267)	(0.0216)		(0.0205)
LoanLucky		−0.0630***	−0.0605***		−0.0331***	−0.0315**
		(0.0145)	(0.0141)		(0.0097)	(0.0099)
Borrower characteristics	YES	YES	YES	YES	YES	YES
Loan characteristics	YES	YES	YES	YES	YES	YES
Year Qtr FE	YES	YES	YES	YES	YES	YES
Borrower province FE	YES	YES	YES	YES	YES	YES
Clustered SE	Loan	Loan	Loan	Loan	Loan	Loan
Observations	5,550,674	5,550,674	5,550,674	5,731,701	5,731,701	5,731,701
No. of listings	217,237	217,237	217,237	217,231	217,231	217,231
No. of failures	52,852	52,852	52,852	393,674	393,674	393,674
Pseudo R^2	0.0789	0.0789	0.0789	0.0743	0.0743	0.0743

Notes. Clustered standard errors in parentheses. FE, fixed effects; Qtr, quarter; SE, standard errors.
$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

which allows multiple delinquencies within a loan. In both of the alternative specifications, we find consistent results that the round-number heuristic leads to more delinquencies, whereas the lucky-number heuristic reduces delinquencies.

We use alternative measures of round and lucky numbers. *LoanRound_Score* is defined as the number of consecutive zeros from the rightmost digit divided by the total number of digits; and *LoanLucky_Score* is defined as the number of eights divided by the total number of digits. Internet Appendix 6 estimates the baseline models in Tables 2 and 3 using the above two continuous measures. We find that the results are consistent with our main findings that the round-number heuristic is associated with lower funding success rates and inferior repayment performance, whereas the effects are the opposite for the lucky-number heuristic.

We also analyze the funding outcomes using the funding time as an alternative dimension. Sophisticated lenders perceive round loan amounts as a sign of a trade-off between accuracy and convenience and are less likely to invest in them. Superstitious lenders favor lucky-amount loans and are more likely to invest in them. Apart from the funding success rate, a direct implication of these preferences is that round-amount loans take longer to be fully funded and lucky-amount loans need less funding time. The funding time is only observable among funded loans, and thus we use the Heckman regression and model the selection process using the regression models in Table 2. Internet Appendix 7 reports the second-stage regression results, where the dependent variables are the loan funding time in hours (*BidTime (hour)*) and the logarithm of funding time (*LogBidTime (hour)*) in different specifications. We find that the loans in round amounts take longer to get funded, whereas lucky-number loans require shorter funding time.

To control for the nonlinear effects of some borrower and loan variables, such as job length, borrower age, loan interest rate, and loan duration, we include the quadratic terms to control for their higher order effects and report the results in Internet Appendix 8. The control variable *NPriorLoan_Applied* is highly right skewed. In Internet Appendix 9, we replace it with the logarithm of one plus the number of prior loans applied. In Internet Appendix 10, we also remove the ongoing loans from the original 611,079 loans to examine funding success. The key findings remain unchanged in all of the above settings.

6. Discussion

6.1. Borrower Learning

Given the opposite effects of the round-number and lucky-number heuristics on funding success, a natural question is whether borrowers improve their use of heuristics based on their borrowing experience. We examine the within-borrower changes of heuristic use over time using the 611,079 loan applications from repeated borrowers. The dependent variables in Internet Appendix 11 are *LoanRound* and *LoanLucky*, and our focal variable is *NpriorLoan_Applied*, which is the number of prior loans applied for by each borrower. Apart from year-quarter fixed effects, we also include borrower fixed effects to control for borrower characteristics.

NpriorLoan_Applied is significantly negative when the dependent variable is *LoanRound* and positive when the dependent variable is *LoanLucky*. The results suggest that borrowers learn from their borrowing experience and switch to the lucky-number heuristic as they become more experienced. However, the learning speed is very slow. One more prior loan application decreases the odds that a borrower uses a round loan amount by 0.80% (= $\exp(-0.0080) - 1$) and increases the odds that a borrower uses a lucky loan amount by 0.23% (= exp (0.0023) − 1), respectively.

6.2. Implications

We discuss the implications of our findings for lenders, platform operators, and more broadly, for market participants beyond the setting of P2P lending. P2P lenders could benefit from our findings by using the information on borrowers' heuristic use more efficiently. In particular, P2P lenders can improve their investment returns by lending less to round-amount borrowers, who are likely to be mentally overloaded and allocate fewer cognitive resources to financial planning and budgeting. Similarly, they can boost their investment performance by providing more lucky amount loans, which are likely to be for more sophisticated borrowers.

Platform operators and designers can use the heuristics usage information to improve the underwriting and screening of borrowers and loans and also enhance the accuracy of their credit ratings. To illustrate this in relation to credit quality prediction, we train two machine learning classification models, one with heuristic usage information and the other without, and then compare their performance in loan delinquency prediction. We first randomly sort all funded loans and use two-thirds of the sample (109,312 loans) as the training set and the remaining one-third (53,840 loans) as the test set. We fit a fully fledged model as in Table 3 and a simplified model that removes *LoanRound* and *LoanLucky* using the training set, and then evaluate their performance on the test set loans using *precision* (which measures the classification accuracy among predicted delinquencies, calculated as true positive divided by the sum of true positive and false positive) and *recall* (which measures the percentage of delinquent loans a model identifies, calculated as true positive divided by the sum of true positive and false negative).

The *precision* increases from 61.07% to 61.90%, thus indicating the heuristic information improves the model's accuracy in delinquency prediction. The *recall* of the simplified model is 21.87%, which increases by more than 1.03 percentage points to 22.90% after the inclusion of heuristic usage, suggesting that the inclusion of heuristic information allows the model to identify more delinquencies. This model improvement is economically significant and meaningful. Given the aggregated delinquency amount is RMB 164.1 million in our sample, the 1.03 percentage points increase in *recall* allows the platform to identify RMB1.69 million more delinquent loans.

Beyond the setting of P2P lending, market participants can also extract valuable information from counterparties' use of certain numbers. Backus et al. (2019) show that sellers on eBay can effectively communicate with buyers by offering round number prices. Buyers interpret the sellers' type from their use of round numbers, and sellers use round numbers to improve the probability of sales at the cost of a lower transaction price. The key difference between e-commerce in Backus et al. (2019) and our P2P lending setting is that prices are negotiable on the eBay platform, and a seller needs to take both the sale price and the deal likelihood into consideration. Moreover, sellers strategically use round numbers to signal their weak position in bargaining and to attract more buyers and improve the deal likelihood. However, P2P lending has no bargaining process, as prices (i.e., interest rates) are predetermined and fixed throughout the funding process. This setup rules out the trade-off between the transaction price and deal likelihood. Instead, borrowers use round numbers for convenience. Despite the different implications, in both settings, market participants obtain information about their counterparties from their use of numerological heuristics.

7. Conclusion

Heuristics play an important role in decision making. The literature generally treats all heuristics as behavioral biases. We conceptualize the round-number heuristic that reduces the cognitive burden of decision makers as a *cognition-conserving heuristic* and the lucky-number heuristic that improves decision outcomes by catering to the counterparty's preferences as a *catering-heuristic.* We hypothesize that individuals use different heuristics to achieve different purposes, thus resulting in the different heuristics having differential effects on the decision outcomes.

Using detailed data on the lending activities and loan repayments on a P2P lending platform, we show that when used to set the loan amount, the round-number and lucky-number heuristics have opposite effects on funding success and loan performance. On average, the use of round numbers in loan amounts reduces the funding success rate and increases the delinquency rate, whereas the use of lucky numbers in loan amounts improves the funding success rate and reduces the likelihood of delinquency. The results are robust to various identification methods, such as matched sample analysis, instrumental variable regressions, and the use of alternative measures and model specifications.

Overall, we show that borrowers use different heuristics depending on their reasons and motives. Our findings thus challenge the conventional wisdom by which all heuristics are treated as behavioral biases. Our analyses provide rich information on credit quality and loan performance, which is valuable for market participants, such as investors and platform operators. Lenders on marketplace platforms, such as P2P lending, can use our findings to make better loan choices and improve their investment returns. P2P platforms can also benefit from our findings by incorporating information on users' choice of heuristics in their credit rating and delinquency prediction algorithms. Furthermore, our findings are generalizable to other settings and can be applied to similar frameworks, such as e-commerce and crowdfunding.

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Endnotes

[1] The implied assumptions of our hypotheses are that (1) some lenders can correctly understand borrowers' use of the round-number heuristic as a trade-off between convenience and accuracy, and (2) some lenders have superstitious beliefs and favor loans with lucky-number amounts. We do not require *all* lenders to meet these two conditions at the same time. Hypothesis A1 and Hypothesis A2 hold true as long as *some* of the lenders can correctly interpret borrowers' usage of the round-number heuristic. In addition, we only need *some* of the lenders to be superstitious for Hypothesis B1 and Hypothesis B2 to be true. These two assumptions do not contradict each other.

[2] As 1,999 loans do not have repayment data, the sample of loans decreases from 219,236 to 217,237 for the robustness test.

[3] The univariate test results only reflect the unconditional differences, which also capture the influence of other factors than the use of the round-number heuristic. Therefore, the 73.79 percentage points gap in funding success rates should not be solely attributed to the influence of heuristic use. We eliminate the impact of borrowers' credit quality by regressing the funding success rate against borrowers' credit grades and extract the residual. The differences diminish to 4.40 percentage points but remain significant at the 0.001 level. Similarly, the gaps in the funding time and delinquency rates are also unconditional differences.

[4] The univariate test results only reflect the unconditional differences, which also capture the influence of other factors than the use of the lucky-number heuristic. Therefore, the 42.12 percentage point gap in the funding success rate should not be solely attributed to the influence of heuristic use. We eliminate the impact of borrowers' credit quality by regressing the funding success rate against borrowers' credit grades and extract the residual. The differences diminish to 2.75 percentage points but remain significant at the 0.001 level. Similarly, the gaps in funding time and delinquency rates are also unconditional differences.

[5] The delinquency rate in our sample is comparable to that in the studies of Hasan et al. (2021) and Li et al. (2020), which use similar data. Summary statistics of the funded loans are not reported but are available upon request.

[6] Internet Appendix 4 panel B presents the distribution of nonzero numbers in loan amounts by digit. We observe an underrepresentation of the unlucky number four in the thousands and 10-thousands digits, and an overrepresentation of the lucky number eight in the hundreds and 10-thousands digits.

[7] Duarte et al. (2012) and Lin et al. (2013) provide evidence on the impact of borrowers' appearance and friendship on funding and repayment performance in P2P lending. The P2P lending platform in our study does not allow borrowers to upload their profile pictures, neither does it have a friendship system. Thus, these two factors should not influence our identification.

[8] The process of separating borrowers into groups by their characteristics is similar to CEM. However, we construct instrumental variables based on the prior choice of heuristics by a group of borrowers, which requires a larger number of borrowers within each group. Instead of using all borrower features and having 151,850 groups as in CEM, we only use the credit grades, education levels, income levels, work experience levels, asset ownership levels, car and mortgage loan levels, and provinces, which provides 14,336 possible groups. However, some of the combinations include no borrowers. For example, borrowers with low education, income, and work experience and located in economically less developed regions should not have the highest credit rating. The total number of groups with at least one borrower is 5,233.

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