

Cost Misperception: The Impact of Misunderstanding Credit Card Debt Expenses*

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Abstract

This paper investigates consumer misperceptions of credit card debt interest costs using administrative data, surveys, and randomized controlled trials. Our findings indicate that borrowers exhibit inaccurate perceptions of the interest costs of unsecured debt, resulting in substantial debt accumulation. A one percentage point lower perceived interest rate leads to 5% higher credit card debt relative to the pre-treatment average. These misperceptions are likely to stem from mistakes driven by financial literacy, particularly in luxury spending decisions, rather than imperfect knowledge of current debt levels or liquidity constraints.

JEL Codes: E21, G40, G51, G53, M37.

Keywords: Household Debt, Beliefs, RCT, Survey.

I Introduction

Credit cards and similar financial products are essential tools for households to acquire debt. Across many economies, at least one-third of borrowers carry positive credit card debt.¹ Understanding borrower incentives in credit card markets is crucial for analyzing household debt-taking behaviors.

A notable characteristic of the credit card market is that borrowers are often unaware of the true marginal costs of their debt. A recent survey by BankRate (2022) found that over 40% of U.S. credit card debtors may not know the interest rates even on their primary credit cards.² Therefore, it is crucial to evaluate how accurately borrowers are informed about the interest-related costs associated with their credit cards and, if present, how perception errors regarding true interest costs influence borrowing decisions.

This paper examines whether borrowers possess imperfect knowledge of the interest-related costs of credit card debt, specifically the total interest incurred when carrying a given balance into the next billing cycle. Studying this relationship is inherently challenging, as it requires simultaneous observations of both the true interest rate and borrowers' perceptions of their current credit card interest rates. To address this challenge, we collaborated with a major commercial bank in China to elicit consumer perceptions regarding the marginal cost of credit card debt using surveys. We refer to these perceptions as *perceived interest rates* and define the corresponding perception errors as *interest rate misperceptions* for brevity.

¹See Gross and Souleles (2002), Zinman (2009), Fulford (2015) for examples in the U.S., Vihriälä (2022) for Finland, Gathergood and Olafsson (2024) for Iceland, Terrell (2023), and Yin (2022) for China.

²One leading possibility is the often complex features of credit cards. Figure B1 in the Online Appendix shows several advertisements for credit card products across different countries. The annual percentage rates (APR) are ambiguously presented in small font despite prominently highlighting benefits.

Analyzing these perceived rates directly, we find that borrowers exhibit substantial variation in perceptions of the interest rates associated with credit card borrowing, even though interest charges are explicitly presented on periodic statements. Despite an average effective annual interest rate of around 20%, survey responses indicate a wide range of perceived interest rates, spanning from 5% to 35%, with an interquartile range of 9% to 20%.

We integrate the beliefs with credit registry data and consumer transaction history to examine the effects of interest rate misperception on unsecured borrowing. To estimate the causal effect of interest rate misperceptions on consumer behavior, we implemented a randomized controlled trial (RCT) that provided true information about the interest costs of credit cards to a randomly selected group of debtors. The straightforward information treatment yielded a substantial instantaneous average treatment effect (ATE) of 5.22 percentage points on perceived interest rates. Furthermore, the treatment significantly reduced the magnitude of perception errors, resulting in a 3.38 percentage points ATE on the absolute value of these errors.

Next, we study how misperceptions of credit card interest rates affect borrowers' debt-taking behavior. While having noisy perceptions of the interest cost is inconsistent with borrowers possessing full information, these imperfect perceptions might also be survey reporting errors rather than genuine informational gaps. Moreover, the perception errors in interest costs might have trivial real effects if most borrowers have only limited debt needs, providing little incentive to correct biases. To investigate whether interest rate misperceptions have actual effects on borrowing, we utilize the experiment to estimate consumer responses in total unsecured debt to an exogenous change in perceived interest rates.

We find a substantial debt response to revisions in perceived interest rates. In total, unse-

cured debt for the treatment group decreased by approximately US\$491.54 three months after the experiment compared to the control group. This corresponds to a decrease in borrowing by \$113.24 (5% of current debt value) for each percentage point increase in the perceived interest rate. Given an average interest rate misperception of -4.39 percentage points, our estimates suggest that misperceptions contribute to an excess borrowing of approximately \$497.12 on average. Since our measure of debt is obtained from the credit registry, this estimate is not confounded by intra- or inter-bank fund transfers across different debt accounts.

The large short-term reduction in debt suggests that a significant portion of borrowing due to interest rate misperceptions is not driven by constrained consumption decisions. To further explore the mechanisms behind these misperceptions and their influence on borrowing, we examine the heterogeneity of treatment effects across various dimensions. Our findings indicate that both the misperceptions and the corrective impact on borrowing behavior are primarily driven by financial literacy, rather than liquidity constraints or inattention to existing debt levels.

To understand the implications of potential policy interventions for households' holistic financial behavior, we continue to explore how borrowers react after learning interest rate misperceptions. Two possibilities exist: 1) consumption remains unchanged, with borrowers shifting from debt-financed spending to liquidity-financed spending, or 2) borrowers reduce spending, leading to lower borrowing. Leveraging our granular measure of spending and savings, we test these hypotheses and find results consistent with the latter. In particular, borrowers reduced spending in the three months following the treatment, primarily by cutting back on luxury purchases. At the same time, we observe evidence that borrowers opt for illiquid assets (e.g., certificates of deposit) over liquid assets after learning about their interest

rate misperceptions. These patterns suggest that suboptimal borrowing linked to interest rate misperceptions reflects a behavioral mistake, primarily overspending on luxuries, rather than a rational response to liquidity constraints or intertemporal smoothing.

Given that our experiment represents a one-time shock, we extended our study to examine the long-run effects of the information treatment on interest rate perception and borrowing. We surveyed borrowers about their perceived interest rates nine months after the treatment and tracked their debt trajectories accordingly. Our findings reveal memory decay of credit card interest rates: the intent-to-treat (ITT) effect of the information treatment on perceived interest rates depreciated by 41% after nine months. Meanwhile, borrowers' deleveraging choices also partially reversed: debt began to increase again four months post-treatment. Therefore, the effects of a one-time shock to the true interest costs on perception biases appear transitory.

In principle, borrowers would gradually learn the true interest rate over time, even if their initial belief about it is highly noisy and imprecise. However, we observe only a modest correlation between years of experience in the credit market and corrected interest rate misperceptions. Together with the finding that one-time information treatment only has transitory effects, these results suggest that full correction of misperceptions is likely inhibited by limited attention to credit card contracting details and memory decay. Using a simple calibrated model, we demonstrate that this persistent pattern of interest rate misperception can be generated by a mechanism where inattentive borrowers quickly forget information about interest rates. As a result, cumulative attention over time would not suffice for borrowers to correct their interest rate misperceptions.

Our design relies on surveys to elicit consumer perceptions of interest rates and to provide

information treatment. While surveys help find the channels driving misperceptions, they can be a costly tool to address such common misperceptions. In a similar approach to Bursztyn et al. (2019) and Grubb et al. (2024), we explore a more scalable policy intervention by conveying the same information through text messages to a different group of debtors without using surveys. Our results show that text messages disclosing the true interest costs, similar to the information provided in surveys, resulted in a 12% reduction in credit card debt three months post-treatment. Although changes in perception errors could not be directly measured, these findings indicate that text alerts can similarly mitigate excess borrowing driven by interest rate misperceptions.

Related Literature This paper mainly contributes to two strands of literature. First, it contributes to the literature on how behavioral biases influence consumer credit decisions (Stango and Zinman, 2009; Meier and Sprenger, 2010; Bertrand and Morse, 2011; Bursztyn et al., 2019; Allcott et al., 2022; Kuchler and Pagel, 2021; Laibson et al., 2024, etc.). Closely related studies include Agarwal et al. (2015), Ferman (2016), Seira et al. (2017), and Levi (2021), which examine the impact of information disclosures on borrowers' awareness of credit card terms and financial choices. Our contribution to this literature is twofold. First, we are the first to quantitatively link biases in consumers' perceived marginal cost of credit card debt to actual borrowing behavior in the credit card market. Second, through an RCT that exogenously varies perceived interest rates, we show that consumers' misunderstanding of the interest rate itself, not merely how interest rate compounds, leads to substantial borrowing, extending prior findings on exponential growth bias (Stango and Zinman, 2009; Bertrand and Morse, 2011). By directly identifying how misperceptions influence not only

borrowing but also consumption and savings behavior, our findings shed new light on the underlying mechanisms of consumer debt decisions and help inform the design of policy interventions aimed at addressing these misperceptions.

In addition, this paper contributes to a growing literature that examines the role of beliefs in household financial decision-making (see DellaVigna, 2009, for a review). Previous studies such as Manski (2004), Ameriks et al. (2020), Giglio et al. (2021), and Gorodnichenko and Yin (2024) examine the link between investor beliefs and stock market participation, while Bucks and Pence (2008), Bailey et al. (2019), and Kuchler et al. (2023) analyzed how beliefs influence mortgage leverage choices. Besides, Farhi and Gabaix (2020) and Rees-Jones and Taubinsky (2020) investigated the implications of tax misperceptions for consumption and welfare. We extend this body of work by employing multiple rounds of surveys designed to elicit beliefs, matched with detailed transaction-level data on consumer borrowing behavior. This approach allows us to directly observe how beliefs evolve and subsequently shape consumer financial decisions.

Roadmap The remainder of the paper proceeds as follows. Section II outlines the sample and survey design. Section III details the interest rate misperceptions and a descriptive analysis of their interaction with borrowing behavior. Section IV elaborates on the use of a randomized controlled trial to evaluate the effect of interest rate misperceptions on behavior, with the main results shown in Section V. Section VI proposes a scalable policy using text alerts to mitigate interest rate misperceptions. Finally, Section VII concludes.

II Institutional Background and Data

A Background

In China, daily transactions are predominantly conducted through mobile payment platforms such as Alipay or WeChat Pay. These payment methods require users to link their accounts with bank cards or credit cards, similar to PayPal or Apple Pay in the U.S. The credit cards under consideration in this study resemble those used in other countries. Typically, each credit card is assigned a credit limit, enabling borrowers to accumulate balances up to this limit each month and utilize the card as a payment method.

Borrowers receive varying levels of discounts and cashback for specific types of purchases. At the end of each billing cycle, a minimum repayment is required, which is 10% of the current outstanding balance. Beyond this minimum, borrowers can choose to repay any portion of their total balance. Paying the entire balance within the billing cycle allows borrowers to avoid interest charges while benefiting from cashback rewards and discounts on transactions. Unpaid balances are carried over to the subsequent billing cycle and accrue daily interest at a rate of around 0.05%. The bank provides a one-month grace period for late payments following the statement due dates. During this period, if the minimum payment is not made, no late penalty is applied. However, interest on the unpaid balance begins to accrue immediately after the due date. A late fee is incurred if the 10% minimum required payments are not made after the first interest-incurring month.

Similar to many other countries, such as the U.S. and the U.K., credit card interest rates in China are advertised using the Annual Percentage Rate (APR), calculated based on

linear compounding with a 30-day horizon per month and 12 months in a year. However, the actual interest costs are determined by the Effective Annual Rate (EAR), which accounts for exponential compounding. For example, if a consumer carries over \$1 of debt on a credit card with a daily interest rate of 0.05%, the APR is calculated as $0.05\% \times (30 \times 12) = 18.25\%$. However, due to daily compounding, the actual annual interest cost is higher, approximately $1.0005^{365} - 1 \approx 20.16\%$.

Following regulations established by the People’s Bank of China, the bank provides key terms, including interest rates and fees, during the application process to inform the borrowers about the cost structure of credit. Similar to those disclosure requirements mandated by the U.S. Credit Card Accountability Responsibility and Disclosure (CARD) Act of 2009, periodic account statements, which detail interest charges and outstanding balances, are delivered to consumers via SMS reminders and can also be accessed through mobile banking apps and online platforms.

Credit card usage in China has grown significantly since 2016. Over the period from 2016 to 2022, the total outstanding balance on credit cards surged from \$500 billion to \$1 trillion. Meanwhile, the aggregate credit limits rose from \$1.2 trillion to \$3 trillion. As of the first quarter of 2024, approximately 759 million credit cards were issued in China (Statista, 2024), translating to an average of 0.54 credit cards per person, given China’s population of around 1.4 billion. Credit cards, along with other forms of personal credit offered by commercial banks, remain the primary means of obtaining consumption-based unsecured debt. Although FinTech platforms and consumer lending companies, such as Alibaba’s Huabei, have introduced similar products, their market share remains relatively modest. As of 2023, these companies collectively accounted for approximately 20% of all

consumption-based credit debt (UnionPay, 2020).

Before 2021, the People’s Bank of China regulated credit card interest rates, setting daily rates between 0.035% and 0.05%, corresponding to APR between 12.78% and 18.25%, or EAR of approximately 13.62% to 20.16%. While these regulations were lifted in January 2021, the policy change had minimal impact on the interest rates set by most national banks.

***B* Data and Survey Design**

Our data comes from a top 10 national commercial bank in China (hereafter referred to as “the bank”) ranked by total assets. As of 2023, the bank reported assets exceeding \$1 trillion, serving over 50 million active customers and managing 80 million active credit cards. This extensive customer base ensures that the sample adequately represents the diverse demographic distribution of borrowers across China.

In this paper, debt is defined as the total unpaid balances at the end of the interest-free billing cycle. Debt information is sourced from the Credit Reference Center (CRS) of the People’s Bank of China, the country’s official credit registry, based on credit reports retrieved by the bank. The CRS consolidates personal credit data from all financial institutions, providing detailed monthly records on credit accounts, including term loans, credit cards, and other personal credit lines, as well as bank names, outstanding balances and limits, recent credit utilization, repayment history, total amount payable at the end of the billing cycle, and unpaid balances. It also includes housing funds and social security contributions. Due to its comprehensive coverage, this dataset offers a complete view of consumers’ borrowing behavior.

We partnered with the bank to administer surveys to a randomly selected sample of

customers. Given the focus of our study, we limited the eligibility of respondents to those borrowers who had incurred positive debt within the 12 months before the study. Additionally, since borrowers can have varying interest rates across their credit cards, we further restricted the sample to include only borrowers with the same interest rate across all their credit cards. Among these debt takers, 57% had only one credit card, while 22% had multiple credit cards but with the same interest rates across all accounts. To further ensure a consistent measure of the interest rates, we excluded borrowers who were on promotional rates, which accounted for approximately an additional 7% reduction in the sample size.

From this eligible pool, we randomly sent two waves of surveys to 2,000 borrowers. The first wave was conducted in November 2020, followed by a second wave in August 2021 sent to those who had completed the first wave.³ The survey was distributed via a mobile application, with links sent through text messages.⁴ To incentivize participation, each respondent received a gift valued at approximately \$2 upon completing the first survey and around \$4 for the second. Given that the surveys required in general less than five minutes to complete, these rewards translated to an effective hourly rate exceeding the 85th income percentile for all urban residents for the first wave and 99th for the second, resulting in high participation rates: 83% of invited customers completed the first wave, and 73% of those completed the second. Ultimately, 1,219 respondents completed both waves, forming the final sample for our analysis.

Despite a high retention rate, concerns arise regarding potential selection bias due to the imperfect survey response rate. As shown in Figure B2 in the Online Appendix, survey re-

³In China, the COVID-19 lockdowns became much less frequent, and most borrowers resumed normal daily activities after June 2020.

⁴See Online Appendix A for the English translation of the survey.

spondents tend to be marginally younger and have lower incomes. However, the histograms of characteristics reveal substantial overlap between respondents and non-respondents, suggesting that survey participation selection is unlikely to be an important issue.

C Eliciting Perceived Interest Costs

In this paper, we focus on the EAR of credit card debt and use surveys to elicit borrowers' corresponding perceptions. Eliciting the perceived average interest costs across multiple credit cards is difficult, as borrowers' mental allocation of debt across different accounts may shape their perceptions. Therefore, when eliciting perceived interest rates, we specifically focus on the credit card with the highest accumulated debt for each borrower.

Borrowers' understanding of percentage values is known to be influenced by framing effects, numerical calculation abilities, and reliance on heuristics. To address these potential biases, instead of asking participants to report an interest rate number, we directly elicited their perceived interest costs for borrowing a specified amount on a credit card, assuming only partial repayment before the expiration of the interest-free period. Specifically, for each participant, we asked the following three questions.

For the following questions, please consider your credit card with the *[bank name]*.

Suppose your billing cycle is at the end of the month. For each of the following scenarios. Please select the closest amount of interest that would be incurred at the end of next month.

- a. You spend 5,000 this month and repay 3,000 at the end of this month.

0
10
20
30
40
50

60

b. You spend 5,000 this month and repay 1,000 at the end of this month.

30

40

50

60

70

80

90

c. You spend 5,000 this month and repay 0 at the end of this month.

45

55

65

75

85

95

105

For a given borrower, *[bank name]* refers to the bank where they have accumulated the highest credit card debt. Borrowers' beliefs about monthly credit card interest rates are calculated using the following formula:

$$\text{Perceived } r = \frac{1}{3} \left(\frac{x_1}{2000} + \frac{x_2}{4000} + \frac{x_3}{5000} \right), \quad (1)$$

where *Perceived r* denotes perceived interest rates, and x_1 , x_2 , and x_3 represent the choices for three different debt amounts. After converting to effective annualized rates, the misperception of credit card interest rates is then defined as $\text{Bias}_i = \text{Perceived } r_i - r_i$. If $\text{Bias}_i < 0$, it indicates that the perceived interest cost of credit card borrowing is lower than the actual value.⁵

Our measure captures the perceived marginal cost of carrying debt to the next billing cycle rather than directly eliciting the APR or EAR figures. It reflects borrowers' subjective

⁵We validate our findings by separately using each of x_1 , x_2 , and x_3 to calculate the perceived rate. Table C3 in the Online Appendix shows that the results remain consistent with the main findings.

expectations of interest charges on a hypothetical unpaid balance. While borrowers may be aware of daily interest rates (e.g., 5 basis points per day), they often misestimate actual borrowing costs due to limited financial literacy or challenges in compounding calculations. Thus, our approach effectively captures realistic, decision-relevant misperceptions of debt costs.

After collecting the survey data, we integrated the responses with consumer bank account data spanning from January 2019 to August 2021. Consequently, we have access to approximately two years of monthly data preceding the survey and an additional nine months afterward.

One concern with discrete multiple-choice formats is that none of the available options precisely match the true incurred interest amount, but only closely approximate it. For example, in question c, the correct value is 75.5, whereas the closest answer choice is 75. However, these discrepancies are quantitatively small and thus unlikely to introduce significant measurement errors. In our subsequent analysis using the RCT, both the control and treatment groups answered the same set of questions within our experimental design. As a result, any potential measurement error in perception elicitation should be addressed through the instrumental variable approach we employed (e.g., Gillen et al., 2019), since these errors are orthogonal to the randomization of the information treatment.

III Descriptive Analyses on Interest Rate Misperceptions

A Summary Statistics

Before proceeding to the main analysis, we present some stylized facts relying on the pre-experiment data. Table 1 shows the summary statistics. All currency units in this paper are converted to US dollars (1 USD = 7.1 CNY) hereafter for comparability. A consumer's highest degree is coded as a categorical variable: 1 for high school and below, 2 for some college, 3 for a bachelor's degree, and 4 for graduate school. Our measure of debt refers to the unpaid balance on credit cards that incurs interest. On average, the debt level is close to monthly income, but the interquartile range is notably wider. Despite accruing high-interest credit card debt, most borrowers also maintain positive savings. This phenomenon aligns with the co-holding puzzle, where individuals simultaneously hold low-interest savings and high-interest credit card debt (Gross and Souleles, 2002; Telyukova, 2013; Gorbachev and Luengo-Prado, 2019; Gathergood and Olafsson, 2024). Approximately 56% of the borrowers in our sample are female, and overall, the sample exhibits a high level of financial literacy, with most participants having completed college or attained advanced degrees.

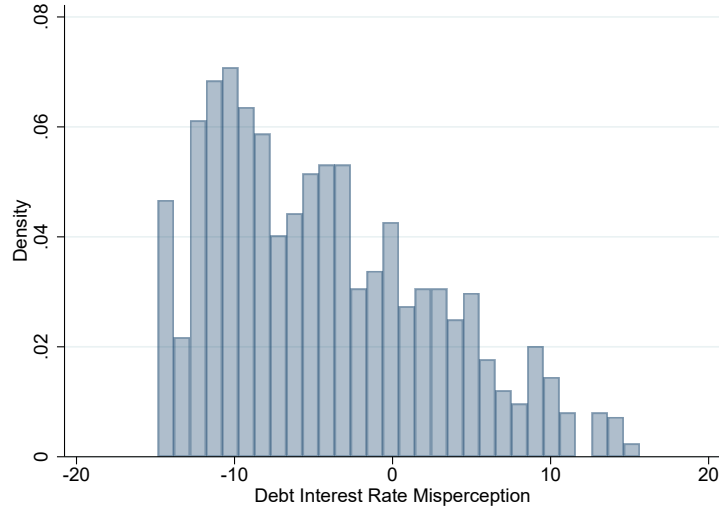
Relative to the true mean EAR of around 19.49%, borrowers tend to underestimate the interest rates associated with their credit card debt, with the mean perceived rate standing at 15.15%. The heterogeneous nature of perceived interest rates is depicted in Figure 1, which shows the distribution of perception errors. The majority of these errors fall within a range of approximately -15 to 15 percentage points. Furthermore, the distribution is right-skewed, indicating that more borrowers underestimate interest rates than overestimate them.

Table 1. Summary Statistics

	All									
	Wave with Surveys					Wave with Text Alerts				
	Control		Treatment			Control		Treatment		
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	
Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	
Debt	2584.79	3080.38	2417.70	3013.69	2219.73	2844.47	3198.70	2688.11	2991.80	
<i>Perceived r</i>	15.15	6.93	15.14	6.99	15.17	6.86	-	-	-	
Interest Rate	19.49	1.14	19.53	1.13	19.49	1.11	1.16	19.42	1.13	
Spending	1150.29	754.25	1538.49	1070.38	1540.13	973.64	628.49	1116.03	640.24	
Perceived Spending	912.06	582.30	907.60	596.51	917.65	564.51	-	-	-	
Necessities Spending	482.82	509.48	624.87	593.72	676.77	593.59	460.92	469.68	498.64	
Luxuries Spending	475.21	645.23	547.25	917.51	517.74	817.08	561.08	487.13	619.55	
Other Spending	193.59	324.57	366.36	525.07	345.62	486.02	234.22	159.88	258.43	
Credit Limit	10560.30	6494.90	10075.93	5687.62	10180.94	6901.14	5580.08	11161.40	7606.60	
Credit Score	55.17	7.79	55.04	7.76	54.80	7.71	7.74	55.16	7.88	
Income	2359.33	1411.96	2324.77	1422.84	2371.24	1378.58	1354.28	2497.02	1478.74	
Assets	7951.53	14742.60	25998.72	25468.46	27213.04	25277.92	20454.97	25729.73	21251.51	
Liquid Assets	17063.67	16060.42	19066.15	19581.12	19605.84	18964.47	14570.68	17686.45	15730.26	
Illiquid Assets	7661.82	7931.71	6932.57	7535.63	7607.20	7905.73	7853.52	8043.28	8142.92	
Age	38.52	11.03	38.39	11.29	37.97	10.09	11.69	38.35	10.26	
Female	0.56	0.50	0.59	0.49	0.55	0.50	0.49	0.52	0.50	
Education	1.76	0.85	1.82	0.87	1.72	0.84	0.89	1.71	0.80	
Experience	3.11	1.30	3.08	1.31	3.14	1.29	-	-	-	
Observations	6219		678		541		2835		2165	

Note: This table provides the summary statistics of our sample, with all variables measured on a monthly basis. Wave with Surveys indicates the initial experimental period, i.e., November 2020, with both perceived interest rate elicitation surveys and text alerts. Wave with Text Alerts indicates the follow-up experimental period, i.e., June 2024, with only text alerts. Monetary values are expressed in US dollars. *Perceived r* represents the perceived interest rate obtained from our survey. Liquid assets are demand deposits, such as balances in checking, savings, and financial investment accounts, while illiquid assets consist of certificates of deposit maturing in three months or more. Luxury goods (necessities) are characterized as those brands whose average consumption share increases (decreases) with income growth. Education levels are coded as follows: 1 for high school and below, 2 for some college, 3 for a bachelor's degree, and 4 for graduate school. Experience represents the years a consumer has been active in the credit card market.

Figure 1. Debt Interest Rates Misperception



Note: This figure illustrates the distribution of debt interest rate misperception among survey respondents. Debt interest rate misperception is computed as the perceived interest rate minus the true interest rate, expressed in percentage points.

Interestingly, despite receiving periodic account statements that include interest charges, borrowers still exhibit substantial misperceptions. This suggests limited attention to or ineffective processing of available credit cost information.

It is important to note that, since our analysis focuses exclusively on individuals with positive debt, the findings do not suggest that all credit card holders underestimate credit card interest rates on average. It remains possible that the broader population has more accurate perceptions, while those who underestimate interest rates are more likely to accumulate debt.

B Static Patterns

We begin by examining how interest rate misperception covaries with other factors using binned scatter plots depicted in Figure 2. Regarding demographics, younger and male borrowers tend to perceive lower interest rates and exhibit larger perception errors. Borrowers

Figure 2. Perceived Credit Card Debt Interest Rates

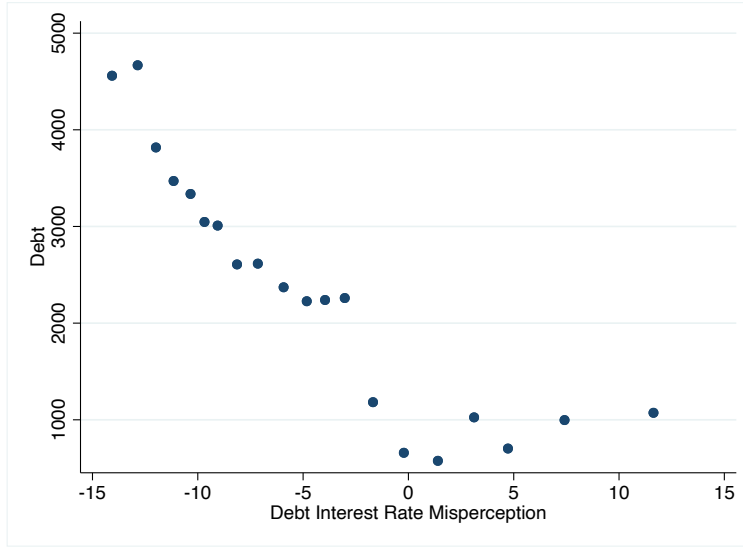


Note: This figure shows the correlation between the perceived interest rates elicited from the survey and covariate variables. Debt interest rate misperception is computed as the perceived interest rate minus the true interest rate, expressed in percentage points. Education levels are coded as follows: 1 for high school and below, 2 for some college, 3 for a bachelor’s degree, and 4 for graduate school. Additional regression results are detailed in Table C1 in the Online Appendix.

with higher levels of financial literacy (as indicated by more advanced education) and greater income tend to perceive higher and more accurate interest rates. Moreover, credit availability metrics such as credit scores and credit limits are negatively correlated with perceived interest rates, with lower scores and limits associated with lower and more erroneous perceptions of interest rates. One possible explanation is that borrowers with higher debt levels (facilitated by high credit scores and limits) may tend to underestimate the cost of borrowing.

We continue to examine the static relationship between interest rate misperception and debt accumulation using a binned scatter plot displayed in Figure 3. Interestingly, we observe a distinct pattern where only downward bias exhibits a negative correlation with debt

Figure 3. Interest Rate Misperception and Borrowing



Note: This figure shows the association between credit card debt and interest rate misperception. Debt interest rate misperception is computed as the perceived interest rate minus the true interest rate, expressed in percentage points. Additional regression results are detailed in Table C2 in the Online Appendix.

accumulation, while the relationship conditional on upward bias appears to be flat. Note that these findings give the equilibrium pattern and do not aim to construct a causal relationship.

IV Identification Strategy: Information Treatment

The previous section highlights that borrowers exhibit heterogeneous perceptions of the true interest rate associated with credit card borrowing, and such misperceptions seem to vary systematically with debt choices. However, the ordinary least squares (OLS) estimates may be subject to endogeneity issues. For instance, the estimated relationship is biased if debt-taking is influenced by latent preference variables not orthogonal to the perceived interest rates. Additionally, debt-taking behavior and perceived interest rate may be involved in simultaneous equation structures.

Identifying the causal effects of interest rate perception on borrowing behavior presents challenges due to the difficulty of randomizing consumer beliefs. To address potential en-

dogeneity issues, we introduced an information treatment for a randomly chosen subset of participants. Specifically, for a random 40% of the participants, we revealed the following information:

The annualized interest rate on your credit card with *[bank name]* is around X_1 . This rate is equivalent to a monthly interest rate of about X_2 . If you carry over 8,000 of debt on a credit card to the next billing cycle, then there will be around X_3 in interest rate in the next month.

Here, X_1 , X_2 , and X_3 correspond to the participant's individual-specific interest rate, the monthly equivalent rate, and the estimated interest cost for carrying over 8,000 CNY for a month, respectively. These values are determined based on the bank where the borrower holds the highest debt. To ensure participants do not reference this information when answering pre-experiment questions, it was presented on a new page, preventing them from returning to previous pages to modify responses.

After providing the information to the treatment group, all the participants were asked the following question:

Suppose your billing cycle is at the end of the month. If you spend 6,000 this month and repay 3,000 in the end, how much interest in total would you incur at the end of next month?

- 15
- 25
- 35
- 45
- 55
- 65
- 75

To avoid repeatedly presenting identical survey questions and potentially frustrating borrowers, we strategically varied spending and repayment levels in the questions administered before the treatment. However, using different questions to elicit posterior beliefs may introduce systematic discrepancies in responses, such as rounding errors. Nonetheless, these

potential issues affect both the treatment and control groups equally and are accounted for in the causal analysis.

Then, we compute the implied perceived interest rate again based on this question. Essentially, our information treatment increased the salience of the interest rate by explicitly presenting the true cost of borrowing in an exogenous way. This approach enables us to assess the effectiveness of the information treatment and identify the causal effect of the perceived interest rate on debt.

To evaluate the effectiveness of the randomization, Table 1 presents the means and standard deviations of demographic variables (age, gender, and education), financial behavior indicators (spending, income, and total assets), and credit availability metrics (credit limit and credit score) for the treatment and control groups. As expected from random assignment, the averages for all variables are closely aligned, indicating that the treatment and control groups are comparable.

V Results

A Intent-to-Treat Effect of Information Treatment on Interest Rate Perceptions

Our information treatment had large effects on interest rate perceptions. Table 2 reports the means and standard errors of the perception errors of the interest rates, $Bias$ and $|Bias|$, grouped by treatment status.⁶ In the control group, borrowers exhibited minimal changes in their perceptions, with little revision observed between the perceived interest rates in our

⁶Figure B4 in the Online Appendix illustrates the distributions of perception revisions for the control and treatment groups, respectively.

Table 2. Perceived Interest Rate Revision

	Control		Treatment	
	(1)	(2)	(3)	(4)
	Before	After	Before	After
<i>Bias</i>	-4.39 (0.27)	-4.72 (0.31)	-4.32 (0.29)	0.62 (0.26)
$ Bias $	7.30 (0.15)	8.17 (0.18)	6.92 (0.18)	4.78 (0.16)

Note: This table shows the mean and absolute value of the bias of the perceived debt interest rate before and after the information treatment for the control and treatment groups, respectively. *Bias* is defined as the difference between the perceived debt interest and the true rate, whereas $|Bias|$ is the absolute value of the difference. Standard errors are reported in parentheses.

two elicitation processes (*Bias* changes from -4.39 to -4.72 percentage points, while $|Bias|$ moves from 7.30 to 8.17 percentage points). In contrast, in the treatment group, borrowers primarily adjusted their perceived interest rates upwardly (*Bias* rises from -4.32 to 0.62 percentage points), and their revised interest rates moved closer to the true rates ($|Bias|$ drops from 6.92 to 4.78 percentage points).

We first evaluate the ITT effect of our information treatment by estimating the regression equation below:

$$y_i = \alpha + \beta Treated_i + \mathbf{X}_i' \gamma + \varepsilon_i \quad (2)$$

where y_i is the variable of interest (i.e., perception errors, debt, etc.) and $Treated_i$ is a dummy variable indicating consumer i 's treatment status. The main parameter of interest, β , captures the causal effect of the information treatment on the perceived interest rate. We also control for covariates \mathbf{X}_i , including pre-treatment perceived interest rate, debt, gender, age, education, assets, income, credit limit, and credit score.

Table 3 presents the instantaneous ITT effects of the information treatment on perceived interest rates, absolute perception errors, and the average borrowing behavior during the

Table 3. Intent-to-Treat Effect of Information Treatment

	All		Downward Bias		Upward Bias	
	(1)	(2)	(3)	(4)	(5)	(6)
ITT Effect on <i>Perceived r</i>	5.24*** (0.40)	5.22*** (0.28)	8.57*** (0.35)	8.34*** (0.22)	-4.00*** (0.65)	-3.52*** (0.62)
ITT Effect on $ Bias $	-3.39*** (0.24)	-3.38*** (0.23)	-3.87*** (0.27)	-3.81*** (0.25)	-2.05*** (0.52)	-1.52*** (0.51)
ITT Effect on Debt	-644.83*** (146.88)	-491.54*** (84.83)	-1061.04*** (277.71)	-855.58*** (182.03)	510.40*** (102.76)	555.26** (104.43)
Observations	1219		899		320	
Baseline <i>Perceived r</i>	15.15		11.73		24.75	
Baseline $ Bias $	7.13		7.79		5.28	
Baseline Debt	2329.84		2851.14		865.32	
Controls	No	Yes	No	Yes	No	Yes

Note: This table presents the ITT effects of the information treatment. Perceived interest rates and absolute perception errors are assessed during the second round of belief elicitation, conducted immediately after the information treatment, while debt effects are evaluated based on the monthly average three months post-treatment. The results in columns (1) - (2) correspond to the entire sample, while columns (3) - (4) and (5) - (6) represent subsamples of borrowers who underestimate and overestimate the interest rate, respectively. Baseline values represent the pre-treatment averages. Controls omitted in the table include pre-treatment perceived interest rate, debt, gender, age, education, assets, income, credit limit, and credit score. Note that *Perceived r* is derived from the average of responses to the three survey questions to alleviate measurement errors. In Table C3 in the Online Appendix, we verify that our ITT results hold when using any one of these questions as the priors. White robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

three months after the treatment, both with and without covariates. Notably, the ITT point estimates remain similar regardless of whether covariates are included, with covariate adjustments improving estimation precision. This suggests the correct implementation of randomization in the experiment.

Columns (1) and (2) report the results for the entire sample. Consistent with the descriptive findings in Table 2, we find that, after controlling for covariates, the information treatment increased borrowers' perceived interest rates by 5.22 percentage points and reduced their perception errors by 3.38 percentage points. Reflecting this adjustment in perceptions, the treatment led to a reduction in average credit card debt of \$491.54 over three months,

representing a 21% decrease relative to the pre-treatment level.

Columns (3) and (4) present the results for borrowers who initially underestimated interest rates. On average, these borrowers increased their perceived interest rates by 8.34 percentage points following the information treatment, while their perception errors decreased by 3.81 percentage points. This adjustment was accompanied by a substantial reduction in credit card debt, with an average decline of \$855.58.

Columns (5) and (6) show the results for borrowers with an ex-ante upward perception bias. For this group, perceived interest rates increased by 3.52 percentage points, and absolute perception errors decreased by 1.52 percentage points. Interestingly, because these borrowers initially overestimated the cost of borrowing, they appear to have been borrowing suboptimally low amounts. As a result, the information treatment led to an average increase in their credit card debt of \$555.26.

B Effect of Interest Rate Misperceptions on Debt

Next, we evaluate the effect of interest rate misperception on credit card borrowing using the information treatment as an instrumental variable (IV) for perceived interest rates.⁷ Our specification follows Coibion et al. (2021), Coibion et al. (2024), and Gorodnichenko and Yin

⁷Since $Bias_i = Perceived\ r_i - r_i$, where the average of r_i is expected to be statistically the same between the control and the treatment groups, results will be the same if using $Bias_i$ instead of $Perceived\ r_i$ as the main regressor. We choose $Perceived\ r_i$ so that the explanation aligns more closely with the interest rate sensitivity of debt.

(2024). The first stage is

$$\begin{aligned} \text{Perceived } r_i^{\text{post}} = & a + b_0 \text{Perceived } r_i^{\text{prior}} + b_1 \text{Treated}_i \\ & + b_2 \text{Perceived } r_i^{\text{prior}} \times \text{Treated}_i + \mathbf{X}'_i \boldsymbol{\omega} + e_i, \end{aligned} \quad (3)$$

and the second stage is

$$y_i = \alpha + \beta_0 \text{Perceived } r_i^{\text{prior}} + \beta_1 \widehat{\text{Perceived } r_i^{\text{post}}} + \mathbf{X}'_i \boldsymbol{\omega} + \varepsilon_i. \quad (4)$$

In the first stage, we fit the posterior perceived interest rates on priors interacted with the treatment dummy. In the second stage, we fit our primary outcome variables of interest (e.g., debt) on the fitted values derived from Equation (3). In both stages, we control for prior expectations, ensuring that the first stage uses only the exogenous variation induced by the treatment.

Notably, the direction of changes in *Perceived* r_i post-treatment may violate monotonicity depending on whether prior expectations are upward- or downward-biased. Suppose we were to use only *Treated* $_i$ as the IV, then if perception errors symmetrically surround zero and all participants update perceptions by the same magnitude, the first stage would yield no average effect on perception errors. To address this issue, we instead employ *Treated* $_i$ and the interaction term *Treated* $_i \times \text{Perceived } r_i^{\text{prior}}$ as the IV. In Equation (3), the coefficient b_0 captures the relationship between prior and posterior beliefs for the control group. In the absence of new information, we expect b_0 to be approximately one. However, due to attenuation bias from measurement errors and different question formats to elicit prior and

Table 4. IV Estimates of Effect of Perceived Interest Rate on Debt

	All		Downward Bias		Upward Bias	
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Perceived r</i>	-128.09*** (22.85)	-113.24*** (13.16)	-123.11*** (21.41)	-103.82*** (12.36)	-95.71*** (31.29)	-110.65*** (13.93)
Constant	4734.02*** (242.37)	3263.87*** (630.93)	5474.59*** (319.58)	3758.53*** (765.44)	1489.97** (644.16)	-1363.56 (945.70)
Observations	1219	1219	899	899	320	320
R^2	0.125	0.175	0.105	0.159	0.094	0.223
First-Stage F	507.22	507.64	792.63	785.19	56.02	47.49
Controls	No	Yes	No	Yes	No	Yes

Note: This table presents the 2SLS estimates of Equations (3) and (4), where the treatment status is used as an IV for the perceived interest rate in the first stage. The effect on debt is evaluated at the monthly average level three months before and after the information treatment. The results in columns (1) - (2) correspond to the entire sample, while columns (3) - (4) and (5) - (6) represent subsamples comprising only borrowers who underestimate and overestimate the interest rate, respectively. The F statistics are well above 10% critical values for all columns, presenting no evidence of weak IV. Omitted controls in the table include pre-treatment, debt, gender, age, education, assets, income, credit limit, and credit score. White robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

posterior, b_0 is often observed to be different from one. The coefficient b_2 measures the incremental relationship between priors and posteriors for the treatment group. Under Bayesian updating, we would expect $b_2 \in [-1, 0]$, representing the negative of the Kalman gain. Therefore, by using the interaction of priors with the treatment indicator as the IV, we address the monotonicity issue, thereby increasing the significance in the first-stage regression. The first-stage results are in Online Appendix Table C4.

As an alternative to solve the monotonicity issue, we estimate a specification using only $Treated_i$ as the IV but restrict the estimation to borrowers with only upward or downward perception biases. Results for these subgroups are expected to satisfy the monotonicity assumption and can be interpreted as the local average treatment effect (LATE) (Imbens and Angrist, 1994) if borrowers adjust perception toward the direction of the signal surprises. Results for this approach, detailed in Table C5 in the Online Appendix, yield similar findings to our primary analysis.

In addition, we include a set of demographic controls, including financial status and credit availability at the pre-treatment level.⁸ Table 4 presents the results of the 2SLS estimation with and without these covariates. The first-stage F statistics in all columns are well above the 10% critical value, indicating that weak instruments are not a concern. Columns (1) and (2) report the results of Equation (4). The debt-taking decision conforms to the law of demand: controlling for covariates, a one percentage point increase in the perceived interest rate decreases debt by \$113.24, which is about 5% of the pre-treatment average debt.

For comparison, our sensitivity of debt to perceived interest rates closely aligns with the interest rate sensitivity documented in the U.S. by Gross and Souleles (2002).⁹ Considering an average interest rate misperception of -4.39 percentage points, the estimated effect of perceived interest rate on debt suggests an excess borrowing of $(-4.39) \times (-113.24) = \497.12 on average, representing approximately 21% of the current debt level.

In columns (3) - (6) of Table 4, we estimate the same 2SLS system using subsamples of borrowers who underestimate and overestimate the interest rate, respectively. We find a significant effect of perceived interest rate on borrowing regardless of the direction of misperception. The sensitivity estimates with covariates, -103.82 for borrowers with negative perception errors and -110.65 for those with positive perception errors, do not exhibit significant differences. This is different from the static pattern observed in Figure 3. These results suggest that the endogeneity of the perceived interest rate is more pronounced for borrowers with positive perception errors, underscoring the importance of IV in the estimation process.

⁸Table C4 in the Online Appendix presents the results of the first-stage regression, where $\hat{\beta}_1 = -0.73$. This suggests that the information treatment substantially revised consumer perceptions of interest rates, indicating a strong first stage.

⁹The study by Gross and Souleles (2002) utilizes an event study regression to estimate the response of debt to changes in interest rates, using credit card account data from various issuers in the U.S. They find an interest rate sensitivity of debt at -112.6, which closely resembles our 2SLS results.

Together, the treatment effects on perceived interest rates reflect that borrowers, on average, underestimated the cost of borrowing; they deemed our treatment as valuable information and updated their beliefs from the provided message as a result. After a more precise interest rate perception, the 21% reduction in debt in the subsequent months indicates that interest rate misperception induced substantial suboptimal borrowing behavior. This suggests that it is important to improve borrowers' understanding of the debt interest rate and make more informed decisions on borrowing.

C Heterogeneous Responses to Information Treatment

We have shown that borrowers have noisy perceptions of the interest cost of credit card debt and tend to underestimate the true interest costs of debt. In addition, these misperceptions affect borrowing behaviors significantly. A disclosure policy that increases the salience of interest rate by showing the dollar amount of interest payment given a hypothetical scenario is helpful in debiasing.

To better understand the mechanism behind interest rate misperception and its influence on borrowing behavior, we illustrate three sets of heterogeneous effects of information treatment on debt in different subsamples: the ITT effect of information treatment on perceived interest rates, the ITT effect on debt, and the sensitivity of debt to perceived interest rates estimated through 2SLS. We seek to understand the heterogeneity in the following dimensions: borrowing levels, credit availability, financial literacy, and attention to credit card accounts. Note that sample split across one characteristic is likely to correlate with that across other characteristics; we view these results as suggestive.

Table 5 presents the heterogeneous effects of the information treatment across different

Table 5. Heterogeneous Responses to Information Treatment

	Debt-to-Income		Utilization		Education		Autopay		Spending Misperception	
	(1) High	(2) Low	(3) High	(4) Low	(5) College	(6) Non-College	(7) Yes	(8) No	(9) Positive	(10) Negative
ITT Effect on <i>Perceived r</i>	6.97*** (0.35)	3.51*** (0.44)	5.89*** (0.42)	4.58*** (0.38)	3.36*** (0.42)	7.43*** (0.36)	5.94*** (0.58)	5.03*** (0.32)	5.61*** (0.44)	4.94*** (0.36)
ITT Effect on Debt	-1075.95*** (150.36)	134.41* (72.73)	-554.82*** (125.37)	-449.98*** (124.08)	-140.07 (92.46)	-904.95*** (149.48)	-467.59** (193.65)	-499.95*** (94.75)	-491.87*** (132.91)	-479.60*** (109.41)
IV Est. of <i>Perceived r</i> on Debt	-147.49*** (19.82)	-54.10*** (9.00)	-119.01*** (15.78)	-106.10*** (21.07)	-80.26*** (14.23)	-133.98*** (19.80)	-117.83*** (26.30)	-109.70*** (15.07)	-106.11*** (20.91)	-114.00*** (16.49)
Observations	609	610	609	610	666	553	359	860	494	725
Baseline <i>Bias</i>	-7.00	-1.73	-3.17	-5.55	-4.36	-6.36	-4.83	-4.24	-4.56	-4.22
Baseline Debt	4263.59	399.26	2324.94	2334.73	2329.84	2978.37	2548.38	2274.02	2341.89	2301.28
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table shows the heterogeneous effects for different subsamples split by debt-to-income ratios, credit utilization, education, enrollment for autopsy, and spending misperception values. We show the ITT effect of information treatment on perceived interest rates, ITT effect on debt, and the sensitivity of debt to perceived interest rates. Baselines represent the pre-treatment averages in each subgroup. All columns include controls (omitted in the table) for pre-treatment perceived interest rate, debt, gender, age, education, assets, income, credit limit, and credit score. White robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

subsamples, grouped by median values of debt-to-income ratios and credit utilization, labeled as high and low, respectively. The sample is also divided based on education level (college degree or not), whether borrowers have set up autopay for credit card balances, and whether they overestimate or underestimate their spending levels in the past month, as determined by the following survey question:

How much in total did you spend last month using the credit cards in our bank?

To illustrate the rates of change, pre-treatment mean interest rate misperception and debt levels for each subsample are included.

In columns (1) and (2), baseline interest rate misperceptions differ considerably by debt-to-income ratio: borrowers with high debt-to-income ratios have a misperception of -7.00 percentage points, while those with low ratios are at -1.73. Reflecting this disparity, the ITT effect of the information treatment on debt reduction is substantial -\$1,075.95 for high debt-to-income borrowers, compared to \$131.41 for low debt-to-income borrowers. Notably, borrowers with high borrowing levels demonstrate greater responsiveness to perceived interest rate adjustments: a one percentage point increase in the perceived rate corresponds to a debt reduction of \$147.49 for high debt-to-income borrowers, compared to \$54.10 for the low-ratio counterparts. Thus, borrowers with high debt levels tend to respond more to a more accurate perceived interest rate.

Columns (3) and (4) reveal no significantly different treatment effects based on liquidity, as measured by credit utilization rates. Columns (5) and (6) divide the sample by education level, showing that post-treatment, borrowers without a college education reduced their debt by \$904.95, whereas college-educated borrowers displayed only a modest and statistically

insignificant debt reduction of \$140.07.

To explore whether attention to credit card accounts mitigates interest rate misperceptions, columns (7) and (8) examine autopay enrollment. The findings indicate that borrowers enrolled in autopay exhibit slightly greater misperceptions about interest rates and are marginally more sensitive to perceived rate changes. However, manually repaying balances, presumably a more active form of account engagement, does not seem to eliminate these misperceptions. One potential explanation is that consumers may not pay specific attention to the information on interest charges, even when it is presented directly on their statements.

We further investigate attention using spending perception as an alternative proxy. The assumption is that individuals who misunderstand their spending levels are less attentive to their credit card accounts overall and, consequently, more susceptible to interest rate misperceptions. However, columns (9) and (10) show similar treatment effects and comparable pre-treatment borrowing behaviors and perceived interest rates across groups with different directions of spending misperception.

Together, these findings suggest that general attentiveness to credit card accounts does not necessarily translate into more accurate perceptions of borrowing costs. Consumers may monitor balances or payments closely but still overlook, or fail to internalize, interest-related information. This interpretation is consistent with the earlier finding that borrowers persistently misperceive interest rates despite receiving regular statements that explicitly detail interest charges.

Overall, except for debt-to-income and education, the heterogeneous effects primarily come from perceived interest rates and debt adjustments, with relatively similar interest rate sensitivities across groups. This suggests that the over-borrowing in the aggregate is

likely driven by the perception errors in interest rates rather than the sensitivity of debt to interest rate changes. From a policy perspective, these results indicate that borrowers with higher debt levels and lower financial literacy are more prone to suboptimal borrowing behaviors due to interest rate misperceptions and therefore could derive greater benefits from interventions aimed at debiasing interest rate misperceptions.

***D* Discussion on Other Potential Mechanisms**

Our information treatment aims to change the participants' perceived interest rates. However, it is possible that the treatment simultaneously affects their perceptions of factors other than interest rates. In particular, if borrowers have noisy perceptions of their total debt and the treatment prompts them to reassess their actual debt levels, the intervention could influence borrowing through changes in the perceived level of current debt, rather than through the perceived marginal cost of debt. If this is the case, we would expect borrowers who tend to have greater debt misperceptions to exhibit stronger reactions to the information treatment.

Evidence from columns (7) - (10) of Table 4 does not support this hypothesis. Debt sensitivities to perceived interest rates are highly similar among borrowers, regardless of whether they are enrolled in autopay or whether they underestimate or overestimate their total debt repayment needs. Given that autopay users and those who initially underestimate their credit card spending should experience a greater degree of surprise regarding their debt levels, the similar treatment effects across these groups suggest that the observed changes in borrowing behavior are not driven by adjustments in perceived total debt costs.

A second possibility is that the treatment acts as a general reminder that borrowing is

costly, prompting consumers to reduce debt usage without directly altering perceived interest rates, as suggested by Stango and Zinman (2014). Yet, our results are inconsistent with this interpretation. As shown in Table 3, borrowers who initially underestimated interest rates actually increased their borrowing levels afterward. This pattern aligns with adjustments in their perceived interest rates. Specifically, with similar sensitivities observed in Table 4, borrowers with downward biases correct their errors and reduce debt, whereas those with upward biases revise their perceived rates downward and increase borrowing. These patterns suggest that the information treatment’s effects on borrowing decisions are likely driven by changes in perception errors, rather than simply reminding borrowers of the “painfulness” associated with borrowing.

A final concern is that the observed improvements in post-treatment interest rate perceptions are not due to true belief updating, but instead stem from a heuristic in arithmetic reasoning. For instance, consumers may use the information treatment as a hint to solve a simplified calculation problem, without truly internalizing the implications of interest rates for borrowing costs. This possibility is not supported by our results. The direction of perceived interest rate changes matches the direction of debt adjustments (Table 3), and the magnitude of estimated sensitivity of debt to perceived interest rates (Table 4) closely aligns with those reported in the literature (e.g., Gross and Souleles, 2002). These patterns indicate that the behavioral responses observed in our study are most plausibly attributed to genuine belief updating rather than mechanical calculation shortcuts.

***E* Behavioral Responses to Correction of Interest Rate Misperceptions**

How do borrowers adjust their consumption-saving patterns to reduce credit card borrowing once they become aware of their interest rate misperceptions? Exploring behavioral changes about not only borrowing but also consumption is important to understand the drives behind interest rate misperception as well as the impact of corresponding policies on households' holistic financial behavior.

There are two possibilities in general: 1) borrowers who reduce their debt may also curtail their overall spending upon realizing the true expenses associated with credit card borrowing; 2) alternatively, consumption patterns may remain unchanged, but borrowers opt to fund their purchases using savings rather than accruing additional debt. To test these two hypotheses, we analyze the ITT effects of the information treatment on spending and various asset types in the three months following the treatment, as presented in Table 6 columns (1) - (4). Liquid assets are demand deposits, such as balances in checking, savings, and financial investment accounts, and illiquid assets consist of certificates of deposit maturing in three months or more.

Compared to the control group, treated borrowers reduced their monthly spending by \$285.22 in the three months post-treatment. With debt decreasing by \$491.54, this translates to an asset increase of \$364.12. From columns (2) - (3), borrowers reduced liquid assets by \$1,550.39 and increased illiquid assets by \$1,772.63. The large ITT effect on illiquid assets is likely induced by the minimum threshold of certificates of deposit at the bank, which is about \$1,400 (10,000 CNY). The movement of assets indicates that apart from debt payoff from liquid assets, borrowers also commonly opt for illiquid assets at least by the minimum

Table 6. Three-Month Intent-to-Treat Effects of Information Treatment on Spending and Assets

	(1)	(2)	(3)	(4)	(5)	(6)
	Spending	Liquid Assets	Illiquid Assets	Necessities Spending	Luxuries Spending	Other Spending
Treated	-285.22*** (45.86)	-1550.39** (676.89)	1772.63*** (254.50)	-14.17 (30.52)	-227.70*** (39.69)	-43.35 (34.29)
Constant	-285.64 (216.30)	-2920.26 (3283.36)	-1069.72 (1117.48)	357.11*** (133.44)	-771.26*** (217.67)	128.52 (165.46)
Observations	1219	1219	1219	1219	1219	1219
R^2	0.562	0.620	0.656	0.083	0.372	0.124
Baseline	1539.21	19305.67	7231.97	647.91	534.15	357.16
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents the ITT effects of the information treatment. Liquid assets include demand deposits, such as balances in checking, savings, and financial investment accounts, while illiquid assets consist of certificates of deposit maturing in three months or more. The spending categories, necessities, luxuries, and others, are predefined by the bank. Baselines denote the pre-treatment averages. All columns include controls (omitted in the table) for pre-treatment perceived interest rate, debt, gender, age, education, assets, income, credit limit, and credit score. White robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

threshold amount. Finally, columns (4) - (6) show the changes in spending share on different categories.¹⁰ We find that around 80% of consumption reduction originates from a decrease of \$227.70 in luxury purchases.

These findings together indicate that lower perceived interest rates reduce borrowing by reducing spending. Consistent with the findings from heterogeneous treatment effects, the reason for borrowing does not seem to stem from liquidity constraints, given the substantial reduction in consumption. Upon discovering that the true interest rate exceeded their expectations, borrowers began to settle high-interest credit card debt by curtailing luxury expenditures. Meanwhile, another interesting observation is that borrowers opted out of liquid assets for inflexible certificates of deposit in nearly a one-to-one ratio. A possible in-

¹⁰The spending categories are defined by the bank. Luxury goods (necessities) are characterized as those brands whose average consumption share increases (decreases) with income growth. The results remain consistent when luxury goods are defined as those with prices in the top quintile within each industry or location.

terpretation is that borrowers view illiquid assets as an implicit commitment device (Laibson, 1997) to restrain from excessive consumption induced by interest rate misperceptions.

A potential concern is that the measure of consumption is incomplete, as our data only captures consumption behavior within the bank. Addressing the inability to observe consumption holistically, as a robustness check, we conducted a supplementary analysis on a subsample of borrowers who exclusively use the bank for their daily consumption. This subsample comprises individuals who responded “one” to the following survey question:

How many banks do you use for daily transactions?

As enclosed in Table C6 in the Online Appendix, this procedure yields similar findings to those in Table 6.

***F* Interest Rate Misperceptions in the Long Run**

Our findings indicate that providing information about the true costs of debt helps correct misperceptions of interest rates and adjust borrowing behavior instantaneously. Since our information treatment offers a one-time signal regarding the cost of borrowing, to understand whether the newly gained information and adjusted behavior are persistent, we continue to test whether the treatment effect remains over time.

For this purpose, we conducted a follow-up survey in August 2021, eliciting the perceived interest rates of the same borrowers again using the same design. Table 7 presents the results along with the corresponding ITT effect estimate using Equation (2). Compared to Table 3, the effect on the perceived interest rate decreases from 5.22 to 3.08 percentage points, while the effect on the absolute perception error decreases from -3.38 to -1.89 percentage points.

Table 7. Perceived Interest Rate Revision in the Long Run

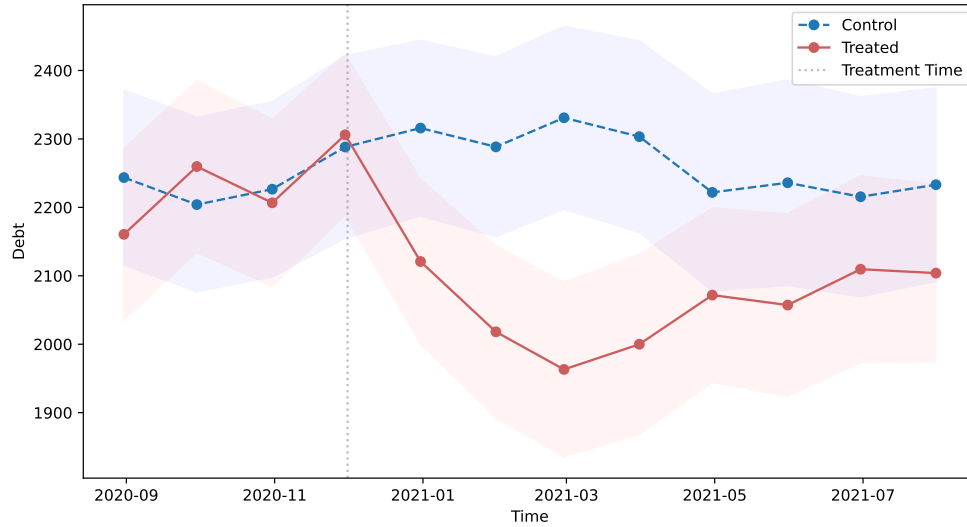
	Control		Treatment		9m Effect
	(1) Before	(2) 9 Months Later	(3) Before	(4) 9 Months Later	
<i>Bias</i>	-4.39 (0.27)	-4.28 (0.27)	-4.32 (0.29)	-1.11 (0.26)	3.08** (0.55)
$ Bias $	7.29 (0.16)	7.23 (0.15)	6.92 (0.18)	4.95 (0.15)	-1.89*** (0.32)

Note: This table shows the mean and absolute value of biases of the perceived debt interest rate before and nine months after the information treatment for the control and treatment groups, respectively. *Bias* is defined as the difference between the perceived debt interest and the true rate, whereas $|Bias|$ is the absolute value of the difference. 9m Effect denotes the corresponding ITT estimates as in Equation (2). Standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Correspondingly, Figure 4 displays the debt trajectories of the treatment and control groups until August 2021, in which the gray dashed vertical line indicates the time of our information treatment. While there are some fluctuations, we do not observe any significant overall debt trends for the control group. In contrast, for the treatment group, the debt level quickly declined from around \$2,300 to \$2,000 until March 2021 following the information treatment. However, the effect of the information treatment begins to diminish over time: the debt level of the treatment group gradually converges to that of the control group for several months but stabilizes from May 2021 onward.

The reversal of interest rate misperception suggests that the underlying reasons for misperception extend beyond merely shrouded attributes or initial inattention to the terms of credit card products. While the information treatment effectively corrected misperceptions in the short run, the effects did not last permanently, consistent with memory decay as documented in the literature (Camerer and Hua Ho, 1999; Malmendier and Nagel, 2011; Gallagher, 2014; Nagel and Xu, 2021; Huffman et al., 2022). The observation of modest long-term effects of information disclosure on behavior also aligns with the findings in some

Figure 4. Long-Run Effect of Information Treatment on Debt



Note: This figure illustrates the credit card debt trajectories of borrowers in the treated group (represented by red solid curves) and the control group (represented by blue dashed curves) from September 2020 to August 2021. The vertical dotted line indicates the time of the information treatment. The shaded areas represent the corresponding 95% confidence regions.

existing literature, such as Fernandes et al. (2014) and Seira et al. (2017).

G Experience and Interest Rate Misperceptions

Our participants exhibit significant perception errors regarding credit card interest rates, likely due to the opaque presentation of borrowing costs when initially accepting credit card terms. However, even with an initially uncertain understanding of true interest rates, borrowers are expected to gradually improve their knowledge as they gain more exposure to the market. Thus, it is worth investigating whether these biases diminish over time.

To explore this evolution, we examine how perception errors relate to the credit card market experience, measured by the years a consumer has been active in this market. The left-hand side of Figure 5 includes binned scatter plots that illustrate the relationship between interest rate misperceptions and absolute errors against market experience. We measure

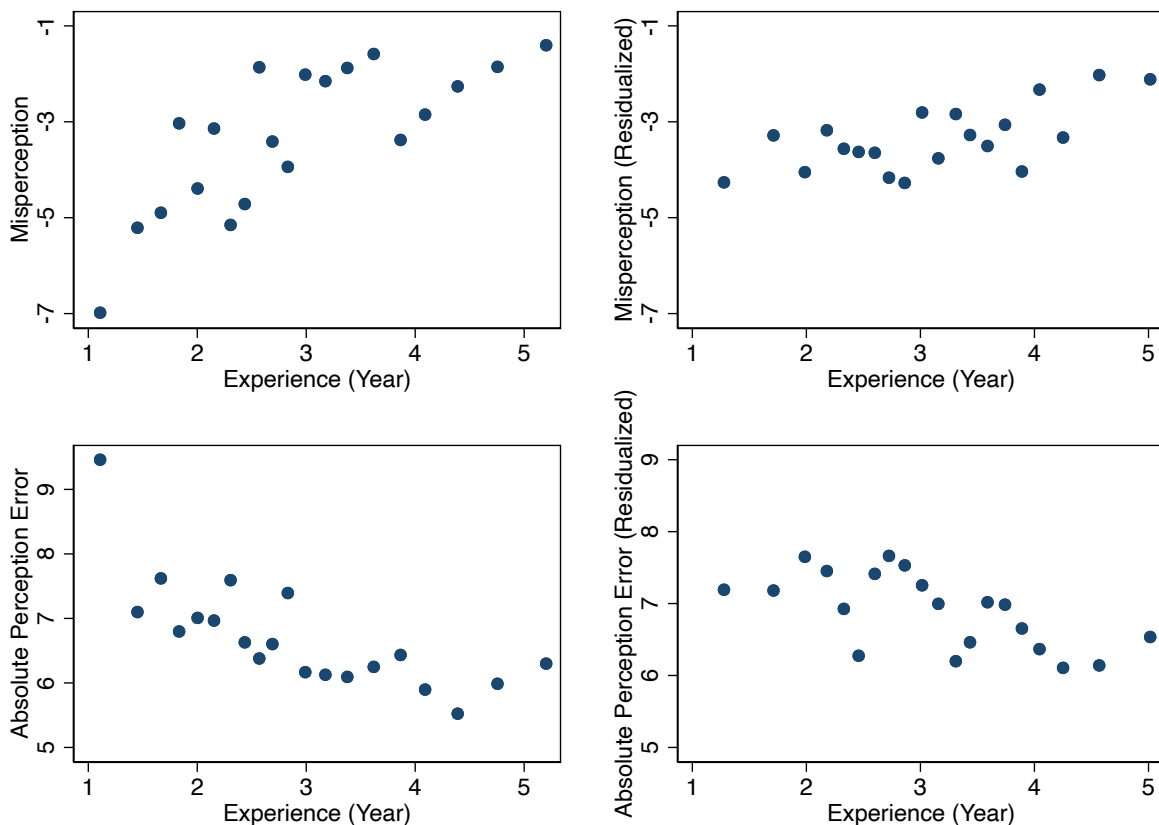
market experience as the number of years from the first time the participants have credit card debt in the credit registry. On the right-hand side, the variables are residualized to account for potential demographic and financial factors, including age, savings, gender, education attainment, credit limit, and credit score, thereby controlling for heterogeneous learning rates.

From the plots, there is a gradual trend toward higher and more accurate interest rate perceptions over time, but the speed of correction appears slow. A comparison between the left and right panels suggests that demographics primarily account for only initial misperceptions. However, even after five years of credit card market exposure, an interest rate misperception of approximately -1.50 percentage points persists, regardless of whether the data is residualized. This limited improvement implies that even with accumulated experience, borrowers do not allocate sufficient attention to their credit card accounts to fully correct misperceptions.

We use a simple model to illustrate how borrowers adjust their interest rate perceptions. Consider a representative borrower learning about the true interest rate on her credit card. Let the true interest rate r_t follow a normal random walk process $r_t = r_{t-1} + \eta_t$ with $\eta_t \sim N(0, \sigma_\eta^2)$. Before entering the market, the borrower has a prior belief that follows $N(r_0, \sigma_0^2)$. In each period, the borrower receives a noisy signal $s_t = r_t + \varepsilon_t$ with $\varepsilon_t \sim N(r_t, \sigma_\varepsilon^2)$. The borrower uses these signals to update her belief about the interest rate, denoted \hat{r}_t .

In addition, the misperception reversal over nine months post-treatment implies that beyond initial inattention, information surprises about true rates are forgotten over time, contributing to the persistence of misperceptions. This aligns with findings from Agarwal et al. (2013), which show that borrowers in the credit card market are slow to learn from

Figure 5. Experience and Interest Rate Misperception



Note: This figure includes the binned scatter plots of interest rate misperceptions on credit card market experience. The y-axes are, respectively, perception errors and absolute perception errors. The x-axes are experiences, which is the number of years since first opening a credit card account (shown from the credit registry). The plots on the left display raw data, while the plots on the right are residualized by age, gender, savings, income, education, credit limit, and credit score. Additional regression results are detailed in Table C7.

their mistakes but quick to forget corrections. To account for forgetting, we assume the borrower does not retain each signal in full.¹¹ Instead, her prior belief decays towards her belief from the previous period, \hat{r}_{t-1} , at a forgetting rate $\lambda \in [0, 1]$. Concretely, her prior belief at the start of period t , before observing the current period's signal, is adjusted as

$$\hat{r}_t^0 = (1 - \lambda)\hat{r}_{t-1} + \lambda\hat{r}_t$$

¹¹See Camerer and Hua Ho (1999), Malmendier and Nagel (2011), and Gallagher (2014) for similar settings of weighting past experience.

where \hat{r}_t^0 represents the adjusted prior belief before receiving the current signal. When $\lambda = 0$, the borrower completely forgets the signals from $t - 1$, and when $\lambda = 1$, she retains all information from previous signals.

After receiving the signal s_t , the borrower updates her belief to form her posterior expectation

$$\hat{r}_t = \hat{r}_t^0 + \kappa_t (s_t - \hat{r}_t^0),$$

where κ_t is the Kalman gain in the Bayesian learning process.¹²

Through our experiment, we can calibrate this process for the average borrower in our sample. In general, we observe a slow learning process with persistent misperceptions. This can be induced by borrowers undergoing an uncertain prior with large signal noises (reflecting inattention to the true rate) and forgetting new signals over time. We calibrate four parameters: σ_η^2 (interest rate shock variance), σ_0^2 (prior belief variance), σ_ε^2 (signal noise variance), and λ (forgetting rate). The calibration process is detailed in Online Appendix D. This stylized exercise aims at shedding light on whether inattention plus forgetting could generate the results.

Table 8 shows the calibrated results. We assume that borrowers receive a signal every quarter. Panels A and B summarize the matched moments and estimated parameters, providing three key insights. First, as shown in Panel A, perception is noisier compared to true interest rate variability. In particular, while the true interest rate standard deviation is 2.48%, the standard deviation of perceived rates reaches 4.00%, approximately 60% higher.

¹²Note that since we do not observe s_t , κ_t and signal variance σ_ε^2 are not separately identified. Alternatively, one can assume that the borrower can observe the true interest rate r_t , but there is only a m probability that she pays attention to the signal surprises. Then $\hat{r}_t = \hat{r}_t^0 + \kappa_t (s_t - \hat{r}_t^0) - m\kappa_t\varepsilon_t$. Therefore, a noisy signal and inattention to interest rates are observationally equivalent and will yield similar results.

Table 8. Calibration Results for Model of Interest Rate Learning and Forgetting

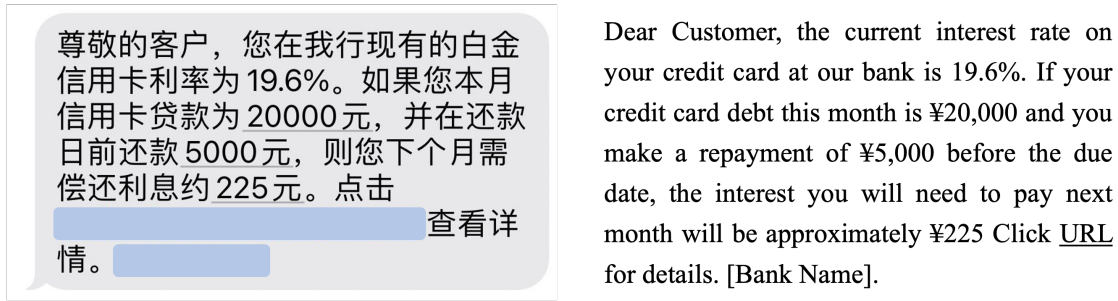
	(1)	(2)	(3)	(4)
Panel A: Targeted Moments				
	SD(r_t)	1-Y SD($ Bias $)	4-Y SD($ Bias $)	1-LR/SR
Data	2.48	4.00	3.70	0.37
Model	2.48	4.00	3.70	0.37
Panel B: Parameters				
	σ_η	σ_0	σ_ε	λ
Estimates	0.91***	4.16***	18.15***	0.39***
Std. Err.	(0.04)	(0.25)	(1.40)	(0.09)

Note: This table presents the results of the calibration exercise. Panel A gives the targeted moments, and Panel B gives the parameters. $SD(r_t)$ is the standard deviation of the true interest rate. 1-Y $SD(|Bias|)$ is the standard deviation of absolute perception errors in the first year of entering the market. 4-Y $SD(|Bias|)$ is the standard deviation of absolute perception errors four years after entering the market. Online Appendix D describes the steps of calibrating the model. 1-LR/SR is one minus the ratio of the 9-month and instant effects of the experiment on absolute perception errors. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Second, signals are much noisier than the prior, as captured by a large σ_ε , which indicates that new information receives minimal weight in updating belief: the Kalman gain remains low and capped at 0.05 given the ratio of prior and signal precision, reflecting borrowers' limited responsiveness to new information. This slow updating process highlights a pattern of inattention to interest rates over time: even when interest charges are explicitly presented on statements, borrowers do not sufficiently pay attention to this information and revise their beliefs accordingly. Lastly, in line with the forgetting mechanism, borrowers forget about 39% of the information from each signal per quarter.

Though stylized, this calibration exercise suggests that a model incorporating inattention and forgetting closely aligns with our observed findings. It suggests the mechanism that inattentive borrowers who quickly forget accumulated information retain persistent biases in their beliefs about interest rates. Hence, consumers paying attention autonomously is insufficient for the long-term correction of such misperceptions, and periodic reminders of

Figure 6. Text Alert with Interest Costs in Dollar Amounts



Note: This figure presents a text alert that details interest costs in dollar amounts, mirroring the information provided in the original treatment. The left side shows the original text screenshot, while the right side provides an English translation. In the message, 20,000 represents the average debt across borrowers in our sample, while the interest rate of 19.6% and a 225 interest payment are tailored to each consumer's specific credit card interest rate.

true borrowing costs may be necessary to consistently reduce these biases.

VI Text Alerts as a Policy

Although we have demonstrated a significant immediate impact on borrowing behavior and a more moderate effect over the long term, the primary objective of the information treatment was to randomly perturb borrowers' interest rate perceptions. However, implementing this treatment style on a frequent basis may not be a practical corrective strategy for the bank due to administrative burdens and the potential to reduce consumer engagement. Additionally, repeated surveys could potentially reduce borrowers' usage of banking services if they perceive excessive data collection.

Building on the effectiveness of the information treatment in correcting interest rate misperceptions, in a similar approach to Bursztyn et al. (2019) and Grubb et al. (2024), we sent text messages detailing interest costs in dollar amounts to 5,000 randomly selected credit card holders in July 2024, as shown in Figure 6. These messages serve as a more salient form of information about interest costs than standard statements, as they are concise and

Table 9. Intent-to-Treat Effects of Text Alerts Only

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Debt	Spending	Necessities Spending	Luxuries Spending	Other Spending	Liquid Assets	Illiquid Assets
Treated	-315.75*** (71.51)	-32.98** (13.91)	49.74*** (11.95)	-76.39*** (15.18)	-6.33 (6.16)	12.21* (6.57)	218.99*** (10.61)
Constant	6689.75*** (976.47)	1674.61*** (199.77)	645.98*** (156.45)	536.67** (211.21)	491.96*** (87.91)	355.20*** (93.48)	305.95** (128.21)
Observations	5000	5000	5000	5000	5000	5000	5000
R^2	0.126	0.600	0.075	0.371	0.114	0.493	0.888
Baseline	2646.94	1055.47	442.58	460.84	152.06	16517.08	7766.62
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents the ITT effects of the information treatment. Baselines denote the pre-treatment averages. All columns include pre-treatment controls (omitted in the table) for interest rate, gender, age, education, assets, income, credit limit, and credit score. White robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

delivered proactively. The primary advantage of this design lies in its scalability, enabling the bank to deliver periodic reminders of borrowing costs with minimal effort. However, this simplicity comes at a cost: without explicit survey questions, we are unable to directly measure borrowers' perceived interest rates using this design. While this policy demonstrates potential as a debiasing tool for addressing excess borrowing caused by interest rate perceptions, it is important to note that it is neither the sole method available nor explicitly designed to improve welfare in a normative sense.

Table 9 presents the ITT effects of the text alerts on borrowing, spending, and assets. Importantly, there should be no measurement errors in the debt data as they were sourced from the credit registry. Consistent with previous findings, borrowers generally manifested excess borrowing, and this behavior appears to stem from mistakes rather than liquidity constraints. Three months post-treatment, borrowers had reduced their credit card debt by \$315.75, which is a 12% decrease compared to the pre-treatment average of the control group. This number is smaller than using the survey instrument, potentially because borrowers are

less attentive to text alerts.

To achieve the reduction in debt, borrowers cut back on spending rather than simply relying on savings to pay down high-interest debt. The ITT effect on monthly spending was -\$32.98, with most of the adjustments coming from fewer luxury and more necessity purchases. Additionally, there is still evidence that borrowers increased their illiquid assets by \$218.99 as a result of the information treatment.

A potential concern is that the text alert sent by the bank may have acted as a general reminder for borrowers to pay back their debt, prompting them to reduce borrowing independently of any changes in their perceived interest rates. Presumably, if the text treatment influenced debt levels primarily by reminding borrowers to make repayments or by altering the salience of debt rather than conveying new information, we would expect stronger effects among borrowers who had not recently received similar text reminders.

To examine this possibility, we analyze treatment effects separately for borrowers who received a text reminder to repay their debt within a week prior to our information treatment and those who did not. As shown in Table C8 in the Online Appendix, the treatment effects on debt and spending do not significantly differ between these two groups. Our heterogeneous effects (Table 5) also indicate that debt perception precision does not systematically influence the treatment effects, so the text reminder itself is unlikely to be a significant driver of the observed changes in borrowing behavior.

These findings also serve as a robustness check for the main results in Tables 3 and 6. While the observed effect sizes are slightly smaller—likely due to the exclusion of the interest rate perception survey, which may have reduced the salience of the information provided—the results consistently demonstrate that the text alert effectively alleviated borrowers’ subop-

timal borrowing decisions.

VII Conclusion

In this paper, we designed a survey to elicit consumer perceptions of the interest cost of credit card borrowing and conducted an RCT to evaluate the implications of interest cost misperceptions for behaviors. Our findings show that borrowers have noisy perceptions and on average underestimate the true interest costs. An information treatment aimed to enhance interest costs salience reduces errors in perceived interest costs and changes debt behavior significantly over a three-month period.

The results demonstrate that suboptimal borrowing caused by these misperceptions reflects a behavioral mistake driven by financial literacy rather than inaccurate awareness of debt levels or binding liquidity constraints. Although the short-term impact is substantial, a follow-up survey conducted nine months post-intervention indicates that the effect of the one-time information treatment diminished by approximately 40%.

To evaluate the effectiveness of a potential policy, we replicated the experiment using easy-to-scale text messages that disclosed the true monthly credit card debt interest rate. Our results indicate that these simple alerts led to a 12% reduction in average borrowing among debt holders over a three-month period. This approach presents a practical and cost-effective strategy for mitigating over-borrowing driven by interest rate misperceptions.

Our research points to several future avenues. First, we find that borrowers' perceptions of credit card interest rates are imprecise, which may stem from the often ambiguous presentation of debt costs in contract terms. Future studies could explore whether the de-

sign of contract terms impacts borrowing behavior. Second, our findings that reduced debt stemmed from lower luxury consumption and increased savings shed light on new aspects of household borrowing decisions beyond liquidity constraints. Future work might explore these determinants of debt in greater depth. Lastly, research could examine financial literacy in other contexts, such as mortgages, student loans, and term loans, where interest rates are presented with greater transparency.

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Online Appendix

for “Cost Misperception: The Impact of Misunderstanding Credit Card Debt Expenses”

A Survey

I First Round of Perceived Interest Rate Elicitation

Credit Card Usage Survey

The use of credit cards is one important channel for residents to make daily spending. To better understand the impact of credit cards on people’s livelihood, we randomly selected a certain number of active users of our bank’s credit cards to send out surveys. We hope to use this survey to study the spending and preferences of Chinese residents generally. Therefore, we will only focus on highly summarized information for scientific research purposes, such as the average value and so on. We will not disclose the personal information of the participants in any respect. We will not, to any extent, change the types of financial products we provide, including credit scores, credit limits, deposit rates, etc., based on the participants’ personal answers.

1. How much in total did you spend last month using the credit cards in our bank?
2. For the following questions, please consider your credit card with the *[bank name]*.^{A1}

Suppose your billing cycle is at the end of the month. For each of the following scenarios, please select the closest amount of interest that would be incurred at the end of next month. Consider the scenario that you start with no debt.

(a) You spend ¥5,000 this month and repay ¥0 at the end of this month

- 45
- 55
- 65
- 75
- 85
- 95
- 105

(b) You spend ¥5,000 this month and repay ¥1,000 at the end of this month

- 30
- 40
- 50

^{A1}For a specific borrower, *[bank name]* is the bank where they have accumulated the highest credit card debt. To minimize the anchoring effect, the order of choices presented to participants was randomized.

- 60
- 70
- 80
- 90

(c) You spend ¥5,000 this month and repay ¥3,000 at the end of this month

- 0
- 10
- 20
- 30
- 40
- 50
- 60

(d) You spend ¥5,000 this month and repay ¥5,000 at the end of this month^{A2}

- 0
- 10
- 20
- 30
- 40
- 50
- 60

3. How many banks do you use for daily transactions?

- 0
- 1
- 2
- 3
- 4 or more

^{A2}This question served as an attention and understanding check. All 1,219 consumers in our final sample who completed both waves of the survey passed this attention check.

The following information was revealed to random 40% of the participants.^{A3}

The annualized interest rate on your credit card with *[bank name]* is around X_1 . This rate is equivalent to a monthly interest rate of about X_2 . If you carry over ¥8,000 of debt on a credit card to the next billing cycle, then there will be around ¥ X_3 in interest rate in the next month.

^{A3}The number of treated consumers is restricted by the bank. We selected the best possible split to maximize statistical power.

4. Suppose your billing cycle is at the end of the month. If you spend ¥6,000 this month and repay ¥3,000 at the end of this month. How much interest in total would you incur at the end of the next month? Consider the scenario that you start with no debt.

- (a) 15
- (b) 25
- (c) 35
- (d) 45
- (e) 55
- (f) 65
- (g) 75

II Second Round of Perceived Interest Rate Elicitation

Credit Card Usage Survey

The use of credit cards is one important channel for residents to make daily spending. To better understand the impact of credit cards on people's livelihood, we randomly selected a certain number of active users of our bank's credit cards to send out surveys. We hope to use this survey to study the spending and preferences of Chinese residents generally. Therefore, we will only focus on highly summarized information for scientific research purposes, such as the average value and so on. We will not disclose the personal information of the participants in any respect. We will not, to any extent, change the types of financial products we provide, including credit scores, credit limits, deposit rates, etc., based on the participants' personal answers.

For the following questions, please consider your credit card with the *[bank name]*.

Suppose your billing cycle is at the end of the month. For each of the following scenarios, please select the closest amount of interest that would be incurred at the end of next month. Consider the scenario that you start with no debt.

(a) You spend ¥5,000 this month and repay ¥3,000 at the end of this month

- 0
- 10
- 20
- 30
- 40
- 50
- 60

(b) You spend ¥5,000 this month and repay ¥1,000 at the end of this month

- 30
- 40
- 50
- 60
- 70
- 80
- 90

(c) You spend ¥5,000 this month and repay ¥0 at the end of this month

- 45
- 55
- 65
- 75
- 85
- 95
- 105

B Additional Figures

Figure B1. Application Landing Page of Various Credit Cards

EARN CASH BACK EVERY DAY WITH CHASE FREEDOM®

CHASE FREEDOM UNLIMITED® **CHASE FREEDOM FLEXSM**

NO ANNUAL FEE!! **NO ANNUAL FEE!!**

APPLY NOW **APPLY NOW**

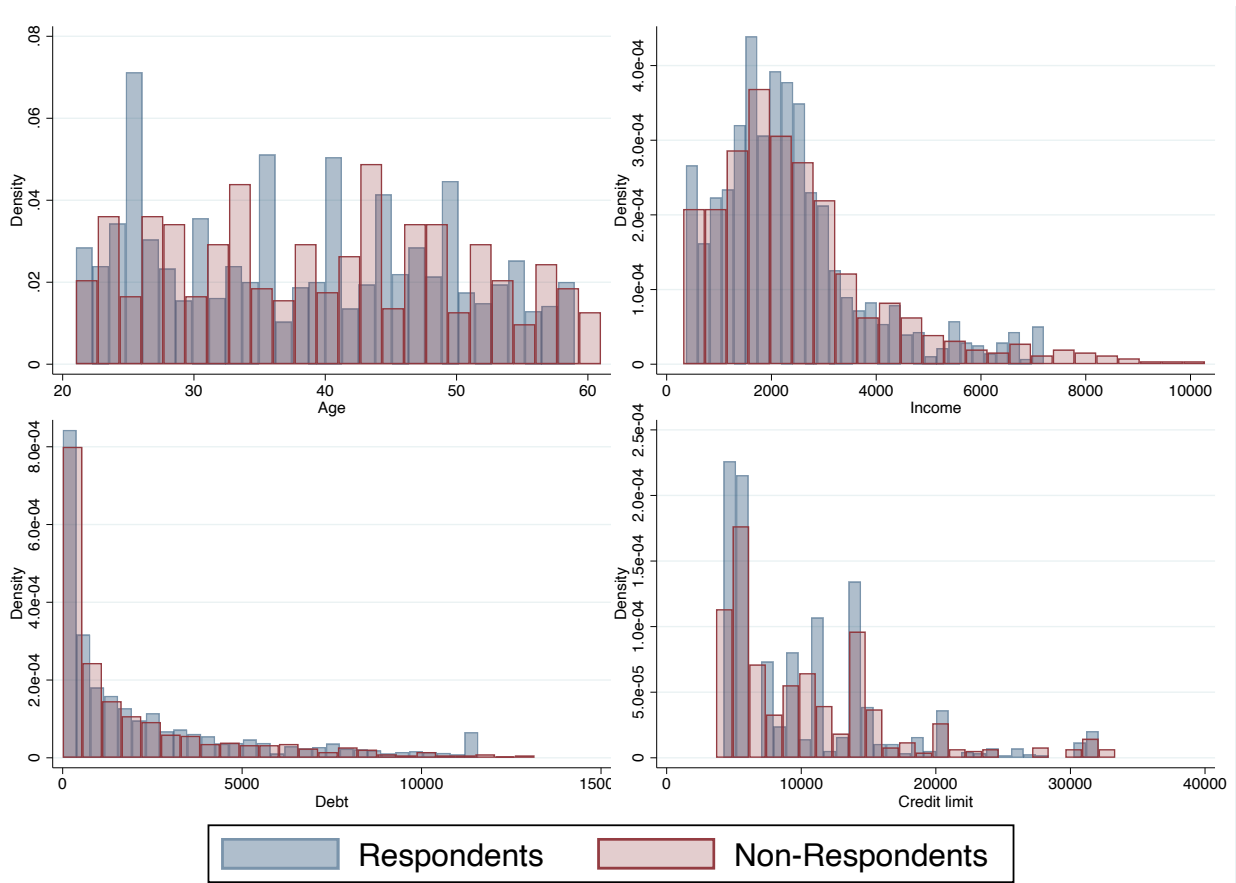
EARN \$200 **5% CASH BACK GROCERY STORE OFFER** **LOW INTRO APR**

HSBC Red Credit Card **HSBC Visa Signature Card**

Bank of America Customized Cash Rewards **WELLS FARGO SIGNIFY Business Card**

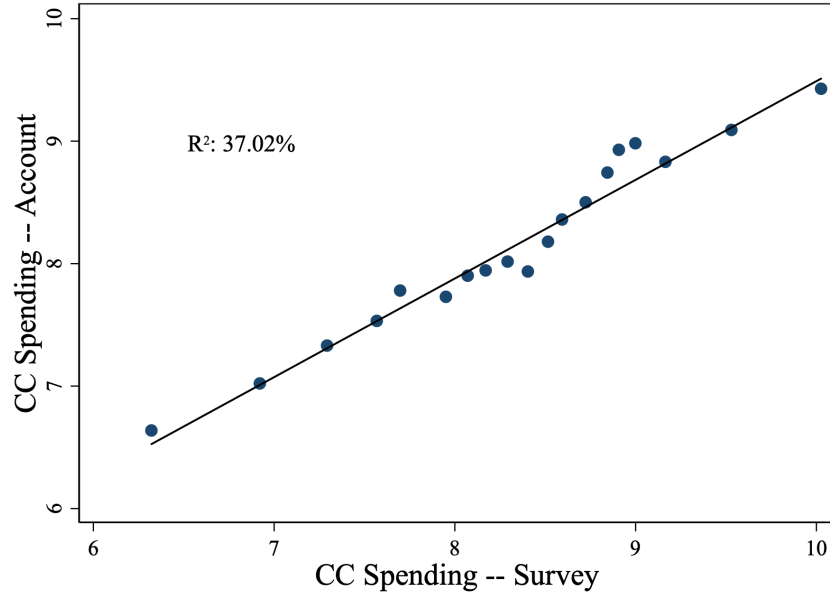
Note: This figure shows some examples of credit card advertisements on the official website application pages. The selective disclosure strategy shown may lead borrowers to misunderstand the true costs of credit card debt, potentially resulting in suboptimal debt levels.

Figure B2. Survey Respondents vs. Non-Respondents



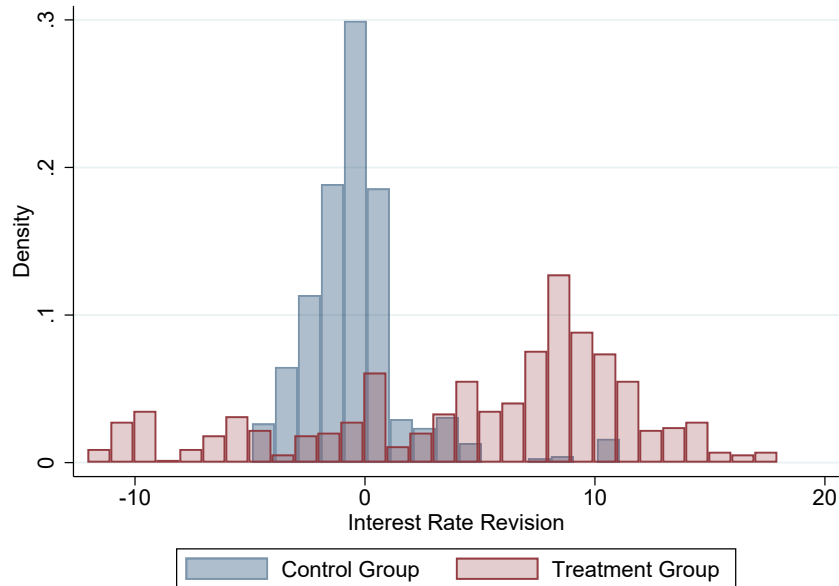
Note: The figure shows histogram plots comparing the distributions of age, income, debt, and credit limits between survey respondents and non-respondents to assess potential selection issues due to attrition. The distributions of all covariates appear similar across groups, suggesting limited selection bias. The mean and standard deviations (omitted in Table 1 in the main text) for non-respondents are as follows: age-39.47 and 11.01, income-\$2,528.81 and 1,687.19, debt-\$1,939.24 and 2,646.11, and credit limit-\$10,538.30 and 6,425.56.

Figure B3. Goodness of Fit of Reported Credit Card Spending on Administrative Data



Note: The figure includes a binned scatter plot of consumer spending from credit cards in the bank last month based on the bank account data and that from survey question 1, serving as a sanity check for the measurement of spending from the credit card. Both measures are in log values.

Figure B4. Perceived Interest Rate Revisions



Note: This figure plots the distribution of interest rate revision after our information treatment. The horizontal axis denotes the difference between the second and the first elicitation of consumer perceived debt interest rate. The red histogram represents the treatment group, while the blue represents the control group.

C Additional Tables

Table C1. Interest Rate Misperception and Borrower Characteristics

	(1)	(2)	(3)	(4)
	<i>Bias</i>	<i>Bias</i>	$ Bias $	$ Bias $
Education	3.31*** (0.21)	3.10*** (0.22)	-0.57*** (0.14)	-0.60*** (0.14)
Age	0.04** (0.02)	0.03** (0.02)	-0.07*** (0.01)	-0.05*** (0.01)
Female	1.37*** (0.36)	1.41*** (0.35)	0.31 (0.23)	0.27 (0.22)
Assets (Thousands)		0.03** (0.01)		-0.01** (0.01)
Income (Thousands)		0.22 (0.20)		-0.43*** (0.12)
Credit Limit (Thousands)		-0.11*** (0.03)		0.16*** (0.02)
Credit Score		-0.07*** (0.03)		-0.06*** (0.02)
Constant	6.84*** (0.76)	11.24*** (1.53)	10.56*** (0.53)	13.11*** (0.94)
Observations	1219	1219	1219	1219
R^2	0.18	0.20	0.05	0.13

Note: This table shows the association between perceived interest rates and other variables of all borrowers in our sample. White robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C2. Interest Rate Misperception and Debt

	(1)	(2)	(3)	(4)
	Debt	Debt	Debt	Debt
<i>Perceived r</i>	-166.00*** (11.25)	-141.35*** (12.29)		
Downward=0 \times <i>Perceived r</i>			31.12 (22.78)	54.47** (25.23)
Downward=1 \times <i>Perceived r</i>			-284.86*** (24.59)	-249.87*** (25.20)
Downward			6098.42*** (637.77)	5951.96*** (674.61)
Female		311.70** (153.90)		168.04 (150.88)
Age		-15.96** (6.93)		-12.71* (6.80)
Education		-232.32*** (88.16)		-294.54*** (85.83)
Assets		0.01** (0.01)		0.01*** (0.01)
Income		-0.16* (0.09)		-0.12 (0.09)
Credit Limit		0.10*** (0.01)		0.08*** (0.02)
Credit Score		4.54 (11.30)		15.86 (11.38)
Constant	4844.88*** (217.85)	4103.94*** (694.67)	95.03 (538.24)	-1081.43 (946.77)
Observations	1219	1219	1219	1219
R^2	0.15	0.22	0.19	0.25

Note: This table illustrates the association between credit card debt and perceived interest rates, alongside other covariates. Columns (1) and (2) present the regression fits of debt on the perceived interest rate for all borrowers, without and with control variables. In columns (3) and (4), we incorporate the interaction between a dummy variable, downward, indicating whether the consumer underestimates the interest rate and the perceived interest rate. White robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C3. Effects Using Interest Rate Misperceptions Elicited from Each Individual Survey Question

	(1)	(2)
	ITT Effect on <i>Perceived r</i>	IV Estimate of <i>Perceived r</i> on Debt
Question a	4.51*** (0.69)	-136.58*** (22.43)
Question b	6.62*** (0.50)	-139.86*** (22.13)
Question c	4.52*** (0.46)	-136.71*** (24.52)
Observations	1219	1219
Controls	Yes	Yes

Note: This table presents the main results based on perceived interest rates derived from each individual survey question a-c. White robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C4. 2SLS First Stage

	(1)	(2)
	<i>Perceived r</i>	<i>Perceived r</i>
<i>Perceived r^{prior}</i>	1.10*** (0.01)	1.08*** (0.01)
Treated	16.28*** (0.52)	16.25*** (0.53)
<i>Perceived r^{prior}</i> × Treated	-0.73*** (0.04)	-0.73*** (0.04)
Constant	-1.93*** (0.16)	-3.39*** (0.87)
Observations	1219	1219
R^2	0.73	0.74
Controls	No	Yes

Note: This table presents the OLS fit of the first stage, following Equation (3). Omitted control variables in column (2) include pre-treatment debt, gender, age, education, assets, income, credit limit, and credit score. White robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C5. 2SLS Estimates of Effect of Perceived Interest Rate on Debt: LATE

	(1)	(2)	(3)
	Debt	Debt (Downward Bias)	Debt (Upward Bias)
<i>Perceived r</i>	-126.41*** (24.56)	-131.42*** (20.03)	-135.65** (53.95)
Constant	3229.45*** (688.61)	3400.06*** (766.40)	3184.38*** (1158.26)
Observations	1219	899	320
R^2	0.18	0.16	0.09
First-Stage F	208.19	701.17	31.08
Controls	Yes	Yes	Yes

Note: This table reports the 2SLS fit of debt on perceived interest rates, where the treatment status is the IV for perceived interest rates in the first stage. The results in column (1) correspond to the entire sample, while columns (2) and (3) represent subsamples comprising only borrowers who underestimate and overestimate the interest rate, respectively. White robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C6. Three-Month Intent-to-Treat Effect of Information Treatment on Spending and Savings: borrowers Who Use Only One Bank

	(1)	(2)	(3)	(4)	(5)	(6)
	Spending	Liquid Assets	Illiquid Assets	Necessities Spending	Luxuries Spending	Other Spending
Treated	-231.480*** (52.364)	-1633.754** (798.940)	2115.396*** (297.764)	-19.698 (36.814)	-143.933*** (44.292)	-67.849* (39.614)
Constant	-181.493 (222.063)	1269.432 (3910.954)	-1126.292 (1313.011)	464.147*** (161.963)	-729.163*** (195.923)	83.523 (198.956)
Observations	832	832	832	832	832	832
R^2	0.586	0.649	0.685	0.086	0.408	0.132
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table studies the ITT effects of the experiment on behaviors for the borrowers who indicated using only one bank for daily transactions in the survey question. As a result, the ITT effects on spending and assets shall not be confounded with inter-bank transfers. White robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C7. Experience and Interest Rate Misperceptions

	(1)	(2)	(3)	(4)
	<i>Bias</i>	<i>Bias</i>	$ Bias $	$ Bias $
Experience	0.81*** (0.15)	0.48*** (0.18)	-0.65*** (0.09)	-0.45*** (0.11)
Female		1.49*** (0.35)		0.25 (0.22)
Age		0.05** (0.02)		-0.01 (0.01)
Education		3.11*** (0.22)		-0.60*** (0.13)
Assets (Thousands)		0.02* (0.01)		-0.01** (0.01)
Income (Thousands)		0.46** (0.20)		-0.45*** (0.12)
Credit Limit (Thousands)		-0.10*** (0.03)		0.16*** (0.02)
Credit Score		-0.06** (0.03)		-0.06*** (0.02)
Constant	-6.88*** (0.52)	-11.72*** (1.51)	9.16*** (0.29)	12.97*** (0.93)
Observations	1219	1219	1219	1219
R^2	0.02	0.21	0.04	0.14

Note: This table shows the relationship between years of credit card market experience and perceived interest rates without and with control variables. White robust standard errors are reported in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C8. Intent-to-Treat Effects of Text Reminders on borrowers with and without Payment Reminder

	Debt		Spending	
	(1) Reminder	(2) No Reminder	(3) Reminder	(4) No Reminder
Treated	-300.87** (119.41)	-323.83*** (89.47)	-21.59 (22.71)	-41.74** (17.68)
Constant	8439.88*** (1640.29)	5732.05*** (1219.01)	1856.01*** (339.98)	1587.62*** (246.80)
Observations	1872	3128	1872	3128
R^2	0.127	0.129	0.597	0.602
Controls	Yes	Yes	Yes	Yes

Note: This table provides a robustness check for Table 9 in the main text. Reminder refers to borrowers who received a text message reminding them to pay back their debt a week before the treatment, whereas No Reminder refers to those who did not receive such a message. The results indicate no significant differences in treatment effects between these groups, suggesting that the observed changes in financial behavior cannot be attributed solely to the reminder effect. All columns include pre-treatment controls (omitted in the table) for interest rate, gender, age, education, assets, income, credit limit, and credit score. White robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

D Calibration Procedure for Model of Interest Rate Learning And Forgetting

In this section, we describe the procedure to calibrate the model in Section V.G.

There are two stages of the estimation. In the first stage, we set σ_η^2 such that the average interest rate in our data is equal to the long-run average implied by the model. In addition, we set the initial value of the actual interest rate as 19.6% to match the sample average. We set the prior average as 11.05%, which is the average perceived interest rate for participants who enter the market within one year.

In the second stage, we use the Simulated Method of Moments (SMM) to estimate σ_ε , σ_0 and λ . Since we do not observe subjective uncertainties, we use the cross-sectional variance with a given year of experience as the subjective uncertainty. For example, σ_0^2 is set to be the cross-sectional standard deviation of absolute perception errors within one year of entering the market. This practice requires an assumption that perception errors do not depend on borrower characteristics other than experience. To absorb potential heterogeneity, we residualize absolute perception error by a saturated group of demographics. Similarly, σ_ε^2 and λ are set to match the cross-sectional standard deviation of absolute perception error and the rate of change nine months after receiving a signal about the true interest rate.

The targeted moments are the standard deviation of absolute perception errors in the first year after entering the market, the standard deviation of absolute perception errors four years after entering the market, and one minus the ratio of the 9-month and instant effects of the experiment on absolute perception errors. The intuition behind the relationship between targeted moments and estimated parameters is as follows. High σ_0 implies a high standard deviation of absolute perception errors right after entering the market. Both forgetting and signal precision affect the four-year standard deviation of absolute perception errors. Meanwhile, λ determines how fast the effects of the experiment decay, which sets one minus the ratio of the 9-month and instant effects of the experiment on absolute perception errors.

The SMM procedure searches for the set of parameters that minimize the weighted deviation between the actual and simulated moments,

$$(m - \widehat{m}(\Theta))' \widehat{W} (m - \widehat{m}(\Theta)) \tag{D1}$$

where \hat{W} is the variance-covariance matrix of the data moments. The calculation of the empirical moments is straightforward and is based on the main sample of analysis. The weight matrix \hat{W} adjusts for the possibility that some moments are more precisely estimated than others. We calculate \hat{W} as the inverse of the variance-covariance matrix of the empirical moments based on 1,000 bootstrap draws with replacements.

For simulated moments, given the optimal estimates of σ_ε , σ_0 , and λ , we simulate 1,000 individuals for a total of 20 periods (5 years). We then calculate the standard deviation of the absolute perception errors in periods 4 and 16 as the moments for the standard deviation of absolute perception errors one year and four years after entering the market.

To calculate one minus the ratio of the 9-month and instant effects of the experiment on absolute perception errors. We simulate the same 1,000 individuals again as a treatment group. For this group, we introduce an exogenous signal that is equal to the true interest rate in period 17. We then measure LR as the difference between the cross-sectional standard deviation in period 20 of the treatment group and that of the original sample, and SR as the difference between the cross-sectional standard deviation in period 17 of the treatment group and that of the original sample.

In the end, we calibrate the model by adjusting the targeted parameters in each moment calculation iteration. We minimize Equation (D1) by employing a global stochastic optimization routine.

The standard errors are obtained using the delta method and the empirical variance-covariance matrix. The formula for the variance-covariance matrix of the SMM estimators is

$$(G'W^{-1}G)^{-1} + (G'\tilde{W}^{-1}G)^{-1}.$$

The first term captures the error coming from the estimation of data moments, where W is the variance-covariance matrix of data moments. The second term comes from the noise when estimating the simulated moments. \tilde{W} is the variance-covariance matrix of moments in simulated moments. G is the Jacobian matrix around the SMM estimate.

We compute \tilde{W} by bootstrapping the simulated sample using SMM-estimated parameters. We start with simulated data (1,000 individuals for 500 periods). We then draw 1,000

individuals from this sample with replacement and compute the moments. We repeat this procedure 1000 times and use these 1000 sets of moments to compute the variance-covariance matrix \widetilde{W} .

We estimate G using the following technique. For the j^{th} parameter $\widehat{\theta}_j \in \{\widehat{\sigma}_\epsilon, \widehat{\sigma}_0, \widehat{\lambda}\}$, we simulate the model, holding the other parameter constant and change $\widehat{\theta}_j$ to $\widehat{\theta}_j + \iota$ and $\widehat{\theta}_j - \iota$. For this we obtain six new moments se_L , se_H , $s0_L$, $s0_H$, l_L , and l_H . Then the j^{th} column of G will be $[se_H - se_L, s0_H - s0_L, l_H - l_L]/(2\iota)$. We set $\iota = 0.001$ for estimating G .