Interest Rate Misperceptions in the Credit Card Market*

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Abstract

This paper investigates consumer misperceptions of credit card debt interest costs through a combination of administrative data, surveys, and randomized controlled trials. Our findings indicate that borrowers possess imperfect knowledge about the interest costs of unsecured debt, resulting in large debt accumulation. Rather than being driven by liquidity constraints, this over-borrowing appears to be a mistake mainly caused by spending on luxury goods. A simple text alert informing debtors of the true interest costs on their credit cards reduces credit card debt by over 10%.

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

Keywords: Randomized Controlled Trials, Survey, Beliefs, Interest Rates, Excess Borrowing.

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I Introduction

Credit cards and similar financial products are essential tools for households to acquire debts. 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 interest rates on 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.

In this paper, we first seek to understand whether borrowers have incomplete knowledge of the interest rates of credit card debts. Studying this relationship is challenging as it requires simultaneous observations of the true interest rate and perceptions about current interest rates on credit card debt. 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. Analyzing these perceived interest rates directly, we find that borrowers exhibit a wide range of perceptions regarding the interest rates associated with credit card borrowing. Despite an average effective annual interest rate of 20%, the perceived interest rates obtained from the survey question span from 5% to 35%, with an interquartile range of 9% to 20%.

[1] See 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.

[2] One 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 debt annual percentage rates (APR) are ambiguously presented in small font despite prominently highlighting benefits.

We next integrate the belief data 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 implement a randomized controlled trial (RCT) that provides 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 5.21 percentage points on perceived interest rates. Furthermore, the treatment significantly reduced the magnitude of perception errors, resulting in a 3.01 percentage point ATE on the absolute value of these errors.

Second, 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 only have limited needs for debt, therefore having little incentives to correct perception 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, unsecured debt for the treatment group decreased by approximately US \$446.86 three months after the experiment compared to the control group, representing a 19% reduction. This is equivalent to a decrease in borrowing by \$138.92 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 \$609.86 on average, accounting for 26% of the current debt level. 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.

To identify which borrowers might benefit most from debiasing interest rate misperceptions, we examine the heterogeneous effects of the information treatment on perceived interest rates and borrowing. Our findings indicate that borrowers with high debt-to-income ratios and those with lower educational attainment are more prone to over-borrowing due to interest rate misperceptions and would therefore benefit substantially from targeted policy interventions.

We continue to explore how borrowers react after learning about interest rate misperceptions. These behavioral responses will help us understand the implications of potential policy interventions for households' holistic financial behavior. Two possibilities exist: 1) consumption remains unchanged, with borrowers shifting from debt-financed spending to liquidity-financed spending, and 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 by 17% during 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. This is consistent with borrowers using illiquid assets as a commitment device for overspending (Laibson, 1997). These findings suggest that rather than facing liquidity constraints, suboptimal borrowing induced by interest rate misperceptions is likely to reflect the effects through which interest rate misperception affects total debt.

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 ITT effect of the information treatment on perceived interest rates depreciated by 42% 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 about 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 reduced interest rate misperceptions. Together with the finding that one-time information treatment only has transitory effects, limited attention to credit card accounts plus memory decay inhibit a full correction of these misperceptions. Using a calibrated model, we demonstrate that this persistent pattern of interest rate misperception can be generated by a simple mechanism where inattentive borrowers quickly forget information about interest rates. As a result, cumulative attention over time would not suffice for borrowers to quickly 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 suggest the channel of misperception, they can be a costly tool to address such widespread misperceptions. At the end of our analysis, we explore a more scalable policy intervention by conveying the same information through text messages to a different group of debtors without using surveys. This approach is similar to that of Bursztyn et al. (2019) and Grubb et al. (2024) and offers a scalable debiasing policy. Our results show that text messages disclosing the true interest costs, similar to the information provided in surveys, resulted in a 10% 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 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.). Our work is the first to directly measure biases in interest rate beliefs and assess their effects on debt behavior within the credit card market. The studies most closely related to ours are those by Ferman (2016), Seira et al. (2017), and Levi (2021) where RCTs were employed to assess the effectiveness of information disclosures in enhancing borrowers' awareness of credit card attributes and their financial decision-making. Building on this prior literature, which suggests the limited efficacy of information disclosures alone, our unique dataset linking belief elicitation with consumer-level transactions and an RCT sheds light on the underlying economic incentives driving these behaviors.

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), and Giglio et al. (2021) examined 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 Data

A Background

The 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 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 amount is mandated, amounting to 10% of the current outstanding balance. Beyond this minimum, borrowers may 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 approximately 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.

Like in many other countries (e.g., the U.S. and the U.K.), in China, credit card interest rates are advertised with annual percentage rate (APR), which is based on linear compounding. However, the actual interest costs incurred are based on the effective annual rate (EAR), which involves exponential compounding. For example, if a consumer carries over \$1 debt on a credit card with a daily interest rate of 0.05%, even if the APR for a year is $0.05\% \times 360 = 18.25\%$, the actual interest cost after a month is higher due to compounding: $1.0005^{365} - 1 \approx 20.16\%$.

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 annual percentage rates (APR) between 12.78% and 18.25%, or effective annual rates (EAR) of approximately 13.62% to 20.16%. These regulations were lifted in January 2021. However, this policy change had a negligible impact on the interest rates set by most national banks. Specifically, excluding any promotional rates, all customers from the bank during our sample period still had a daily interest rate of 0.05%.

Following regulations established by the People's Bank of China, the bank provides key terms, including interest rates (expressed as daily rates) and fees, during the application process to inform the borrowers about the cost structure of credit. Periodic account statements, which detail interest charges and outstanding balances, are delivered to clients via SMS reminders and can also be accessed through mobile banking apps and online platforms.

B Survey Design

We partnered with the bank to administer surveys to a randomly selected sample of customers. Given the focus of our study, we first limited the eligibility of respondents to those who had incurred positive debt within the past 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 the eligible debt holders, 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 only about 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

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

[4]See Online Appendix A for the English version of the survey.

respondents completed both waves, forming the final sample for our analysis.

In this paper, we focus on the EAR of credit card debt and use the survey to elicit borrowers' corresponding perceptions. 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 in a random order for belied elicitation:

> 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

To account for the possibility of participants simply adhering to rules of thumb when selecting their responses (such as consistently choosing the middle or last option), we implemented a randomization procedure for the sequence of choices presented to each participant.[5] Therefore, if participants consistently gravitated towards specific positions within the response list, the resulting responses would exhibit purely random patterns devoid of any systematic relationships.

We calculate borrowers' beliefs regarding credit card monthly interest rates using the following formula:

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

where x_1, x_2, and x_3 represent the choices for the three values of repayment. After converting to annualized rates, the misperception of credit card interest rates is then defined as $Bias_i = Perceived\ r_i - r_i$. If $Bias_i < 0$, it indicates that the perceived interest cost of credit card borrowing is lower than the actual value.[6]

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.

[5] We utilized survey question 1 to assess the quality of the responses. This question inquired about the participants' total spending via credit cards with the bank in the preceding month. Figure B2 in the Online Appendix illustrates a binned scatter plot depicting the logarithm of total credit card spending as measured by the bank versus the survey responses. Notably, the plot exhibits a discernible linear trend, with an R^2 value of 37.02%. Despite the inherent noise in the survey data, attributable to responses often being rounded to the nearest thousands or hundreds, the substantial R^2 value attests to the reliability of the responses.

[6] We verify our results by only using one of x_1, x_2, and x_3 in Section VB.

III Descriptive Analyses on Interest Rate Misperceptions

A Summary Statistics

Before proceeding to the main analysis, we first present some stylized facts relying on the pre-experiment data. Table 1 shows the summary statistics. The currency units are converted to US dollars (1 USD = 7.1 CNY) hereafter for comparability. A consumer's highest degree is coded as a categorical variable Education: 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 about the same as monthly income, but the interquartile range is notably wider. Despite accruing high-interest credit card debt, nearly 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 debts (Gross and Souleles, 2002; Telyukova, 2013; Gorbachev and Luengo-Prado, 2019; Gathergood and Olafsson, 2024). Approximately 57% 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 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 ($Bias_i$). 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.

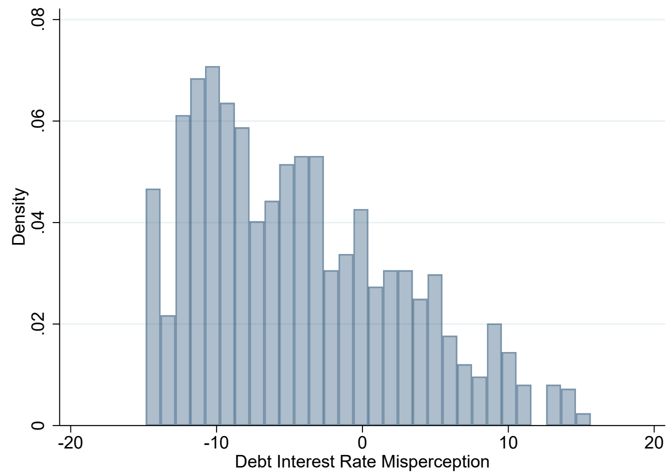
Note that our results do not indicate that credit card holders on average underestimate credit card interest rates. Since we only focused on borrowers, it is possible that credit card holders on average have a correct perception, while those who un-

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	2615.51	3198.70	2688.11	2991.80
Perceived r	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	19.53	1.16	19.42	1.13
Spending	1150.29	754.25	1538.49	1070.38	1540.13	973.64	1009.23	628.49	1116.03	640.24
Necessities Spending	482.82	509.48	624.87	593.72	676.77	593.59	421.88	460.92	469.68	498.64
Luxuries Spending	475.21	645.23	547.25	917.51	517.74	817.08	440.77	561.08	487.13	619.55
Other Spending	193.59	324.57	366.36	525.07	345.62	486.02	149.01	234.22	159.88	258.43
Credit Limit	10560.30	6494.90	10075.93	5687.62	10180.94	6901.14	10289.48	5580.08	11161.40	7606.60
Credit Score	55.17	7.79	55.04	7.76	54.80	7.71	55.28	7.74	55.16	7.88
Income	2359.33	1411.96	2324.77	1422.84	2371.24	1378.58	2260.18	1354.28	2497.02	1478.74
Assets	7951.53	14742.60	25998.72	25468.46	27213.04	25277.92	23179.40	20454.97	25729.73	21251.51
Liquid Assets	17063.67	16060.42	19066.15	19581.12	19605.84	18964.47	15624.06	14570.68	17686.45	15730.26
Illiquid Assets	7661.82	7931.71	6932.57	7535.63	7607.20	7905.73	7555.34	7853.52	8043.28	8142.92
Age	38.52	11.03	38.39	11.29	37.97	10.09	38.78	11.69	38.35	10.26
Female	0.56	0.50	0.59	0.49	0.55	0.50	0.59	0.49	0.52	0.50
Education	1.76	0.85	1.82	0.87	1.72	0.84	1.79	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.

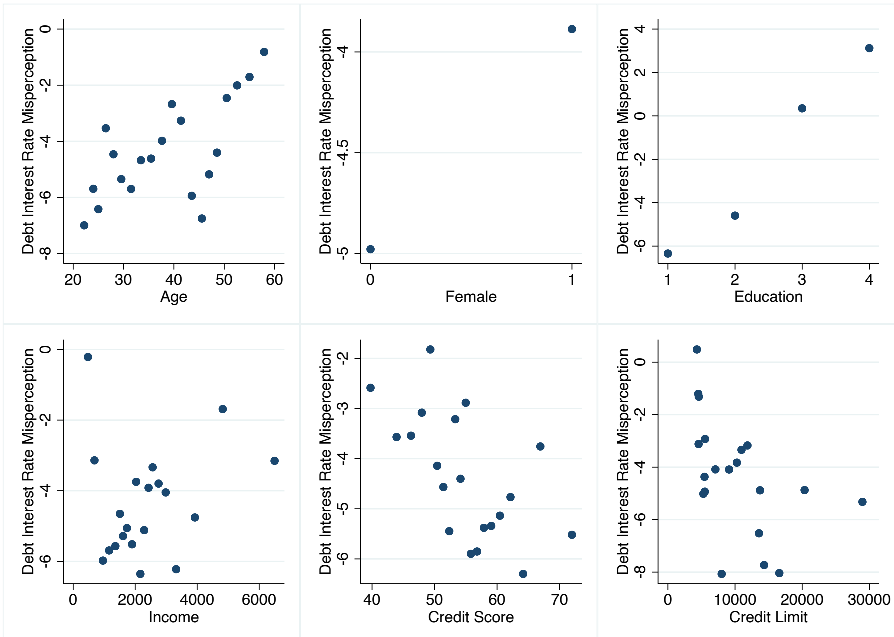
derestimate credit card interest rates end up taking positive debt.

B Static Patterns

We begin by examining how interest rate misperception co-varies 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 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

Figure 2. Perceived Credit Card Debt Interest Rates



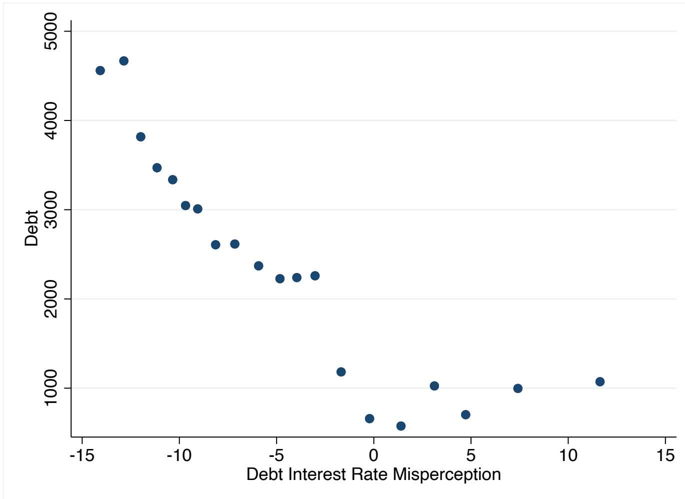
Note: This figure shows the correlation between the perceived interest rates elicited from the survey and covariate variables. Debt interest rate misperception is computed as the perceived interest rate minus the true interest rate, expressed in percentage points. Education levels are coded as follows: 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 debt 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 systematic 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

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.

perceived interest rate may be involved in simultaneous equation structures. For example, a positive coefficient of debt on perceived rate may reflect the law of demand, wherein a higher cost of borrowing reduces debt.

Identifying the causal effects of interest rate perception on borrowing behavior is challenging due to the difficulties of randomizing consumer beliefs. To address potential endogeneity issues, we implemented an information treatment for a randomly chosen subset of participants. Specifically, for random 40% of the participants, we revealed the following information:

> The annualized interest rate on your credit card 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.

where X_1, X_2, and X_3 are respectively the individual specific interest rates, monthly interest rate, and CNY amount of interest payment incurred given carrying over ¥8,000 for a month. To make sure participants do not use this question to answer pre-experiment questions, we revealed this information on a new page and borrowers cannot go back to previous pages to change answers.

After proving 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?
>
> 30
> 40
> 50
> 60
> 70
> 80
> 90

We strategically selected different spending and repayment levels from those presented in the survey questions before the treatment to prevent antagonizing the borrowers for asking the same questions multiple times. Note that using different questions to elicit posterior might induce systematically different answer due to, for example, rounding errors. However, such problems will also apply to the control group, which will be taken care of in the causal analysis.

Again, the order of the choices to elicit posterior expectations was randomized to alleviate the anchoring effect. 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 debts.

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.

Table 2. Perceived Interest Rate Revision

	Control		Treatment	
	(1)	(2)	(3)	(4)
	Before	After	Before	After
Bias	-4.39	-4.72	-4.32	0.62
	(0.27)	(0.31)	(0.29)	(0.26)
$\lvert Bias \rvert$	7.30	8.17	6.92	4.78
	(0.15)	(0.18)	(0.18)	(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.

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 bias and absolute bias of the perceived interest rates grouped by treatment status.[7] In the control group, borrowers exhibited minimal changes in their perceptions, with little revision observed between the perceived interest rates in our 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 predominantly 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. Specifically, we employ a difference-in-difference (DID) design. We estimate the following regression

[7] Figure B3 in the Online Appendix illustrates the distributions of perception revisions for the control and treatment groups, respectively.

equation:

$$y_i = \alpha + \beta_1 \mathit{Treated}_i + \beta_2 \mathit{After}_i + \gamma(\mathit{Treated}_i \times \mathit{After}_i) + \mathbf{X}_i'\theta + \varepsilon_i \tag{2}$$

where y_i is the variable of interest (i.e., perception errors, debt, etc.), $\mathit{Treated}_i$ is a dummy variable indicating consumer i's treatment status, and After_i is a dummy variable representing whether it is before or after our information treatment. The main parameter of interest, γ, captures the causal effect of the information treatment on the perceived interest rate. We also control for covariates $\mathbf{X}_i$, including 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 changes in borrowing behavior during the three months before (September, October, and November 2020) and after (December 2020, January, and February 2021) the treatment, both with and without covariates. Notably, the ITT point estimates remain the same regardless of whether covariates are included, with covariate adjustments improving estimation precision. This suggests the correct implementation of randomization in the experiment.

Columns (1) - (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 5.21 percentage points and reduced their perception errors by 3.01 percentage points. Reflecting this adjustment in perceptions, the treatment led to a reduction in average credit card debt of $446.86 over three months, representing a 19% decrease relative to the pre-treatment level.

Columns (3) - (4) present the results for borrowers who initially underestimated interest rates. On average, these borrowers increased their perceived interest rates by 8.36 percentage points following the information treatment, while their perception errors decreased by 3.53 percentage points. This adjustment was accompanied by a

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

	All		Downward Bias		Upward Bias	
	(1)	(2)	(3)	(4)	(5)	(6)
ITT Effect on *Perceived r*	5.21***	5.21***	8.36***	8.36***	-3.72***	-3.72***
	(0.56)	(0.52)	(0.44)	(0.41)	(0.79)	(0.75)
ITT Effect on $\|Bias\|$	-3.01***	-3.01***	-3.53***	-3.53***	-1.54**	-1.54**
	(0.34)	(0.33)	(0.38)	(0.36)	(0.67)	(0.65)
ITT Effect on Debt	-446.86**	-446.86**	-800.20***	-800.20***	556.99**	556.99**
	(223.44)	(210.68)	(277.71)	(261.84)	(251.72)	(239.26)
Observations	1219		899		320	
Baseline *Perceived r*	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 OLS estimates of a DID framework. Effects on perceived interest rates and absolute perception errors are obtained from the two rounds of belief elicitation before and after the information treatment. 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. Baselines denote the pre-treatment averages. Controls omitted in the table are gender, age, education, assets, income, credit limit, and credit score at the pre-treatment level. White robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

substantial reduction in credit card debt, with an average decline of $800.20.

Columns (5) - (6) show the results for borrowers with an ex ante upward perception bias. For this group, perceived interest rates increased by 3.72 percentage points, and absolute perception errors decreased by 1.54 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 $556.99.

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. Our specification follows Coibion et al. (2021), Coibion et al. (2024), and

Gorodnichenko and Yin (2024). The first stage is

$$\begin{aligned} \textit{Perceived } r_i^{post} = a + b_0 \textit{Perceived } r_i^{prior} + b_1 \textit{Treated}_i \\ + b_2 \textit{Perceived } r_i^{prior} \times \textit{Treated}_i + \mathbf{X}_i' w + e_i, \end{aligned} \tag{3}$$

and the second stage is

$$y_i = \alpha + \beta_0 \textit{Perceived } r_i^{prior} + \beta_1 \widehat{\textit{Perceived } r_i^{post}} + \mathbf{X}_i' \omega + \varepsilon_i. \tag{4}$$

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 (e.g., debt) on the fitted values derived from Equation (3). In both stages, we control for prior expectations, ensuring that the first-stage regression uses only the exogenous variation induced by the treatment.

Notably, the direction of changes in $\textit{Perceived } r_i$ post-treatment may violate monotonicity depending on whether prior expectations are upward- or downward-biased. Suppose we were to use only $\textit{Treated}_i$ as the IV, then if perception errors symmetrically surround zero and all participants update perceptions to the same degree, the first stage would yield no average effect on perception errors. For this reason, we instead employ $\textit{Treated}_i$ and the interaction term $\textit{Treated}_i \times \textit{Perceived } r_i^{prior}$ 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 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, increasing the significance in the first-stage regression. The

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

	All		Downward Bias		Upward Bias	
	(1)	(2)	(3)	(4)	(5)	(6)
Perceived r	-128.09***	-138.92***	-123.11***	-131.62***	-95.71***	-107.54***
	(22.85)	(22.57)	(21.41)	(21.16)	(31.29)	(32.50)
Constant	4734.02***	3263.87***	5474.59***	3758.53***	1489.97**	-1363.56
	(242.37)	(630.93)	(319.58)	(765.44)	(644.16)	(945.70)
Observations	1219	1219	899	899	320	320
R^2	0.13	0.18	0.11	0.16	0.09	0.22
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 are gender, age, education, assets, income, credit limit, and credit score. White robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

first-stage results are in online appendix Table C3.

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 towards the direction of the signal surprises. Results for this approach, detailed in Table C4 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-

[8]Table A4 in the Online Appendix presents the results of the first-stage regression, where $\widehat{\beta}_1 = -0.73$. This suggests that the information treatment substantially revised consumer perceptions of interest rates, indicating a strong first stage.

taking decision conforms to the law of demand: a one percentage point increase in the perceived interest rate decreases debt by \$138.92 controlling for covariates. Given an average interest rate of 19.49% and an average debt of \$2,329.84, this corresponds to an elasticity measure of -1.16.[9]

For comparison, our elasticity of debt to *perceived* interest rates closely aligns with the interest rate elasticity in the U.S. documented by Gross and Souleles (2002).[10] 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 $(-4.39) \times (-138.92) = \$609.86$ on average, representing approximately 26% 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, -131.62 for borrowers with negative perception errors and -107.54 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 instrumental variables in the estimation process.

Collectively, 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 misperception, the 26% reduction in debt in

[9] Since $Bias_i = Perceived\ r_i - r_i$, 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 interest rate elasticities.

[10] The 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 amounting to -112.6, which translates to elasticity of -1.3. Remarkably, these estimates closely resemble our 2SLS results.

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 effect of interest rate misperception on borrowing behavior, we question which borrowers would benefit more from interest rate debiasing. We illustrate this by showing the 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 five dimensions: borrowing levels, credit availability, wealth, financial literacy, and attention to borrowing status. Note that sample split across one characteristic is likely to correlate that across other characteristics, we view these results as suggestive.

Table 5 presents the heterogeneous effects of the information treatment across different subsamples, grouped by median values of debt-to-income ratios, credit utilization, and savings, labeled as high and low, respectively. The sample is also divided based on education level (college degree or not) and whether borrowers have set up autopay for credit card balances. 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

Table 5. Heterogeneous Responses to Information Treatment

	Debt-to-Income		Utilization		Savings		Education		Autopay	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	High	Low	High	Low	High	Low	College	Non-College	Yes	No
ITT Effect on *Perceived* r	7.02***	3.49***	5.49***	4.91***	6.57***	4.15***	2.99***	7.60***	5.91***	5.03***
	(0.64)	(0.75)	(0.76)	(0.68)	(0.77)	(0.69)	(0.72)	(0.68)	(1.12)	(0.58)
ITT Effect on Debt	-1093.79***	107.59	-404.92	-490.64*	-530.18	-390.01	-38.44	-862.88**	-330.95	-477.47**
	(321.40)	(82.97)	(306.33)	(284.13)	(325.09)	(270.76)	(238.16)	(359.26)	(477.44)	(234.06)
IV Est. of *Perceived* r on Debt	-173.08***	-47.88***	-157.91***	-125.06***	-147.53***	-122.39***	-121.33***	-159.42***	-161.02***	-135.85***
	(31.11)	(9.89)	(28.38)	(33.17)	(28.20)	(31.78)	(27.14)	(32.59)	(43.09)	(26.86)
Observations	609	610	609	610	556	663	666	553	359	860
Baseline *Bias*	-7.00	-1.73	-3.17	-5.55	-3.48	-5.19	-4.36	-6.36	-4.83	-4.24
Baseline Debt	4263.59	399.26	2324.94	2334.73	2510.96	2159.39	2329.84	2978.37	2548.38	2274.02
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table shows the heterogeneous effects for different subsamples split by median values of debt-to-income ratios, credit utilization, liquid savings, education, and enrollment for autopay. 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 gender, age, education, assets, income, credit limit, and credit score. White robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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 -$1,093.79 for high debt-to-income borrowers, compared to a statistically insignificant $107.59 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 $173.08 for high debt-to-income borrowers, compared to $47.88 for the low-ratio counterparts. Thus, borrowers with high debt levels tend to respond more to a more accurate perceived interest rate.

Columns (3) - (6) show no significantly different treatment effects based on liquidity measures, specifically credit utilization rates and liquid savings. Columns (7) and (8) divide the sample by education level, revealing that, post-treatment, borrowers without a college education reduced their debt by $862.88, whereas college-educated borrowers show only a modest and statistically insignificant reduction of $38.44. Lastly, columns (9) and (10) indicate that borrowers enrolled in autopay display slightly greater misperceptions about interest rates and are marginally more sensitive to perceived rate changes. However, the practice of paying down credit card balances manually does not seem to eliminate the misperception of interest rates.

Overall, the heterogeneous effects primarily manifest in 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 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. For example, if debtors have noisy perceptions about their total debt and the treatment prompts them to reassess their actual debt levels, the intervention could influence borrowing through changes in perceived total costs of current debt, rather than through perceived interest rates. If this is the case, we would expect borrowers who tend to have greater misperceptions about their debt to exhibit stronger reactions to the information treatment. This is not supported by our empirical results. From columns (9) and (10) of Table 4, debt sensitivities to perceived interest rates are very similar for those who have autopay and do not have autopay, and the difference is not statistically significant at the 10% level. Assuming that borrowers with autopay may have noisier perceptions about their debt levels than those without autopay, this observation suggests that the effects of the information treatment are unlikely to be driven by changes in perceptions of total debt costs.

Another potential mechanism concerns the possibility that simply reminding borrowers that credit cards are a costly debt instrument could prompt them to reduce debt usage, as suggested by Stango and Zinman (2014). However, as shown in Table 3, borrowers who underestimated interest rates before treatment increased their borrowing levels afterward. This pattern aligns with adjustments in their perceived interest rates, with similar sensitivities observed in Table 4. Specifically, 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 by simply reminding borrowers of the "painfulness" associated with borrowing.

Lastly, we consider whether limited mathematical ability among borrowers might play a role. Under this hypothesis, borrowers may understand interest rates but fail to accurately calculate interest for specific debt amounts. If true, we would expect borrowers with lower mathematical ability–proxied by lower educational attainment–to manifest greater interest rate elasticity of debt. However, our results do not support this hypothesis. Columns (7) and (8) Table 5 illustrate that while treatment effects on perceived interest rates differ significantly between borrowers with and without college degrees, the sensitivity of borrowing behavior to these perceptions remains similar and significant for both groups. This finding suggests that limited calculation ability is not a driving factor behind the observed treatment effects.

E Behavioral Responses to Correction of Interest Rate Misperceptions

How do borrowers adjust their consumption-saving pattern 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 \$254.91, representing a 16% decrease in the three months post-treatment. With debt decreasing by \$446.86, this translates to an asset increase of \$317.87. From columns (2) - (3). borrowers reduced liquid assets by \$1,224.61 and increased illiq-

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

	(1) Spending	(2) Liquid Assets	(3) Illiquid Assets	(4) Necessities Spending	(5) Luxuries Spending	(6) Other Spending
After × Treated	-254.91***	-1224.61*	1361.19***	-56.80	-184.32***	-13.79
	(53.10)	(740.00)	(345.80)	(44.55)	(51.28)	(45.14)
After	152.13***	668.49	-32.41	12.96	38.73	100.44***
	(33.08)	(491.89)	(221.34)	(29.87)	(33.83)	(28.70)
Treated	-28.86	-306.26	413.50*	44.69	-46.30	-27.25
	(27.41)	(273.24)	(233.58)	(32.62)	(33.28)	(29.11)
Constant	-144.63	-915.12	-1059.84	344.94***	-598.08***	108.51
	(120.44)	(1737.11)	(750.56)	(98.67)	(124.86)	(105.93)
Observations	2438	2438	2438	2438	2438	2438
R^2	0.66	0.78	0.69	0.09	0.46	0.08
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 OLS estimates of a DID framework. 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 gender, age, education, assets, income, credit limit, and credit score. White robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

uid assets by $1,361.19. 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 threshold amount. Finally, columns (4) - (6) show the changes in spending share on different categories.[11] We find that around 72% of consumption reduction originates from a decrease of $184.32 in luxury purchases.[12]

These findings together indicate that lower perceived interest rates reduce bor-

[11]The 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.

[12]Note that we used three questions to elicit prior beliefs to alleviate measurement errors. In Table C5, we verify that our results hold when using any one of these questions as the priors.

rowing through 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 interpretation 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 estimates 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

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	
Bias	-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)

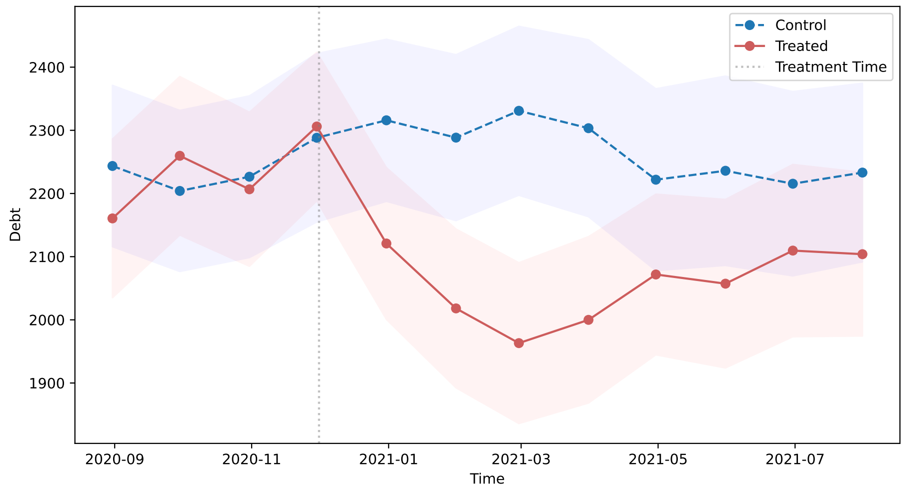
Note: This table shows the mean and absolute value of biases of the perceived debt interest rate before and nine months after the information treatment for the control and treatment groups, respectively. *Bias* is defined as the difference between the perceived debt interest and the true rate, whereas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

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 5.21 to 3.08 percentage points, while the effect on the absolute perception error decreases from -3.01 to -1.89 percentage points.

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,

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



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.

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

G Attention and Interest Rate Misperceptions

The participants in the study 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.

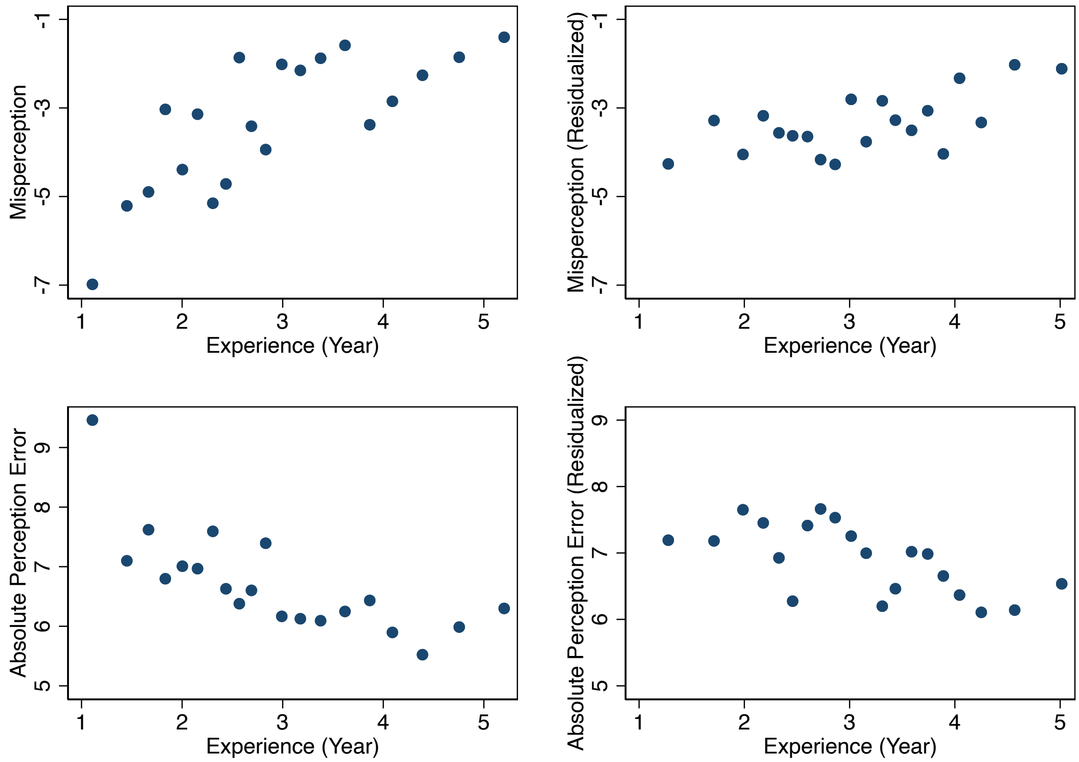
From the plots, there is a gradual trend toward higher and more accurate interest rate perceptions over time, but the speed of correction appears slow. A comparison between the left and right panels suggests that demographics primarily account for only initial misperceptions. However, even after five 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 $\widehat{r}_t$.

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 their mistakes but quick to forget corrections. To account for forgetting, we assume the borrower does not retain each signal in full.[13] Instead, her

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

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.

prior belief decays towards her belief from the previous period, $\widehat{r}_{t-1}$, 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

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

where $\widehat{r}_t^0$ 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

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

where κ_t is the Kalman gain in the Bayesian learning process.[14]

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 considerably noisy 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. 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. 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

[14] Note 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 $\widehat{r}_t = \widehat{r}_t^0 + \kappa_t \left(s_t - \widehat{r}_t^0\right) - m\kappa_t\varepsilon_t$. 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)

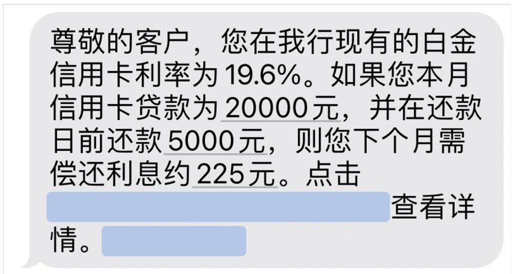
Note: This table presents the results of the calibration exercise. Panel A gives the targeted moments, and Panel B gives the parameters. SD(r_t) is the standard deviation of the true interest rate. 1-Y SD($|Bias|$) is the standard deviation of absolute perception errors in the first year of entering 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 absolution perception errors. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

inattention and forgetting closely aligns with our observed findings. It supports the mechanism that inattentive borrowers who quickly forget accumulated information retain persistent biases in their beliefs about interest rates. Consequently, simply gaining attention may not be sufficient to correct these misperceptions permanently, and periodic reminders of true borrowing costs may be necessary to consistently reduce these biases.

VI Text Alerts as a Debiasing 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.

Figure 6. Text Alert with Interest Costs in Dollar Amounts



Dear Customer, the current interest rate on your credit card at our bank is 19.6%. If your credit card debt this month is ¥20,000 and you make a repayment of ¥5,000 before the due date, the interest you will need to pay next month will be approximately ¥225 Click URL for details. [Bank Name].

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.

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. 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 \$276.62, which is a 10% decrease compared to the pre-treatment average of the control group. This number is smaller than using the

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

	(1) Debt	(2) Spending	(3) Necessities Spending	(4) Luxuries Spending	(5) Other Spending	(6) Liquid Assets	(7) Illiquid Assets
After × Treated	-276.62***	-31.13*	21.13	-49.72**	-2.54	9.25	206.41***
	(107.30)	(16.14)	(17.90)	(19.94)	(9.25)	(8.02)	(12.19)
After	154.57**	20.84**	-37.02***	55.56***	2.29	4.43	4.32
	(77.15)	(9.42)	(11.05)	(11.86)	(5.79)	(4.74)	(5.12)
Treated	-57.61	3.53	25.05*	-21.51*	-0.00	3.56	4.72
	(80.42)	(7.97)	(12.96)	(12.49)	(6.91)	(4.20)	(4.41)
Constant	5154.88***	1103.79***	863.82***	-13.64	253.62***	2.54	310.68***
	(758.65)	(121.40)	(123.57)	(148.30)	(67.04)	(60.46)	(76.90)
Observations	10000	10000	10000	10000	10000	10000	10000
R^2	0.14	0.68	0.08	0.40	0.08	0.61	0.94
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 OLS estimates of a DID framework. 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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 -$31.13–a 3% reduction relative to the control group average–with most of the reduction coming from fewer luxury purchases. Additionally, there is still evidence that borrowers increased their illiquid assets by $206.41 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 our text treatment changed debt level by reminding the borrowers about repaying debt or served as any shocks that changed the salience of debt other than the information content, then we would expect the results to be stronger for those who have not recently received any similar text. To address this concern, we analyze the treatment effect separately for borrowers who had received a text reminder to repay their debt within a week before our information treatment versus those who did not. As shown in Table C8 in the Online Appendix, although the statistical significance generally becomes smaller due to smaller sample sizes, the treatment effects do not significantly differ between these two groups. This indicates that the reminder itself does not seem to be a significant driver of the observed changes in behaviors.

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' suboptimal 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 rate misperceptions for behaviors. Our findings show that borrowers have noisy perceptions and on average underestimate the true interest rates. An information treatment aimed to enhance interest rate salience reduces errors in perceived interest rates and changes debt behavior significantly over a three-month period. However, a follow-up survey nine months post-intervention reveals that the effect of the one-time information treatment decreased by approximately 40%.

To assess the effectiveness of a potential policy, we replicate the experiment with easy-to-scale text messages informing the true monthly credit card debt interest rate. We demonstrate that those simple text alerts decreased average borrowing among debt holders by around 10% over a three-month period. This approach, therefore, offers a feasible intervention to mitigate over-borrowing by interest rate misperception.

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 design 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 "Interest Rate Misperceptions in the Credit Card Market" by Tianyu Han and Xiao Yin

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. 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
       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[A1]

0
10
20
30
40
50
60

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

0
1
2
3
4 or more

[A1] This question is used as an attention and understanding check. We excluded borrowers who failed to answer this question correctly.

The following information was revealed to random 40% of the participants.

The annualized interest rate on your credit card 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.

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.

> 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

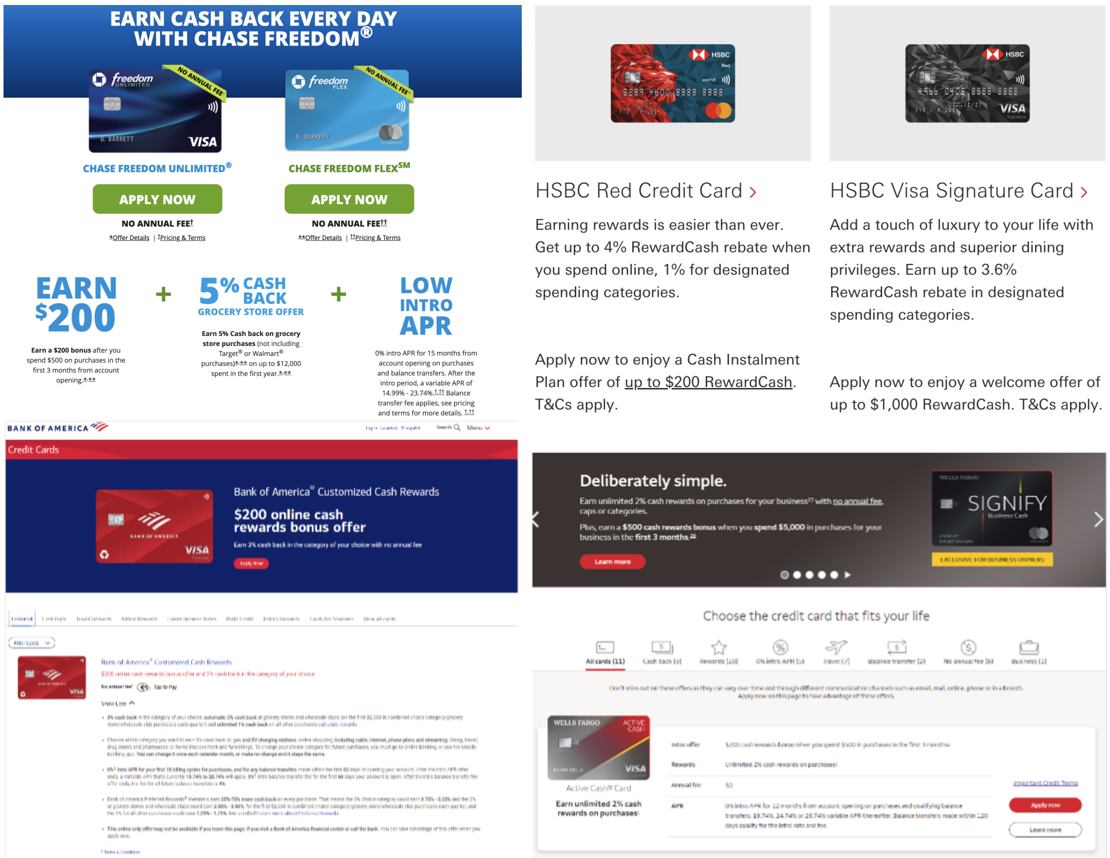
(c) You spend ¥5,000 this month and repay ¥0 at the end of this month

45
55
65
75

85
95
105

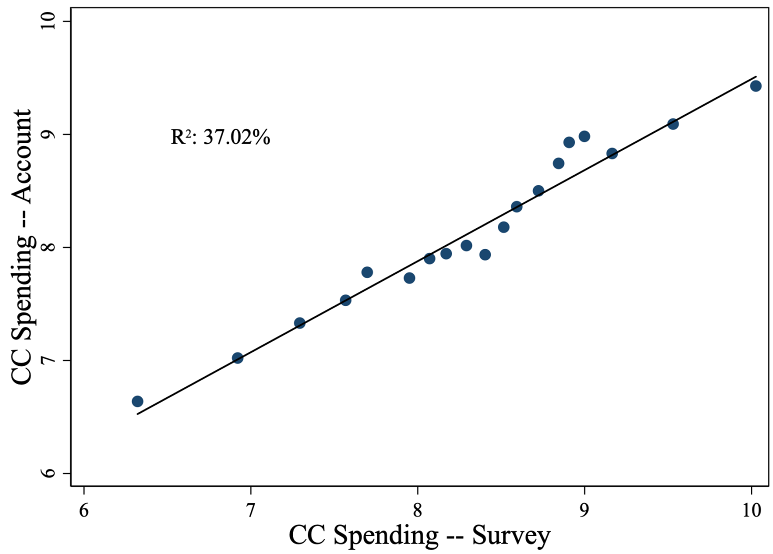
B Additional Figures

Figure B1. Application Landing Page of Various Credit Cards



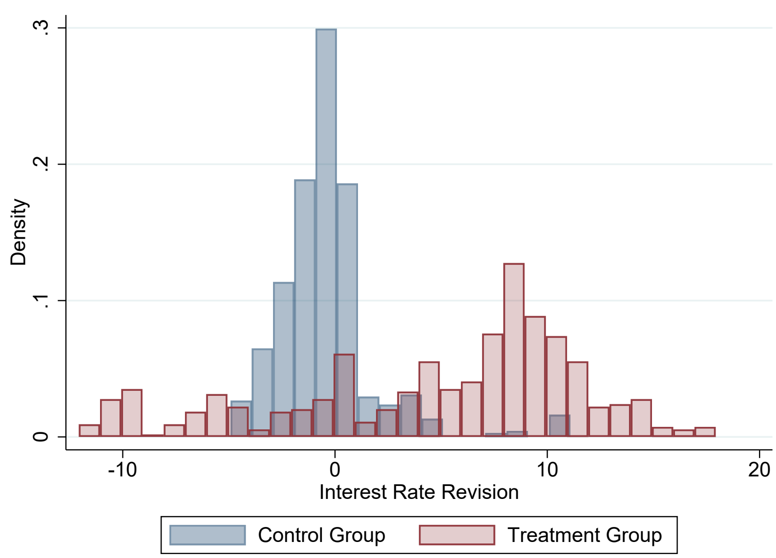
Note: This figure shows some examples of credit card advertisements on the official website application pages. The selective disclosure strategy shown may lead borrowers to misunderstand the true costs of credit card debt, potentially resulting in suboptimal debt levels.

Figure B2. 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 B3. 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)
	Bias	*Bias*	$\|Bias\|$	$\|Bias\|$
Education	3.31***	3.10***	-0.57***	-0.60***
	(0.21)	(0.22)	(0.14)	(0.14)
Age	0.04**	0.03**	-0.07***	-0.05***
	(0.02)	(0.02)	(0.01)	(0.01)
Female	1.37***	1.41***	0.31	0.27
	(0.36)	(0.35)	(0.23)	(0.22)
Assets (Thousands)		0.03**		-0.01**
		(0.01)		(0.01)
Income (Thousands)		0.22		-0.43***
		(0.20)		(0.12)
Credit Limit (Thousands)		-0.11***		0.16***
		(0.03)		(0.02)
Credit Score		-0.07***		-0.06***
		(0.03)		(0.02)
Constant	6.84***	11.24***	10.56***	13.11***
	(0.76)	(1.53)	(0.53)	(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) Debt	(2) Debt	(3) Debt	(4) Debt
Perceived r	-166.00***	-141.35***		
	(11.25)	(12.29)		
Downward=0 × *Perceived r*			31.12	54.47**
			(22.78)	(25.23)
Downward=1 × *Perceived r*			-284.86***	-249.87***
			(24.59)	(25.20)
Downward			6098.42***	5951.96***
			(637.77)	(674.61)
Female		311.70**		168.04
		(153.90)		(150.88)
Age		-15.96**		-12.71*
		(6.93)		(6.80)
Education		-232.32***		-294.54***
		(88.16)		(85.83)
Assets		0.01**		0.01***
		(0.01)		(0.01)
Income		-0.16*		-0.12
		(0.09)		(0.09)
Credit Limit		0.10***		0.08***
		(0.01)		(0.02)
Credit Score		4.54		15.86
		(11.30)		(11.38)
Constant	4844.88***	4103.94***	95.03	-1081.43
	(217.85)	(694.67)	(538.24)	(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 debts 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) - (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. 2SLS First Stage

	(1)	(2)
	Perceived r	*Perceived r*
Perceived r^{prior}	1.10***	1.08***
	(0.01)	(0.01)
Treated	16.28***	16.25***
	(0.52)	(0.53)
Perceived r^{prior} × Treated	-0.73***	-0.73***
	(0.04)	(0.04)
Constant	-1.93***	-3.39***
	(0.16)	(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 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 C4. 2SLS Estimates of Effect of Perceived Interest Rate on Debts: LATE

	(1)	(2)	(3)
	Debt	Debt (Downward Bias)	Debt (Upward Bias)
Perceived r	-126.41***	-131.42***	-135.65**
	(24.56)	(20.03)	(53.95)
Constant	3229.45***	3400.06***	3184.38***
	(688.61)	(766.40)	(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 C5. Effects Using Interest Rate Misperceptions Elicited from Each Individual Survey Question

	ITT Effect on *Perceived r*			IV Estimate of *Perceived r* on Debt		
	(1)	(2)	(3)	(4)	(5)	(6)
	All	Downward Bias	Upward Bias	All	Downward Bias	Upward Bias
Question a	4.51***	7.65***	-4.45***	-136.58***	-133.65***	-99.46***
	(0.69)	(0.53)	(1.02)	(22.43)	(22.13)	(32.03)
Question b	6.62***	9.64***	-1.88**	-139.86***	-134.11***	-181.21***
	(0.50)	(0.44)	(0.76)	(22.13)	(18.68)	(56.47)
Question c	4.52***	7.83***	-4.77***	-136.71***	-126.68***	-102.60***
	(0.46)	(0.40)	(0.70)	(24.52)	(22.00)	(31.89)
Observations	2438	1798	640	1219	899	320
Controls	Yes	Yes	Yes	Yes	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 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
After × Treated	-194.63***	-1190.12	1551.36***	-47.84	-90.90	-55.89
	(61.30)	(877.03)	(402.19)	(54.07)	(59.57)	(53.03)
After	126.52***	633.56	-88.45	3.92	-7.52	130.12***
	(38.18)	(577.54)	(265.42)	(36.36)	(39.34)	(36.35)
Treated	-32.12	-436.58	575.48**	29.72	-52.91	-8.93
	(31.89)	(320.87)	(273.06)	(39.94)	(39.78)	(36.54)
Constant	-83.30	766.76	-1050.58	509.39***	-644.76***	52.06
	(132.65)	(2021.40)	(906.35)	(117.50)	(131.26)	(126.85)
Observations	1664	1664	1664	1664	1664	1664
R^2	0.68	0.79	0.72	0.09	0.49	0.08
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table studies the ITT effects of the experiment on borrower 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) *Bias*	(2) *Bias*	(3) $\|Bias\|$	(4) $\|Bias\|$
Experience	0.81***	0.48***	-0.65***	-0.45***
	(0.15)	(0.18)	(0.09)	(0.11)
Female		1.49***		0.25
		(0.35)		(0.22)
Age		0.05**		-0.01
		(0.02)		(0.01)
Education		3.11***		-0.60***
		(0.22)		(0.13)
Assets (Thousands)		0.02*		-0.01**
		(0.01)		(0.01)
Income (Thousands)		0.46**		-0.45***
		(0.20)		(0.12)
Credit Limit (Thousands)		-0.10***		0.16***
		(0.03)		(0.02)
Credit Score		-0.06**		-0.06***
		(0.03)		(0.02)
Constant	-6.88***	-11.72***	9.16***	12.97***
	(0.52)	(1.51)	(0.29)	(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		Necessities Spending		Luxuries Spending		Other Spending		Liquid Savings		Illiquid Assets	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Reminder	No Reminder	Reminder	No Reminder	Reminder	No Reminder	Reminder	No Reminder	Reminder	No Reminder	Reminder	No Reminder	Reminder	No Reminder
After × Treated	-324.53*	-252.20*	-27.22	-33.41*	11.57	26.22	-44.56	-53.13**	5.77	-6.50	9.50	9.04	190.12***	214.47***
	(185.65)	(131.42)	(27.92)	(19.77)	(30.97)	(21.92)	(33.89)	(24.61)	(15.58)	(11.46)	(13.41)	(10.00)	(21.39)	(14.81)
After	179.48	142.61	23.93	19.34*	-25.77	-42.77***	48.58**	59.40***	1.12	2.71	11.18	1.00	11.28	1.02
	(135.53)	(93.84)	(15.94)	(11.67)	(18.96)	(13.59)	(20.30)	(14.57)	(9.42)	(7.29)	(8.05)	(5.86)	(8.88)	(6.26)
Treated	19.10	-96.95	16.67	-3.61	45.48**	14.33	-33.60	-15.28	4.78	-2.67	2.95	3.78	9.46	2.83
	(140.51)	(98.11)	(13.81)	(9.75)	(22.17)	(15.95)	(21.49)	(15.27)	(11.59)	(8.59)	(7.28)	(5.14)	(7.66)	(5.42)
Constant	6057.94***	4693.75***	1184.92***	1069.33***	842.55***	879.86***	242.17	-141.62	100.20	331.09***	-57.05	34.26	490.05***	219.84**
	(1341.92)	(919.96)	(217.21)	(146.29)	(218.46)	(149.44)	(265.82)	(178.07)	(115.80)	(82.23)	(100.59)	(75.62)	(135.27)	(93.78)
Observations	3374	6626	3374	6626	3374	6626	3374	6626	3374	6626	3374	6626	3374	6626
R^2	0.14	0.15	0.68	0.69	0.07	0.09	0.43	0.39	0.07	0.09	0.62	0.61	0.93	0.94
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	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 absolution 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 precisions 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 absolution 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 $\widehat{W}$ adjusts for the possibility that some moments are more precisely estimated than others. We calculate $\widehat{W}$ 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 absolution 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

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

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. $\widetilde{W}$ is the variance-covariance matrix of moments in simulated moments. G is the Jacobian matrix around the SMM estimate.

We compute $\widetilde{W}$ 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 $\widehat{\theta}_j \in \left\{\widehat{\sigma}_\epsilon, \widehat{\sigma}_0, \widehat{\lambda}\right\}$, 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.