Interest Rate Misperception and Excess Borrowing in the Consumption Credit Market*

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Abstract

We elicit consumer perceptions about the interest rate associated with credit-card borrowing. Combining bank account data and surveys, we find that consumers have very noisy perceptions about the true interest costs associated with credit card debt. Total borrowing decreases with perceived interest rates only for those with negative perception errors. Using an information treatment that informs the true costs of credit-card borrowing, we find that every percentage point decrease in the perceived rate increases borrowing by 143.1 US dollars.

Keywords: Excess Borrowing, Expectations, Randomized Controlled Trials, Shrouded Attributes.
JEL codes: G40, G51, G53, E21.

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1 Introduction

Consumers often take on large amounts of debt to smooth consumption inter-temporally, and the optimal level of debt critically depends on the associated costs. Recent literature documents that consumers usually have various behavioral biases, inducing them to make sub-optimal leverage decisions (Meier and Sprenger, 2010; Stango and Zinman, 2009; Bertrand and Morse, 2011). While there is rich literature explaining excess debt-taking based on consumers having non-traditional preferences or heterogeneous levels of financial literacy, less research directly studies how consumer beliefs about the marginal cost of debt causally affects borrowing. This paper focuses on the credit card market and studies consumers' perceptions about the marginal costs of consumption debt.

The credit card is an important tool for households to take on debt. For example, from the 2019 Survey of Consumer Finance, around 40% of US families carry credit card debts of an average of around 6,000 US dollars. Understanding borrower incentives in the credit card markets is important in analyzing household debt-taking behaviors. A specialty of credit cards is that generally they are not viewed solely as a loan vehicle. Particularly, credit cards are usually advertised as a financial product with high quality (e.g., high values of cash back and the like) but very obscure costs. Take a credit card issued by the Chase Bank as an example; at the credit card application web page shown in Figure 1, the quality-associated aspects are very salient. Consumers can earn introductory bonus points worth 200 dollars and 5% cash back when purchasing certain types of products. However, the price, or the annual percentage rate (APR) of the debt interest rate, appears to be evasive: other than a vague description of being "low" with a very small font size, no specific number associated with interests on borrowing is boxed in the figure. Given the selective disclosure strategy[1], consumers might perceive the true costs of credit card debt with noises, thereby having suboptimal level of debt. For example, a recent survey by Bank Rate (Johnson, 2022) finds that more than 40% of the credit card holders in the US do not know their cards' interest rates. Therefore, a natural question is how common it is for consumers to misperceive the interest-related costs associated with their credit cards, and whether interest rate misperception would affect their borrowing behaviors.

We combine consumer bank account and survey data to study the effects of interest rate misperception on credit-card borrowing. The data is from a large commercial bank in China

[1]See Ru and Schoar (2016) for a discussion that banks may strategically shroud unappealing features such as high APRs in credit card offers.

that operates nationally and is among the top 10 commercial banks as ranked by total assets. We first document whether consumers know the true interest rate of credit-card borrowing. We infer consumer beliefs through a survey directly administered by the bank. The key variable we are interested in is the consumer's perceived interest rates on credit card debt. As consumers may not intuitively understand a percentage value, we directly elicit the customers' belief about the interest incurred before the next billing cycle when a certain amount of credit is borrowed from the credit card but only a portion is repaid before the end of the current billing cycle. We find that consumers have a very heterogeneous perception about the interest rate associated with credit-card borrowing. In China, the interest rate associated with credit cards during our sampling period is five basis points for all participants (approximated 20% annualized). However, the perceived interest rates based on the survey question range from 5% to 35% with a inter-quartile range of 12.7% to 21.9%.

We then observe a significant cross-sectional relationship between borrowing and perceived interest rate. Specifically, for each percentage point (ppt) of lower perceived APR, debt is more than 60.8 dollars higher. Additionally, the negative relationship seems to hold only if consumers have a negative perception bias. Particularly, conditional on having a negative perception bias in the APR (i.e., perceived interest rate being smaller than 20%), each ppt of lower perceived APR is associated with more than 141.3 dollars higher credit card debt. On the other hand, conditional on making a positive perception bias, perceived APR does not seem to co-vary with the level of debt.

The asymmetric relationship between perceived interest rates and debt-taking behavior indicates that consumer perception errors towards interest rates have first-order effects in the aggregate. Specifically, borrowers have different levels of inattention, and those who perceive debt as cheaper would take more debt. However, those who perceive debt as more expensive would not take less debt. Hence, apart from debt misallocation, consumer inattention to interest rate also induces excess aggregate borrowing. The empirical results reveal a strongly positive relationship between the absolute value of perception errors and borrowing. Specifically, consumers with one ppt higher absolute error on average have around 92.9 dollars higher debt.

The ordinary least square (OLS) estimates of the relationship between perceived interest rate and borrowing suffer from potential endogeneity problems. For example, suppose consumers have motivated reasoning, they would choose to believe that the costs of debt are lower when they take on more debt. In this case, regressing debt on perceived interest rate would have reverse causality. Besides, unobserved individual characteristics might simultaneously increase consumer-borrowing and decrease perceived interest rates. To cope with these problems, we design a randomized controlled trial (RCT) that informs about the true interest costs of credit card debt. The information treatment seeks to signal the true effective debt interest rate on credit card. Specifically, after eliciting consumer perception about the interest rates, for a random 40% of debt-takers in our sample, we disclose the following information:

> *The annualized interest rate on a credit card is around 20%, which is equivalent to a monthly interest rate of about 1.51%. If you carry over 8,000 CNY of debt on a credit card this month, then you will incur around 120.8 CNY in interest rate in the next.*

We then elicit the perceived interest rates of all debt-takers using a question similar to our main elicitation strategy. The difference between borrowers' answers before and after the experiment provides the causal effects on borrowers' expectations of providing them with the true interest rate costs.

The information treatment has large instantaneous effects on borrowers' perceived interest rates. After seeing the information, borrowers in the treatment group revised their perception errors from -4.2% to 0.3%. For those in the control group, the perception errors before and after the experiment were, respectively, -4.6% and -5.0%. This value indicates a difference-in-differences (DID) estimate of the information treatment of 4.9% on the perception errors. The experiment also had large effects on the absolute perception errors of the treated borrowers. After seeing the information, the absolute perception errors of the treatment group reduced from 6.81% to 4.58%, compared with an insignificant change from 7.2% to 8.1% for the control group. This value indicates a DID estimate of the information treatment of 3.0% on the absolute perception errors.

We then use the experiment to estimate consumer debt responses to an exogenous change in perceived interest rate. Using the experiment as an instrumental variable for interest rate perception, we find that debt decreases by 143.1 dollars three months after the experiment for each ppt increase in perceived interest rate. Similarly, using the experiment as an instrument for absolute perception errors, we find that a one-ppt decrease in absolute perception errors reduces debt by around 227.4 dollars. Total debt for the treatment group decreased by around 696.3 dollars three months after the experiment, as compared to the control group. Splitting debt into different categories, we find that treated borrowers mainly decreased their debt on non-durable goods that have high demand elasticities.

One possibility for decreased debt is that borrowers do not reduce spending but substitute spending financed with debt by drawing down liquidity. We find that the borrowers indeed substituted debt by drawing down saving to some extent, however, the degree of substitution is relatively small. Specifically, for each ppt increase in perceived interest rate, debt decreases by 143.1 dollars three months after the experiment, and spending decreases by 184 dollars over three months cumulatively. At the same time, liquid saving increases by 257.8 dollars. Therefore, for each ppt increase in perceived interest rate, around 70 dollars of spending is substituted from debt-financed to liquidity-financed.

We conclude our analysis by analyzing the long-run effects of the experiment. The experiment served as a one-time shock to consumers' beliefs. However, consumers in the consumption debt market are observed to very quickly forget the newly-learned information (Agarwal et al., 2013). Therefore, in the long run, the perceived interest rate of the treated borrowers might revert to their original values. We measure the long-run effects of the experiment with a followup survey of the same participants 12 months after the experiments. We find evidence that the experiment had long-run effects, but the effects were much smaller compared to the shorter-run effects. Specifically, 12 months after the experiment, the average perception errors of the treated borrowers dropped to -2.6%. For those in the control group, the average perception errors 12 months after the experiment were -4.8%. This value indicates a DID estimate of the information treatment on the perception errors of 1.8% over 12 months. The estimate was only around 37% of the instantaneous effects. The findings are similar for the absolute perception errors. After 12 months of the experiment, the average absolute perception errors of the treated borrowers dropped to 4.7%. For those in the control group, the average perception errors 12 months after the experiment were 7.3%. This value indicates a DID estimate of the information treatment on the perception errors of -2.2% over 12 months, which was around 73% of that over three months.

Related Literature This paper is mainly related to three strands of literature. First, it contributes to the study of how consumer behavioral biases affect consumer borrowing decisions (Stango and Zinman, 2009; Meier and Sprenger, 2010; Laibson et al., 2020; Bertrand and Morse, 2011; Allcott et al., 2021; Kuchler and Pagel, 2021)[2]. While most existing studies focus on non-traditional preferences or financial literacy, we contribute to this strand of literature by combining survey data, transaction-level data, and an RCT to directly test the effects of

[2]See Beshears et al. (2018) for a review.

biased beliefs on consumer-borrowing. The study closest to ours is Bertrand and Morse (2011). Specifically, Bertrand and Morse (2011) rely on observational data to test different types of information disclosure on the take-up of pay-day loans. Our study, on the other hand, collects a panel of consumer beliefs and directly studies how information disclosure about the costs of debt changes consumers' beliefs. Additionally, our questions about the one-month costs of debt speak to the findings that borrowers misperceive the costs of debt even if the debt is repaid in a very short duration. Thus, our setting also contrasts the previously documented exponential bias (Stango and Zinman (2009) and Bertrand and Morse (2011)) that relies on a longer loan maturity in inducing excess borrowing.

Our study also contributes to the literature on attribute salience and product demand. In theoretical literature, Ellison (2005), Gabaix and Laibson (2006), and Bordalo et al. (2015) study firm pricing strategies when consumers pay less attention to non-salient features. Empirically, Hossain and Morgan (2006), Chetty et al. (2009), Dertwinkel-Kalt et al. (2019), and Blake et al. (2021) explore how prices on shrouded attributes could increase product demand. In the existing literature, identification strategies seek to rely on revealed preferences by studying consumer demand after varying the salience of add-on prices. We contribute to this strand of literature by directly measuring consumer perception on the effective prices of non-salient features, and study how an exogenous variation in attribute salience affects product demand, i.e., credit card debt in our setting, through changing consumer beliefs.

Lastly, this paper contributes to a growing literature focusing on the role of beliefs in explaining consumer spending-saving decisions (see DellaVigna (2009) and Benjamin (2019) for a review). For example, Ameriks et al. (2016), Ameriks et al. (2020a), and Ameriks et al. (2020b) have provided recent advances by linking survey evidence to retirement choices. Manski (2004), Ameriks et al. (2020c), and Giglio et al. (2021) study the relationship between investor beliefs and stock investment. Bucks and Pence (2008), Bailey et al. (2019), and Kuchler et al. (2022) analyze how beliefs affect mortgage leverage choices. Our work builds on this literature by exploring a quantitative survey matched to transaction-level data on consumer-borrowing decisions. Our survey designed to directly elicit consumer perceptions about interest rates instead of the perceived total costs given the current debt condition allows us to discover new channels that affect consumer borrowing, both quantitatively and qualitatively in terms of variation across individuals and over time.

2 Research Design and Sample Construction

2.1 Data

We collect the data from a large Chinese commercial bank. The bank operates nationally and is among the top 10 Chinese commercial banks as ranked by total assets, which in 2020 were over one trillion US dollars. With this large customer base, the sample therefore strongly represents consumers across the demographic distribution.

A recent report[3] mentions that credit card use in China has grown significantly since 2015. The total number of credit card transactions in the top 14 Chinese commercial banks grew from 2.6 trillion dollars in 2015 to 5.6 in 2019. Simultaneously, the total number of credit cards increased from 0.47 billion in 2015 to 0.78 in 2019. Among the different types of consumption loans, credit card debt accounts for the largest proportion in China: around 51.3% of non-durable household debt comes from credit cards. In comparison, credit card debt accounted for about 32% of non-durable household debt in the US in 2019.

2.2 Sample Restrictions

Consumers might have multiple bank accounts. Therefore, single-provider transaction-level data sets raise concerns about the completeness of the data in covering the full extent of consumers' spending and cash savings. To alleviate this concern, we follow recent work (e.g., see Ganong and Noel (2019)) and impose two restrictions on the accounts that enter our empirical analysis to capture consumers who are most likely to use the bank as their primary banking institutions.

First, we include in the sample only consumers whose checking accounts include at least 15 outflow transactions during the sampling period. An outflow is any debit from a checking account, including a cash withdrawal, an electronic payment, or a debit card transaction. Imposing this criterion reduces the original sample by approximately 35%. The second restriction is that consumers' income can be identified and calculated directly by the bank by observing regular inflows to the checking accounts, which amounts to a drop of about 10% of the observations.

[3] See here for the report.

2.3 Measuring Income and Spending

The transaction-level data allow direct measurement of consumers' income inflows and spending outflows. In terms of income, we follow the bank's steps, which identify individual income following a classification rule of regular inflows. The bank classifies income into three main categories: salary, business cash flows, and financial investment.

Salary is defined as the regular monthly income flow over the total of annual income flows and bonuses if the customers declare that they are working as employees. The bank calculates this number in one of two alternative ways. First, if income is paid as a direct deposit from the consumers' employers to this bank, then this number is directly labeled as salary in the bank's system. Otherwise, the bank can identify monthly income if the consumer's social security insurance is paid through this bank, which is a fixed portion of the consumer's income.[4]

The bank computes the income from financial investment as the difference between the total inflow and outflow from an investment account with the financial institutions. Income from business operations is the difference between total inflow and outflow when these transactions are categorized as business operations. When aggregating all incomes in our sample, the split of the three components is 63.3% from salary, 22.7% from business operations, and 14.1% from financial investment.

To measure spending, we calculate consumer monthly total spending as the sum of all non-durable purchasing transactions from consumers' checking account plus the total amount of repayment of linked credit cards' end-of-month balances between the end of the last and the current billing cycles. Debt is the outstanding interest-incurring balance on the credit card.

Lastly, to ensure that all customers have to pay interest if the full amount borrowed is not repaid within one month, we restrict our sample to those not using the credit card with teaser rate or during any grace period with no interest rate incurred within the next year. In this case, all participants face the same annualized interest rate of 20% on credit card debt. This restriction is more important for us when running the survey, which we elaborate more in the

[4]In China, social security payments have six components: five types of insurance and a housing provident fund. These five are paid from a fixed proportion of workers' monthly income. One such insurance is retirement saving insurance, similar to the retirement savings plan in the US. With a monthly income of 5,000 CNY, the monthly contribution is 8%. However, the income base for social security is usually capped at the two tails of the income distribution. The numbers differ by geographic area but are usually at 30% and 300% or 40% and 400% of the previous year's average income in that area. Therefore, for those who earn more than 300% of the last year's average income in the area, the total monthly payment is equal to $8\% \times 300\% \times \bar{Y}$, in which $\bar{Y}$ is the previous year's average income in the area. However, the uncapped distribution is wide enough to cover most Chinese workers. In the analysis, we exclude the consumers in the capped region from the final sample. Removing customers whose incomes are capped drops the sample online by 9.6%.

next section.

2.4 Survey Design

In November 2020, we collaborated with the bank and sent out surveys to a randomly selected group of customers who satisfied the criteria in Section 2.2. The survey was designed in a survey APP. Its link was then sent to the customers through both text messages and WeChat. Within a week of its completion, each participant received a gift worth around 2 dollars. To ensure that the participants did not just select the answers with some rules of thumb for the multiple answer questions (e.g., select the middle option or the last option always), we randomized the sequence of the choices for each participant[5].

The key variable we are interested in is the consumer's perceived interest rate on credit card debt. As consumers may not intuitively understand a percentage value, we directly elicit the customers' belief about the interests cost that should be paid when a certain amount of credit is borrowed from the credit card and only a portion is repaid before the end of the interest-free period. Question 2 in the survey (See Appendix A) lists our strategy. Specifically, for each participant, we ask the following three questions

> *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.*
>
> *You spend 5,000 CNY this month, and repay XXX CNY at the end of this month. Choice: ______.*
>
> (a) 45/30/0
> (b) 55/40/10
> (c) 65/50/20
> (d) 75/60/30
> (e) 85/70/40
> (f) 95/80/50
> (g) 105/90/60

The question comprises three separate sub-questions, in which XXX takes each of the three values 3,000, 1,000, and 0 in each sub-question, thus imposing three scenarios for which the consumers bear interest-incurring debt of 2,000, 4,000, and 5,000. Given an annualized interest

[5]We use survey question 1 to verify the quality of the answers. Question 1 asked the participants their total spending from credit cards last month in the bank. Figure B.1 in the online appendix is a binned scatter plots of the log total spending from credit cards measured from the bank and that from the survey answers. The plot shows a very clear linear pattern. The R^2 is 37.02%. Given the noise in the survey data, of which the answers are usually rounded to thousands or hundreds, the R^2 is quite large, and indicates the quality of the answers.

rate of 20%, the right answer to each question is always (d). To ensure that the consumers' answers are not based on some rules of thumb (always selecting the middle one or the last one), we randomize the sequence of the choices. Therefore, if the consumers' choices are always the answers that are in certain places of the list, then the answers will be purely random and will have no systematic relationships.

We calculate consumers' belief about the credit card interest rate as

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

where x_1, x_2, and x_3 are, respectively, the choices for the three values of repayment. The misperception in credit card interest rate is then $Bias = Perceived\_r - 0.0151$. If $Bias < 0$, then the perceived interest cost of credit-card borrowing is smaller than the true value.

After collecting the survey data, we merge the answers with consumer bank account data from January 2019 to February 2021. Therefore, we have about two years of monthly data before the survey and 3 months after.

A novelty of our question is its high-frequency nature. Specifically, consider a consumer who borrows a present value P at a periodic interest rate r over time horizon T, with periodic compounding. The future value F is

$$F = P(1 + r)^T. \tag{2}$$

From Equation (2), a consumer's biased perception of F could stem from three components: P, r, and T. As in Stango and Zinman (2009) and Bertrand and Morse (2011), consumers could have exponential bias if they perceive the functional form of $(1 + r)^T$ as $(1 + r)^{(1-\theta)T}$, in which $\theta \in (0, 1)$ depicts a consumer's mistakes in compounding interest rate payments. Therefore, an exponentially biased consumer would underestimate T. Additionally, an inattentive consumer who does not know the true level of debt in his account would misperceive P. For example, a consumer could misperceive his total consumption or total assets, therefore having an inaccurate belief about the total outstanding balance (Agarwal et al., 2008; Stango and Zinman, 2014; Pagel, 2017, 2018). Alternatively, the consumer could misperceive the true value of interest rate r. In our survey, when eliciting the consumer's belief about the total payment of a consumption debt, we directly ask the required total payment in the next billing cycle. Therefore, we essentially fix $T = 1$, and vary P with hypothetical values. Doing so, we control for any misperception in

T or P. Based on the answered F, we can directly measure the perceived value of r.

3 Descriptive Evidence

3.1 Summary Statistics

We surveyed 1,166 credit card users (consumers, hereafter) and collected their monthly checking and credit card account data from January 2019 to February 2021. Table 1 summarizes the statistics of our sample. The currency unit of all monetary values is converted to US dollars for simplicity. A consumer's (whose pronoun is she/her, hereafter) highest degree information is coded as a categorical variable `Education`: 1 - high school and below, 2 - some college, 3 - bachelor's degree, and 4 - graduate school. The bank categorizes credit card transactions into four types: 1) `Durable`: rents, installment payments on mortgages, cars, and furniture, etc.; 2) `Necessity`: food, tobacco, alcohol, and medical expenses; 3) `Luxury`: apparel, accessories, appliances, and services; and 4) `Other`. We elicit consumer perceived interest rates as described in Section 2.4 and record them as `Perceived r` in Table 1.

Among the consumers in our sample, around 55% are female. The financial literacy of our sample is high: most have college and more advanced education experience. Credit-card spending is usually used for necessities in our sample, but the proportion of durable goods and luxuries can be very high for some. Additionally, around 31% have ever taken debt over the sampling period, and the debt level can be significant conditional on debt takers; some debts are as high as ten times the monthly income. Most in our sample have positive savings. Interestingly, for those active debt-takers, almost everyone holds positive savings. This observation is consistent with the puzzle of simultaneous holding of low-interest savings and high-interest credit card debts recorded in consumer finance literature (Gross and Souleles, 2002; Telyukova, 2013; Gorbachev and Luengo-Prado, 2019; Gathergood and Olafsson, 2022).

We present some summary statistics of the perceived interest rates collected from our surveys. Figure 2 illustrates very heterogeneous perceived interest rates in our sample ranging from around 5% to 35%. However, the distribution is roughly centered and symmetric around the true rate (20%), so beliefs about credit card debt interest rates are approximately close to the right level. Debt-takers generally have lower perceived interest rates than non-debt-takers have. These observations reveal consumer misperception of the marginal costs as an important bias in inducing high leverage in addition to exponential bias and inattention to total assets:

consumers do not know the credit card debt interest rate even in a single period, no matter whether they understand how to calculate compound rates, and if they know the true level of current debt.

3.2 Debt Interest Rate Misperception

We first explore how the interest rate misperception co-varies with other factors. We begin with the following regression specification:

$$y_i = \alpha + \mathbf{X_i'}\beta + \varepsilon_i \tag{3}$$

where y_i denotes $Perceived\_r_i$ or |bias|, respectively. $Perceived\_r_i$ is the perceived debt interest rate of consumer i; |bias|, the absolute perception error, is defined as the absolute value of the difference between the perceived and true interest rates (20%) for consumer i. $\mathbf{X_i}$ is a vector of the control variables for consumer i, and ε_i is the regression error. The control variables include a consumer's demographic data (education, age, and gender), financial behavior (income and saving), and credit availability (credit score and credit limit).

Columns (1) - (2) of Table 2 show the results for $Perceived\_r_i$, and columns (3) - (4) of Table 2 show the results for |bias|. The low/high values in the regressors denote whether the regressor is below/above median. There are several interesting findings. First, the perceived interest rates and financial literacy share a clear positive relationship. From column (2), conditional on other demographics, the consumer's perceived interest rate tends to be 2.1 ppt higher than those who received a high school diploma or lower if they received some college degree. This difference increases monotonically and is 9.8 ppt higher for those with a graduate degree. Looking at column (4), conditional on other demographics, the higher perception interest rate along with education attainment is accompanied by a lower absolute perception error: those with a graduate degree on average have 2.0 ppt lower absolute errors as compared to those having only a high-school degree.

Table 3 shows the counterpart results for debt-takers. Overall, the correlation between interest rate misperception and other factors is in the same direction but at a larger magnitude for debt-takers. Different from non-debt-takers, debt-takers appear to respond more to credit availability: consumers with a above-median credit limit correspond to around 1.4% lower perceived rate than those with below-median credit limit.

3.3 Debt Taking Behavior

Our observation of perceived interest rates shows that consumers, generally, do not know the true cost of borrowing well. Recent literature documents that heterogeneous beliefs sometimes are only mildly correlated with their actions (Ameriks et al., 2020c; Giglio et al., 2021). We continue to study whether interest rate misperception affects consumer borrowing behaviors.

Table 4 columns (1) - (2) analyze the relationship between debts and perceived interest rates using the regression framework:

$$Debt_i = \alpha + \beta Perceived\_r_i + \mathbf{X_i'}\pi + \varepsilon_i \tag{4}$$

where $Debt_i$ denotes the debt balance on consumer i's account. From column (2), conditional on demographics, one ppt of perceived lower interest rate is associated with \$60.8 more debt. Not surprisingly, the direction of this effect is consistent with the law of demand for debt – the higher the debt interest rate one perceives, the lower the debt one will bear. Columns (3) - (4) of Table 4 show the relationship between |bias| and total borrowing. Interestingly, in spite of the fact that perceived interest rates are about symmetric around the truth, the misperception is associated with excess borrowing in aggregate. Conditional on consumer characteristics, a one ppt increase in the absolute perception error is associated with a \$92.9 increase in the debt. The asymmetric relationship between perceived interest rate and total borrowing sheds light on this finding. Specifically, Figure 3 gives a binned scatter plot of the relationship between interest rate misperception and debt taken by each consumer when misperception is defined as the difference between consumer's perceived rate and the true rate of 20%. A clear pattern is that only the downward bias significantly correlates with debt-taking, while the relationship conditional on having an upward bias appears flat. Concretely, we examine this asymmetric relationship by adding an interaction between the interest rate misperception and the direction of bias in the regression framework:

$$\begin{aligned} Debt_i = \alpha &+ \gamma_{up} Perceived\_r_i \, \mathbb{1}\{Perceived\_r_i \geq r_d\} + \gamma_{down} Perceived\_r_i \, \mathbb{1}\{Perceived\_r_i < r_d\} \\ &+ \eta \, \mathbb{1}\{Perceived\_r_i < r_d\} + \mathbf{X_i'}\pi + \varepsilon_i \end{aligned} \tag{5}$$

where $\mathbb{1}\{Perceived\_r \geq r_d\}$ ($\mathbb{1}\{Perceived\_r < r_d\}$) is an indicator function that equals 1 when a consumer's interest rate perception is higher (lower) than the true value r_d. In Equation 5,

γ_{up} and γ_{down}, respectively, measure the relationship between debt and perceived interest rates when the consumers make positive (negative) perception errors. Table 4 columns (5) - (6) reveal the asymmetric relationship of interest rate misperception to debt-taking behavior. If consumers underestimate the debt interest rate by 1 ppt, they tend to have around \$141.3 more debt. On the other hand, evidence is not clear that consumers who overestimate the interest rate will take less debt. These findings are consistent with the nature that debt is left-truncated at 0: once the debt amount already reaches \$0, a positive perception error cannot induce the borrowers to take on less debt. However, these asymmetric effects have an important implication: in a market where consumers have noisy perceptions about the interest costs of debt, even if the errors are on average zero, other than second-order inefficiencies caused by misallocation, interest rate misperception could induce a first-order inefficiency such that excess debt is taken at the aggregate level.

4 Information Treatment on Debt Interest Rate

The previous sections document that consumers have a very noisy perception of the true interest rate with credit-card borrowing. Those with a negative perception tend to take on more debt, and the pattern between misperception and debt does not seem to be clear when the misperception is positive. However, the OLS estimates may suffer from potential endogeneity problems. For example, confounders such as unobserved heterogeneity can contaminate the regression results through the omitted variable bias if debt-taking is affected by latent taste variables not orthogonal to the perceived interest rates. Though the direction of bias is ambiguous. Moreover, debt-taking behavior and perceived interest rate may be involved in some simultaneous equation structures. For example, a positive coefficient of debt on perceived rate may indicate the law of demand: a higher cost of borrowing lowers debt. On the other hand, motivated reasoning could potentially be another channel: if consumers hold too much debt, they may intentionally ignore or project a lower interest rate to "rationalize" the suboptimal borrowing behavior. To address these potential endogeneity issues, we design an RCT to identify the effect of the perceived interest rate on borrowing behavior.

We show that consumers, generally, do not correctly understand the true cost of borrowing, which is potentially due to the obscure presentation of the APR such as that in Figure 1. In light of these observations, we design and implement an information treatment to manipulate the salience of true interest rate-related costs, and consequently, consumer interest rate perception.

4.1 Identification Strategy

Identifying the causal effect of interest rate perception on borrowing behavior is challenging because randomizing consumer beliefs is generally quite impossible. To address this problem, we survey the consumers for a second round in which we design an information treatment for a randomly selected group of participants described in Section 2.

Information Treatment Design For a random 40% of the participants who have repaid any interest-incurring credit card debt in 2020 and before the experiments, we reveal the following information at the end of the survey in a new page.

> *The annualized interest rate on credit card is around 20%. This rate is equivalent to a monthly interest rate of about 1.51%. If you carry over 8,000 CNY of debt on a credit card to the next billing cycle, then there will be an around 120.8 CNY in interest rate in the next month.*

Then all the participants that have paid interests in 2020 were asked the following question.

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

(a) 15

(b) 25

(c) 35

(d) 45

(e) 55

(f) 65

(g) 75

The order of the choices is randomized to avoid the anchoring effect. We, again, calculate the implied perceived interest rate using Equation (1). We compute the update as the difference between the perceived second-round and first-round interest rates for each consumer.

Essentially, our information treatment increases the salience of the interest rate by explicitly presenting the true cost of borrowing in an exogenous fashion. This approach allows us to evaluate the effectiveness of the information treatment and identify the causal effect of the perceived interest rate on debt. The information treatment *per se*, if it indeed revises consumers' perceived interest rates, can also serve as a debiasing policy to alleviate interest rate misperception and excess borrowing behavior.

To examine the effectiveness of the randomization, Table 6 reveals the means of the demographic (age, gender, and education), financial behavior (spending, income, and saving), and credit availability (credit limit and credit score) variables of the treatment and control groups. As expected, the averages for all variables are very close, suggesting that the treatment and control groups are comparable.

4.2 Effects of Information Treatment

Probing consumer reactions before formal analysis is useful. Figure 4 illustrates the distributions of interest perception revision between the treatment (red bins) and control group (blue bins). Overall, the bins for the control groups are centered and clustered around 0, indicating that, despite some noise, consumers in the control group do not change their perception much. Rather, the distributions of perceived interest rate update of the treatment group are much more dispersed, and the majority adjust their perceived interest rate upwardly. Concretely, Table 7 reports the means and standard errors of the bias and absolute bias of the perceived interest rates grouped by treatment status. For the control group, consumers do not change their perceptions much: we observe little revision between the perceived interest rates in our two elicitation processes (the bias changes from -4.6% to -5.0% whereas |bias| moves from 7.2% to 8.1%). For the treatment group, on the other hand, consumers largely upwardly adjust their perceived interest rates (the bias rises from -4.2% to 0.3%), and their revised interest rates move closer to the true rates (|bias| drops from 6.8% to 4.6%).

These comparisons between the treatment and the control groups naturally compose a difference-in-differences (DID) design. We first measure the change in perceived interest rates within individuals before and after the information treatment; this difference captures any individual and intra-group fixed effect. Then, we compare the changes in perceived interest rates between the treatment and control group; this contrast is the intention-to-treat (ITT) effect, which captures the effect of the information treatment on the perceived interest rate.

We focus on the three months before (September, October, and November 2020) and after (December 2020, January, and February 2021) the information treatment and estimate the ITT effect on perceived interest rate using a regression DID framework

$$Perceived\_r_i = \alpha + \beta_1 Treated_i + \beta_2 After_i + \gamma(Treated_i \times After_i) + \varepsilon_i \tag{6}$$

$$|Bias|_i = \alpha + \beta_1 Treated_i + \beta_2 After_i + \gamma(Treated_i \times After_i) + \varepsilon_i \tag{7}$$

where $Treated$ is a dummy variable of consumer treatment status and $After$ is a dummy variable representing whether it is before or after our information treatment. Our main parameter of interest, γ, captures the causal effect of the information treatment on perceived interest rate.

Table 8 column (1) reports the result of Equation (6) and column (2) reports the result of Equation (7). Consistent with the descriptive observations of Table 7 and Figure 4, on average, after the information treatment, consumers increased their perceived interest rates by 4.9 ppt, and their misperception errors decreased by 3.0 ppt.

We further estimate the ITT effect of the information treatment on consumer debt-taking behavior using a similar regression DID framework:

$$Debt_i = \alpha + \beta_1 Treated_i + \beta_2 After_i + \gamma(Treated_i \times After_i) + \varepsilon_i. \tag{8}$$

Table 8 column (3) reports the result of Equation (8). After the information treatment, in the subsequent three months, consumers reduced their debt by around \$696.3 at 10% significance level. The average debt of debt-takers being \$1,999.5, the magnitude of the effect is very large and is equivalent to an around 35% decrease.

We continue to evaluate the effectiveness of the information treatment on different groups of consumers. We examine the ITT effect of the information treatment on the perceived interest rate for consumers with different financial status (income), financial literacy (education), and credit availability (credit limit) by applying the DID regression, Equation (8), on different subsamples. The utilization rate is defined as the ratio of a consumer's credit card balance and credit limit before the experiment. Table 9 shows these results, in which the cutoffs between low and high are the median values. In terms of financial status, the ITT effect of our information treatment on the perceived interest rate is slightly larger for the high income group (5.9 ppt increase) than for the low income group (3.8 ppt increase). The effect shows up differently in terms of financial literacy, in which consumers with only a high school diploma react more to the information treatment (8.6 ppt increase) than do the rest of the sample (3.6 ppt increase). Lastly, for credit availability, our information treatment seems to be more effective on consumers with a high utilization rate (5.4 ppt increase), compared to a 4.3 ppt increase for low-utilization borrowers.

4.3 Effect of Perceived Interest Rate on Debt-Taking

The information treatment largely affects consumer perception of the interest rates. Generally, borrowers negatively perceive errors before the experiment, and the information treatment on average brought their beliefs to a level quite close to the true value. We continue to study whether the changes in belief are associated with changes in debt-taking behaviors. We can use the treatment status as an instrumental variable (IV) for perceived interest rate to identify its causal effect on borrowing behavior.

Specifically, the second stage of our 2SLS framework is

$$\Delta Debt_i = \alpha + \beta \Delta Perceived\_r_i + \mathbf{X_i'}\pi + \varepsilon_i \tag{9}$$

where *Treated* is an IV for *Perceived_r* in the first stage and X denotes covariates. The parameter of interests is β, which measures the average causal response of total borrowing in response to changes in perceived interest rates. Similar to the OLS procedure, we include three types of control variables: demographics (gender, education, and age), financial status (income and saving), and credit availability (credit score and credit limit). All controls are at the pre-treatment level. The treatment status is a valid IV for $\Delta Perceived\_r$: the random selection of the treatment group satisfies the exclusion restriction, and the large ITT effect of our information treatment on interest rate perception and debt shown in Table 8 strongly suggests the satisfaction of the first-stage relevance condition. Notice that the covariates, X, are not required to identify the causal effect because our RCT guarantees randomly assigned treatment *unconditionally*. Notwithstanding, we still report both results without and with control variables customarily to avoid any accidental association between X and *Treated* and increase estimation precision.

Table 10 columns (5) - (6) report the result of Equation (9) using 2SLS, whereas columns (1) - (2) report the counterpart using OLS as a comparison. Additionally, we run a similar 2SLS regression by instrumenting $\Delta|Bias|$ using the treatment status. Table 10 columns (7) - (8) report the 2SLS result, and columns (3) - (4) report the OLS counterpart. First, the distinct discrepancy between our OLS and 2SLS results suggests the importance of our IV: OLS regression underestimates the effect of perceived interest rate on debt by over 50%. From column (3), for every ppt increase in the perceived interest rate, an average consumer will reduce their debt by \$142.2, which is about twice as large as estimated in columns (1) - (2). This positive bias could result from some consumers taking on a larger debt while having higher perceived interest rates. The estimate with covariates, \$143.1, is very close to that without covariates; this comparison indicates the unconditional IV validity of our information treatment. In terms of the absolute perception error, for every ppt increase in the misperception, an average consumer will increase their debt by \$228.7 (or \$227.4 with covariates).

Understanding how consumers reduce debt after the treatment is also important. There are two potential possibilities: 1) consumers who reduce debt also reduce total spending after realizing the true costs of credit-card borrowing; 2) consumers shift spending from financing-by-debt to financing-by-savings. To evaluate these two channels, respectively, we apply a similar 2SLS framework on consumer spending and saving changes as well:

$$\Delta Spending_i = \alpha + \beta \Delta Perceived\_r_i + \mathbf{X_i'}\pi + \varepsilon_i \tag{10}$$

$$\Delta Saving_i = \alpha + \beta \Delta Perceived\_r_i + \mathbf{X_i'}\pi + \varepsilon_i \tag{11}$$

where spending is the total monthly spending minus the newly accumulated debt. Table 11 columns (1) - (2) report the results of Equations (10) - (11) using 2SLS without and with covariates. The estimates show that every ppt increase in the perceived interest rate decreases consumer spending by \$61.3, which is equivalent to a \$183.9 decrease in total non-debt financed spending three months after the experiment. At the same time, liquid saving increases by \$257.8. Since debt debt reduces by \$143.1 in three months after the experiment for each ppt increase in perceived interest rate, around \$70 of spending is substituted from debt-financed to liquidity-financed for each ppt increase in perceived interest rate.

Finally, identifying the spending categories consumers adjust to reduce their debt is interesting. Using a similar 2SLS framework, we estimate the effect of change in the perceived interest rate on change in the proportion of debt spent on each category. Table 12 presents the 2SLS results with and without covariates. We find strong evidence that every ppt increase in perceived interest rate causes consumers to spend 1.4% less on luxuries using their credit card, while durable good purchases evidently increase by 0.9% . These results suggest that excess borrowing reflects excess spending. Consumers desire to exploit credit card rewards as much as possible, but this tendency backfires in their eventually spending too much money on luxury goods. After revealing the true cost of borrowing through our information treatment, consumers become aware of their excess spending behavior and adjust their purchases consequently.

4.4 Information Treatment – Long Run Effect

Our results suggest that information treatment can serve as a debiasing policy in the short run: it increases the salience of the interest rate by revealing the true cost of borrowing in dollars, and consumers instantaneously respond to our policy by reducing total debt significantly in the subsequent months. Evaluating the policy's effects in the long run is also important: will the policy effect persistent over time, or will consumers eventually rewind to the original perception and borrowing behavior?

To understand how consumers behave after the information treatment, we elicit the perceived interest rates of the same consumers for the third time by running a followup survey as described in Section 2.4 in late October 2021. Table 13 shows the results and the corresponding DID estimate using Equations (6) and (7). Compared to Table 8, the effect on perceived interest rate shrinks from 4.89 to 1.83 ppt, while the effect on the absolute perception error shrinks from -3.0 to -2.2 ppt. This shrinkage illustrates that the information treatment has a long-run effect on perceived interest rate, although the effect depreciates by nearly 63% relative to the initial three months.

Correspondingly, Figure 5 plots the debt trajectories of the treatment and control group until July 2021 in which the gray dashed line denotes the time of our information treatment. We do not observe any overall trends in debts for the control group despite some fluctuations. For the treatment group, on the contrary, the debt level plumped quickly until March 2021 from around $1,250 to $1,075. Afterwards, the effect of our information treatment starts to fade: the debt level of the treatment group converges to that of the control group for several months, but plateaus in May 2021 eventually. Consistent with Agarwal et al. (2013), consumers in the consumption debt market forget new information over time. However, our information treatment still has a long run and persistent effect after 12 months.

Lastly, we find that our information treatment has heterogeneous effects on consumers with different demographic backgrounds as illustrated in Figure 6. To emphasize the post-treatment changes, we subtract all debt levels from the pre-treatment average (September 2020 to November 2020). In the long run, female consumers respond less to our information policy than male consumers do. The effect on consumers with higher education seems to persist more than that on those with lower education. Young consumers rewind the debt level almost to the pre-treatment level while old consumers observe a mild but consistent downward trend in debts. High-income consumers also appear to experience a more persistent long-run effect than low-income consumers do, although their difference is not as large.

5 Conclusion

In this paper, we design and implement an RCT to directly elicit consumer's perception about the cost of credit card borrowing and manipulate the salience of the interest rate. We find that consumers have a noisy perception about the true cost of borrowing. The misperception disproportionately relates to borrowing: only consumers with downwards misperception would borrow more, while those who perceive debt to be more expensive do not take less debt.

Our information treatment increases the salience of interest rate on a randomly selected group of consumers by explicitly reminding them of the true cost of borrowing in monetary amounts. Consumers respond to our information treatment largely as follows: relative to the control group, on average, consumers in the treatment group revise their interest rate perception upwardly by 4.9 ppt, and the absolute perception error reduces by 3.0 ppt as a result. Therefore, in the subsequent three months, an average consumer reduces debt by 696.3 US dollars. Using the treatment status as an instrumental variable for the perceived interest rate, we recover the consumer price (interest rate) elasticity of demand for credit-card borrowing: every ppt increase in the perceived interest rate causes an average consumer to reduce debt by 143.1 dollars. We also find that excess borrowing reflects excess spending: after learning the true cost of borrowing, consumers reduce debt by cutting down the expenditure on durable goods.

In light of the large instantaneous effect, our information treatment is a competent debiasing policy in the short run. In the long run, consumers quickly forget the newly gained information: one year after the experiment, the difference in perceived interest rate revision between the treatment and control groups shrinks to 1.8 ppt, which is around 37% of the instantaneous effects. The debt trajectory also manifests a similar pattern: consumer debt plumped quickly in the three months after the experiment, followed by a gradual upward rewind afterwards. Eventually, the debt level of the treatment group plateaus, and a persistent gap between the treatment and control groups still remains. These observations imply that our debiasing policy has a persistent long run effect on consumer-borrowing behavior, although the effect depreciates relative to the short run.

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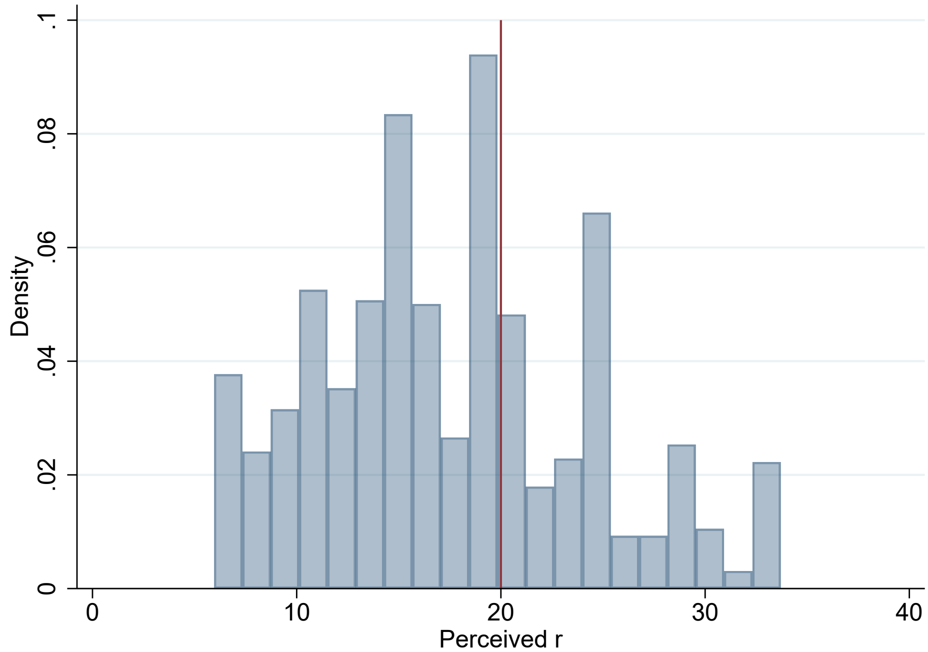
Figures

Figure 1. Application Landing Page of Chase Credit Cards

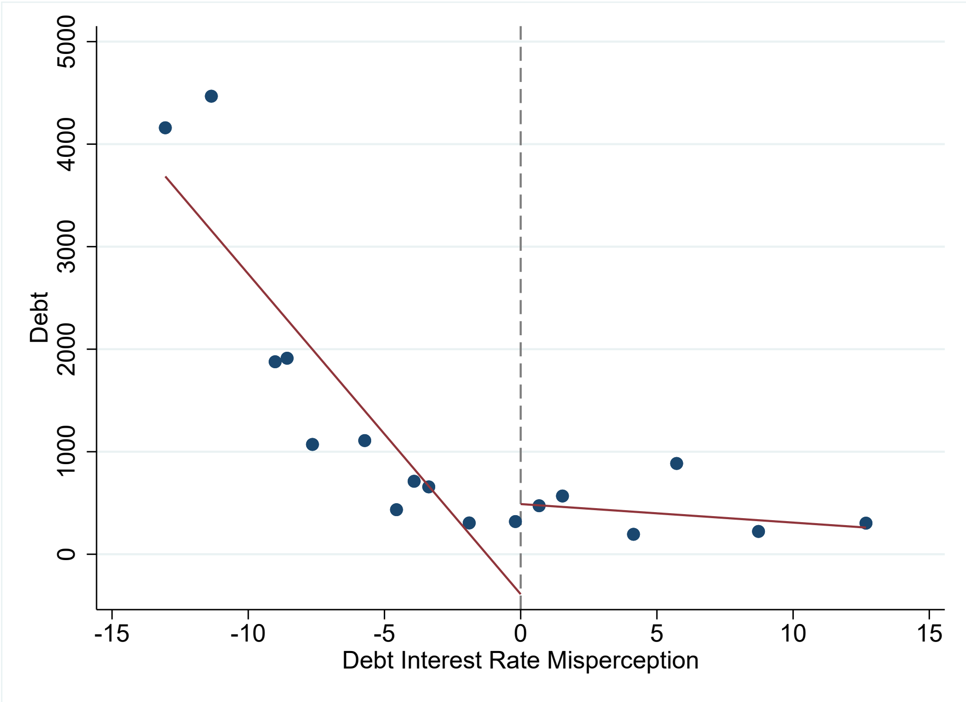
Note: This figure shows an example of credit card advertisements. Source: Chase Freedom Credit Card, captured on Oct 15, 2021.

Figure 2. Perceived Credit Card Debt Interest Rates



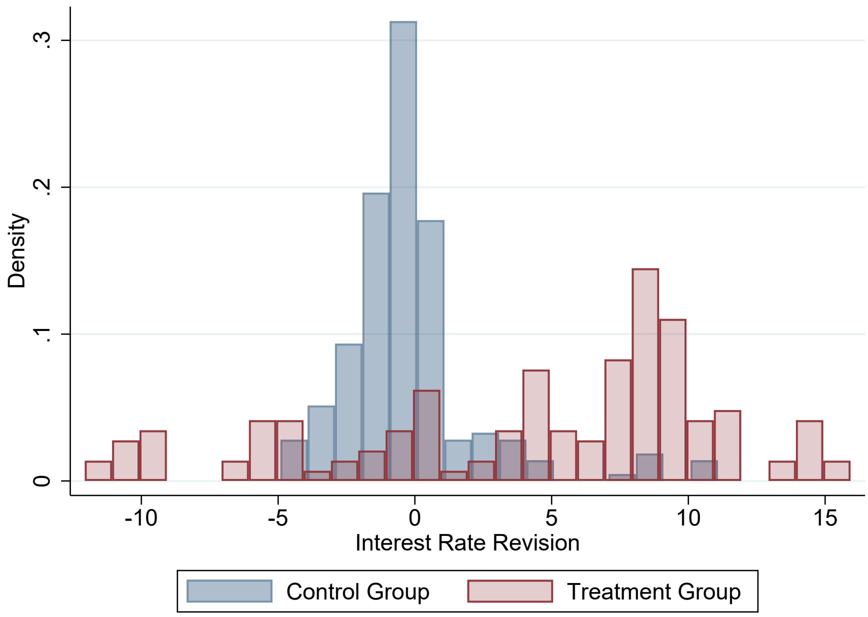
Note: This figure shows the distribution of the consumer-perceived debt interest rate before the information. The horizontal axis, perceived r (in percentage), denotes consumers' debt interest rates in our survey (see text for details).

Figure 3. Interest Rate Misperception and Borrowing



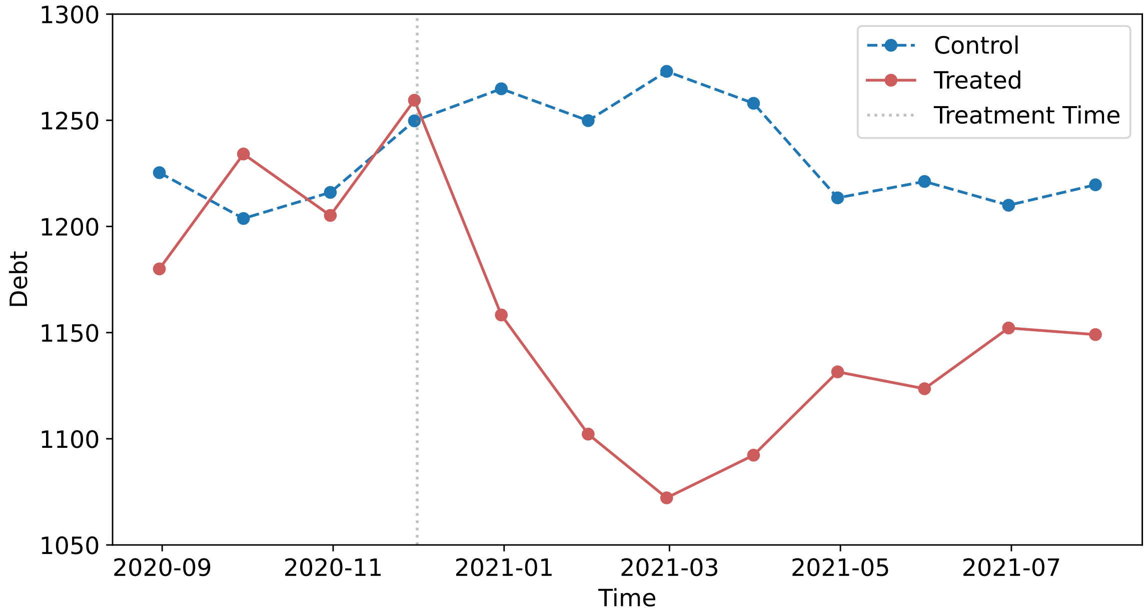
Note: This figure shows the association between credit card debt and interest rate misperception. The vertical dashed line labels the true interest rate (APR 20%).

Figure 4. Perceived Interest Rate Revision



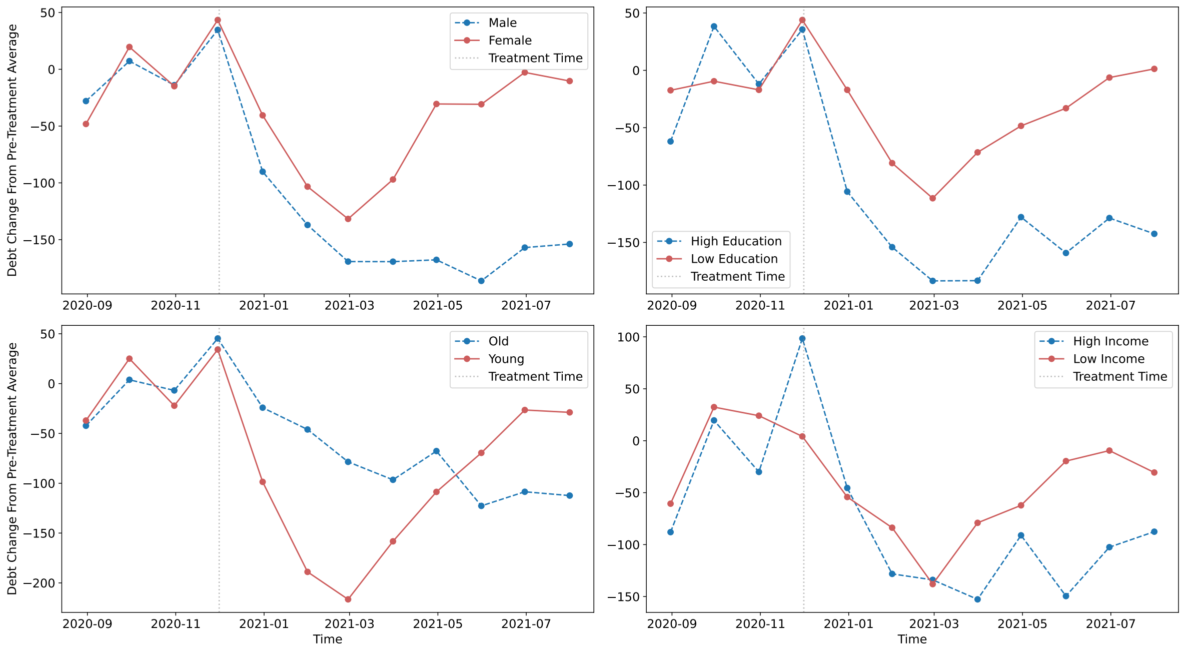
Note: This figure plots the distribution of interest rate revision after our information treatment. The horizontal axis, interest rate revision, denotes the difference between the second (after the information treatment, if any; see text for details) and the first elicitation of consumer perceived debt interest rate. The red histogram represents the treatment group (who received our information treatment), while the blue represents the control group.

Figure 5. Long-Run Effect of Information Treatment on Debt



Note: This figure plots the credit card debt trajectories of the consumers of the treated and control groups from September 2020 to 2021. The vertical dotted line denotes the time of the information treatment (see text for details).

Figure 6. Heterogeneous Long-Run Effect of Information Treatment on Debt



Note: This figure plots the credit card debt trajectories of different demographic groups of treated consumers from September 2020 to 2021. All debt levels are subtracted from the pre-treatment average (September to November 2020) to show the post-treatment changes. The demographic covariates are pre-treatment and therefore exogenous. The vertical dotted line denotes the time of the information treatment (see text for details).

Tables

Table 1. Summary Statistics

	Mean	Std. Dev.	25 pct	Median	75 pct	Count
Panel A: All consumers						
Debt	615.6	1381.1	0	0	443.6	1166
Credit limit	1413.7	894.0	769.2	1096.2	1846.2	1166
Credit score	55.04	5.501	51.20	54.49	58.13	1166
Spending	1667.0	1706.5	612.6	1063.5	1928.0	1166
Income	2587.9	1229.7	1873.3	2387.4	3096.2	1166
Saving	25437.4	13548.5	14385.3	22150.3	33883.3	1166
Age	37.29	10.47	28	36	46	1166
Gender: female	0.590	0.492	0	1	1	1166
Education	2.117	0.869	2	2	3	1166
Perceived r	17.70	6.584	12.68	16.77	21.94	1166
Panel B: Debt-takers						
Debt	1999.5	1852.8	570.9	1269.8	2861.9	359
Durable %	0.283	0.335	0	0.148	0.591	359
Necessity %	0.353	0.324	0	0.299	0.447	359
Luxury %	0.217	0.295	0	0	0.425	359
Other %	0.151	0.265	0	0	0.152	359
Credit limit	1529.4	912.2	807.7	1230.8	2076.9	359
Credit score	55.20	5.631	51.41	54.62	58.41	359
Spending	1383.5	1511.5	340.0	769.5	1845.2	359
Income	2295.6	1203.2	1592.5	2115.4	2712.3	359
Saving	26202.3	15063.1	13236.3	23482.4	34960.8	359
Age	38.38	10.99	28	39	47	359
Gender: female	0.579	0.494	0	1	1	359
Education	2.053	0.836	1	2	2	359
Perceived r	15.35	6.903	9.164	15.16	19.56	359

Note: This table presents the summary statistics of our sample. All variables are monthly. All currency numbers are in USD. Debt-takers are the consumers with positive interest, incurring balances on their credit cards. Perceived r denotes the perceived interest rates of the consumers in our survey (see text for details). Spending categories are classified by the bank into the following: 1) Durable: rents, installment payments on mortgages, cars, and furniture, etc.; 2) Necessity: food, tobacco, alcohol, and medical expenses; 3) Luxury: apparel, accessories appliances, and services; and 4) Other.

Table 2. Misperception of Debt Interest Rate

	(1) Perceived r	(2) Perceived r	(3) |Bias|	(4) |Bias|
Degree: some college	2.003***	2.116***	-0.569*	-0.902***
	(0.430)	(0.431)	(0.295)	(0.284)
Degree: bachelor's degree	5.137***	5.440***	-1.382***	-2.055***
	(0.522)	(0.562)	(0.334)	(0.348)
Degree: grad school	9.225***	9.760***	-0.647	-1.953***
	(0.647)	(0.732)	(0.508)	(0.545)
Age: old	-0.455	-0.001	-0.128	-0.082
	(0.357)	(0.377)	(0.233)	(0.250)
Gender: female	1.659***	1.742***	0.385	0.367
	(0.350)	(0.348)	(0.239)	(0.232)
Income: high		2.212***		-1.773***
		(0.433)		(0.267)
Saving: high		-1.592***		0.574**
		(0.434)		(0.273)
Credit score: high		-0.223		-1.105***
		(0.451)		(0.283)
Credit limit: high		-0.216		0.715***
		(0.386)		(0.245)
Constant	14.216***	13.697***	6.033***	7.216***
	(0.432)	(0.539)	(0.313)	(0.363)
Observations	1166	1166	1166	1166
R^2	0.161	0.186	0.015	0.078

Note: This table explores the association between the perceived interest rate and the other variables of all consumers in our sample. Column (1) reports the OLS fit of the perceived debt interest rate on demographic variables (education, age, and gender). Additionally, column (2) also includes the financial behavior variables (income, saving, credit score, and credit limit) in the regression. The low/high values of the regressors denote whether a regressor is below/above median. Columns (3) - (4) report the counterparts of columns (1) - (2) with the dependent variable being absolute perception error. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3. Misperception of Debt Interest Rate for Debt-Takers

	(1)	(2)	(3)	(4)
	Perceived r	Perceived r	|Bias|	|Bias|
Degree: some college	1.665**	1.743**	-0.606	-0.659
	(0.755)	(0.766)	(0.533)	(0.523)
Degree: bachelor's degree	6.297***	5.950***	-2.183***	-2.221***
	(1.003)	(1.038)	(0.612)	(0.615)
Degree: grad school	10.384***	10.166***	-1.827**	-2.384**
	(1.393)	(1.447)	(0.910)	(0.935)
Age: old	0.123	0.691	-1.229***	-1.030**
	(0.688)	(0.711)	(0.429)	(0.467)
Gender: female	1.629**	1.786***	0.316	0.250
	(0.652)	(0.660)	(0.436)	(0.434)
Income: high		1.289		-0.910*
		(0.851)		(0.535)
Saving: high		-1.416*		-0.414
		(0.856)		(0.507)
Credit score: high		0.184		-0.878*
		(0.798)		(0.509)
Credit limit: high		-1.369*		1.376***
		(0.786)		(0.460)
Constant	11.708***	12.260***	8.341***	8.581***
	(0.716)	(0.843)	(0.559)	(0.595)
Observations	359	359	359	359
R^2	0.182	0.198	0.054	0.089

Note: This table explores the association between the perceived interest rate and other variables of all the debt-takers in our sample. A consumer is defined as a debt taker if the consumer ever has a positive interest payment in the credit card account. Column (1) reports the OLS fit of the perceived debt interest rate on demographic variables (education, age, and gender). Additionally, column (2) also includes the financial behavior variables (income, saving, credit score, and credit limit) in the regression. The low/high values of the regressors denote whether a regressor is below/above median. Columns (3) - (4) report the counterparts of columns (1) - (2), with the dependent variable being the absolute perception error. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4. Misperception of Debt Interest Rate and Debt-Taking

	(1) Debt	(2) Debt	(3) Debt	(4) Debt	(5) Debt	(6) Debt
Perceived r	-68.675***	-60.813***				
	(6.933)	(7.090)				
|Bias|			99.885***	92.891***		
			(11.975)	(11.864)		
Downward=1 × Perceived r					-149.706***	-141.266***
					(15.614)	(15.656)
Downward=0 × Perceived r					-5.681	-0.228
					(9.202)	(9.898)
Downward					2506.377***	2438.636***
					(355.330)	(373.649)
Degree: some college		30.225		-14.688		76.037
		(110.220)		(110.302)		(109.268)
Degree: bachelor's degree		-72.525		-212.416		15.873
		(131.373)		(130.772)		(130.885)
Degree: grad school		-197.015		-609.084***		-150.769
		(146.526)		(141.575)		(141.698)
Age: old		216.227**		223.897***		221.382***
		(85.129)		(85.137)		(82.380)
Gender: female		16.561		-123.472		-22.427
		(80.342)		(78.335)		(78.249)
Income: high		-588.313***		-558.123***		-477.461***
		(105.196)		(108.772)		(105.884)
Saving: high		-76.981		-33.458		-86.178
		(95.664)		(94.413)		(92.807)
Credit score: high		358.088***		474.251***		444.782***
		(92.164)		(95.464)		(92.353)
Credit limit: high		394.484***		341.166***		336.327***
		(77.699)		(76.806)		(74.748)
Constant	1830.861***	1548.732***	55.292	45.440	389.569	80.061
	(150.617)	(177.799)	(52.436)	(162.090)	(245.277)	(296.671)
Observations	1166	1166	1166	1166	1166	1166
R^2	0.107	0.166	0.083	0.163	0.160	0.214

Note: This table explores the association between the credit card debt and the perceived interest rate along with other covariates of all the consumers in our sample. Column (1) reports the OLS fit of debt on the perceived interest rate of all consumers in our sample. In the same regression, column (2) also includes the demographic variables (education, age, and gender) and financial behavior variables (income, saving, credit score, and credit limit) as control. The low/high values of the regressors denote whether a regressor is below/above median. Columns (3) - (4) report the counterparts of columns (1) - (2) by replacing perceived the debt interest rate with the absolute perception error. In columns (5) - (6), instead of the perceived interest rate, we include the interaction between the downward bias (if perceived interest rate is lower than the true APR, 20%) and perceived interest rate. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5. Misperception of Debt Interest Rate and Debt-Taking for Debt-Takers

	(1) Debt	(2) Debt	(3) Debt	(4) Debt	(5) Debt	(6) Debt
Perceived r	-104.678***	-80.725***				
	(12.586)	(13.233)				
|Bias|			135.517***	130.727***		
			(23.015)	(21.735)		
Downward=1 × Perceived r					-158.702***	-159.298***
					(25.257)	(24.721)
Downward=0 × Perceived r					-35.530	-1.354
					(32.684)	(33.203)
Downward					2232.628**	2632.946***
					(958.802)	(943.367)
Degree: some college		-15.516		-70.089		9.061
		(224.198)		(226.716)		(225.051)
Degree: bachelor's degree		-249.396		-439.397*		-233.025
		(262.647)		(261.206)		(265.595)
Degree: grad school		-849.887***		-1358.896***		-947.378***
		(297.278)		(273.701)		(280.816)
Age: old		366.650*		445.461**		455.237**
		(188.854)		(189.999)		(188.208)
Gender: female		-11.969		-188.809		-91.603
		(183.584)		(176.784)		(179.711)
Income: high		-511.970**		-497.061**		-455.781*
		(236.760)		(236.155)		(234.087)
Saving: high		-228.159		-59.770		-160.802
		(232.957)		(228.325)		(228.056)
Credit score: high		887.611***		987.627***		954.618***
		(218.342)		(216.932)		(215.085)
Credit limit: high		637.651***		568.196***		564.445***
		(193.549)		(195.302)		(194.120)
Constant	3606.389***	2656.786***	1043.478***	545.255*	1989.599**	840.975
	(248.483)	(332.360)	(148.565)	(326.606)	(882.517)	(893.753)
Observations	359	359	359	359	359	359
R^2	0.152	0.268	0.090	0.272	0.169	0.300

Note: This table explores the association between the credit card debt and perceived interest rate along with the other covariates of all debt-takers in our sample. A consumer is defined as a debt taker if the consumer ever has a positive interest payment in the credit card account. Column (1) reports the OLS fit of debt on the perceived interest rate. In the same regression, column (2) also includes the demographic variables (education, age, and gender) and financial behavior variables (income, saving, credit score, and credit limit) as control. The low/high values of the regressors denote whether a regressor is below/above median. Columns (3) - (4) report the counterparts of columns (1) - (2) by replacing the perceived debt interest rate with the absolute perception error. In columns (5) - (6), instead of perceived interest rate, we include the interaction between the downward bias (if perceived interest rate is lower than the true APR, 20%) and the perceived interest rate. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6. Comparison between Control and Treatment Groups

	Control Mean	Treatment Mean
Age	38.573	38.258
Gender: female	0.588	0.563
Education	2.071	2.028
Spending	1772.53	1881.99
Income	2311.66	2327.04
Saving	25828.30	26244.44
Credit Limit	1694.50	1718.31
Credit Score	55.30	54.90

Note: This table shows the means of the demographic (age, gender, and education), financial behavior (spending, income, and saving), and credit availability (credit limit and credit score) variables of the treatment and control groups. Education denotes the highest degree of consumers and is coded as 1 - high school and below, 2 - some college, 3 - bachelor's degree, and 4 - graduate school. The means are very close for all variables, suggesting that the treatment and control groups are comparable.

Table 7. Perceived Interest Rate Revision

	Control		Treatment	
	Before	After	Before	After
Bias	-4.63	-5.00	-4.19	0.33
	(0.48)	(0.54)	(0.57)	(0.51)
|*Bias*|	7.24	8.06	6.81	4.58
	(0.28)	(0.31)	(0.35)	(0.33)

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, 20%, whereas |*Bias*| is the absolute value of the difference. Standard errors are reported in parentheses.

Table 8. ITT Estimates of Information Treatment

	(1)	(2)	(3)
	Perceived r	|Bias|	Debt
After × Treated	4.896***	-3.044***	-696.300*
	(1.047)	(0.638)	(392.678)
After	-0.376	0.814*	315.600
	(0.718)	(0.421)	(254.618)
Treated	0.440	-0.438	369.792
	(0.742)	(0.445)	(266.367)
Constant	15.072***	7.246***	4338.775***
	(0.475)	(0.279)	(527.931)
Observations	706	706	706
R^2	0.077	0.080	0.006

Note: This table reports the intent-to-treat (ITT) effects of the information treatment by fitting the dependent variable on $After$ (whether it happens after information treatment), *Treated* (whether a consumer is assigned to the treatment group), and their interaction. Columns (1) - (2) use perceived interest rate and absolute perception error as the dependent variable, respectively. Debt is the dependent in column (3). Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9. Heterogeneous ITT Estimates of Information Treatment on Perceived Interest Rate

	Income		Education		Utilization	
	(1)	(2)	(3)	(4)	(5)	(6)
	Low	High	Low	High	Low	High
After × Treated	3.849***	5.943***	8.611***	3.591***	4.344***	5.436***
	(1.454)	(1.509)	(1.804)	(1.236)	(1.498)	(1.419)
After	-0.334	-0.418	-0.806	-0.227	-0.128	-0.673
	(0.978)	(1.056)	(1.179)	(0.858)	(1.013)	(0.956)
Treated	0.863	0.014	-0.586	0.820	-0.092	1.390
	(1.062)	(1.041)	(1.125)	(0.889)	(1.069)	(1.004)
Constant	14.842***	15.304***	12.899***	15.819***	16.386***	13.497***
	(0.653)	(0.694)	(0.814)	(0.564)	(0.669)	(0.638)
Observations	354	352	182	524	356	350
R^2	0.063	0.093	0.213	0.052	0.048	0.136

Note: This table reports the heterogeneous intent-to-treat (ITT) effects of the information treatment on the perceived interest rate for different groups of consumers in terms of financial status, financial literacy, and credit availability, by fitting the perceived interest rate on $After$ (whether it happens after information treatment), *Treated* (whether a consumer is assigned to the treatment group), and their interaction in separate regression specifications. The covariates are pre-treatment and therefore exogenous. Low and high denotes whether a covariate is below/above median. Columns (1) - (2) divide the sample by income, (3) - (4) divide the sample by education, and (5) - (6) divide the sample by credit utilization (ratio of debt and credit limit). Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10. IV Estimates of Effect of Perceived Interest Rate on Debt

	OLS				2SLS			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Δdebt	Δdebt	Δdebt	Δdebt	Δdebt	Δdebt	Δdebt	Δdebt
Δ*Perceived_r*	-63.808***	-65.901***			-142.216***	-143.099***		
	(22.215)	(22.335)			(49.250)	(49.869)		
Δ|*Bias*|			-16.484	-22.608			228.735**	227.380**
			(26.809)	(26.712)			(90.544)	(90.730)
Constant	137.204	334.425	28.734	123.317	262.176**	538.256	129.422	533.607
	(112.625)	(334.306)	(113.864)	(337.195)	(130.363)	(345.561)	(122.970)	(384.734)
Control	No	Yes	No	Yes	No	Yes	No	Yes
Observations	353	353	353	353	353	353	353	353
Fstat					69.876	69.058	33.823	33.039

Note: This table reports the estimated effect of perceived interest rate on credit card debt. Columns (5) - (8) are the 2SLS fit of Δdebt (difference between debt after/before treatment) on Δ*Perceived_r* (difference between perceived interest rate after/before treatment) or Δ|*Bias*| (difference between absolute perception error after/before treatment) in which the information treatment status is an IV for perceived interest rate in the first stage. Control denotes whether the regression includes covariates: demographics (gender, education, age, and age squared), financial status (log income and log saving), and credit availability (credit score and log credit limit). The covariates are the pre-treatment level. Columns (1) - (4) report the OLS counterparts as a comparison. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11. IV info treatment on spending and saving

	(1)	(2)	(3)	(4)
	Δspend	Δspend	Δsaving	Δsaving
$\Delta Perceived\_r$	-72.369**	-61.313**	241.837***	257.842***
	(29.335)	(27.524)	(50.170)	(51.269)
Constant	206.687***	578.995***	-688.705***	-911.362***
	(72.946)	(198.552)	(128.244)	(336.773)
Control	No	Yes	No	Yes
Observations	353	353	353	353
Fstat	69.876	69.058	69.876	69.058

Note: This table reports the estimated effect of perceived interest rate on credit card spending and saving. Columns (1) - (2) are the 2SLS fit of Δspend (difference between spending after/before treatment) on $\Delta Perceived\_r$ (difference between perceived interest rate after/before treatment) in which the information treatment status is an IV for perceived interest rate in the first stage. Columns (3) - (4) are the counterparts of Δsaving (difference between saving after/before treatment). Control denotes whether the regression includes covariates: demographics (gender, education, and age), financial status (income and saving), and credit availability (credit score and credit limit). The covariates are at the pre-treatment level. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12. IV Estimates of Effect of Perceived Interest Rate on Spending Categories

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	d_dur%	d_dur%	d_nec%	d_nec%	d_lux%	d_lux%	d_oth%	d_oth%
Δ*Perceived_r*	0.837**	0.861**	0.312	0.345	-1.296***	-1.349***	-0.148	-0.155
	(0.349)	(0.371)	(0.396)	(0.403)	(0.406)	(0.410)	(0.357)	(0.386)
Constant	1.845*	3.887	0.995	-1.262	-2.624***	-5.784**	-0.507	1.430
	(1.011)	(2.474)	(0.951)	(2.504)	(0.901)	(2.544)	(0.779)	(2.267)
Control	No	Yes	No	Yes	No	Yes	No	Yes
Observations	353	353	353	353	353	353	353	353
Fstat	69.876	69.058	69.876	69.058	69.876	69.058	69.876	69.058

Note: This table reports the estimated effect of the perceived interest rate on credit card spending categories. Columns (1) - (2) are the 2SLS fit of d_category% (difference between proportion of spending on a certain category after/before treatment) on Δ*Perceived_r* (difference between perceived interest rate after/before treatment) in which the information treatment status is an IV for the perceived interest rate in the first stage. Spending categories are classified by the bank as follows: 1) Durable: rents, installment payments on mortgages, cars, and furniture, etc.; 2) Necessity: food, tobacco, alcohol, and medical expenses; 3) Luxury: apparel, accessories appliances, and services; and 4) Other. Control denotes whether the regression includes covariates: demographics (gender, education, age, and age squared), financial status (log income and log saving), and credit availability (credit score and log credit limit). The covariates are pre-treatment and therefore exogenous. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13. Perceived Interest Rate Revision in the Long Run

	Control		Treatment		DID
	Before	1 Year Later	Before	1 Year Later	
Bias	-4.63	-4.82	-4.19	-2.55	1.83
	(0.48)	(0.46)	(0.57)	(0.44)	(0.87)
|*Bias*|	7.24	7.32	6.81	4.67	-2.22
	(0.28)	(0.28)	(0.35)	(0.28)	(0.75)

Note: This table shows the mean and absolute value of biases of the perceived debt interest rate before and 1 year 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, 20%, whereas |*Bias*| is the absolute value of the difference. DID denotes the corresponding difference-in-differences estimates. Standard errors are reported in parentheses.

Online Appendix

for "Interest Rate Misperception and Excess Borrowing in the Consumption Credit Market" by Tianyu Han and Xiao Yin

5.1 Survey

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 credit card in our bank?
2. Suppose your billing cycle is at the end of the month. For each of the following scenario, please select the closest amount of interests that would incur at the end of next month.
   (a) You spend 5,000 RMB this month, and repay 3,000 RMB at the end of this month
      i. 0
      ii. 10
      iii. 20
      iv. 30
      v. 40
      vi. 50
      vii. 60
   (b) You spend 5,000 RMB this month, and repay 1,000 RMB at the end of this month
      i. 0
      ii. 20
      iii. 40
      iv. 60
      v. 80
      vi. 100
      vii. 120
   (c) You spend 5,000 RMB this month, and repay 0 RMB at the end of this month
      i. 45
      ii. 55
      iii. 65
      iv. 75
      v. 85

vi. 95
vii. 105

3. Suppose your total saving is 10,000 RMB, how much interests will you earn in the next month.
   (a) 0
   (b) 10
   (c) 20
   (d) 30
   (e) 40
   (f) 50
   (g) 60
4. How many times did you pay interests on credit card in the last year.
   (a) 0
   (b) 1-3
   (c) 4-6
   (d) 7-9
   (e) more than 9 times.
5. The bank assigns each customer with a credit score to label the relative safeness for granting a loan. What would be the credit score you believe you have at the bank? (Please give a number between 0 and 10, 10 being the safest).

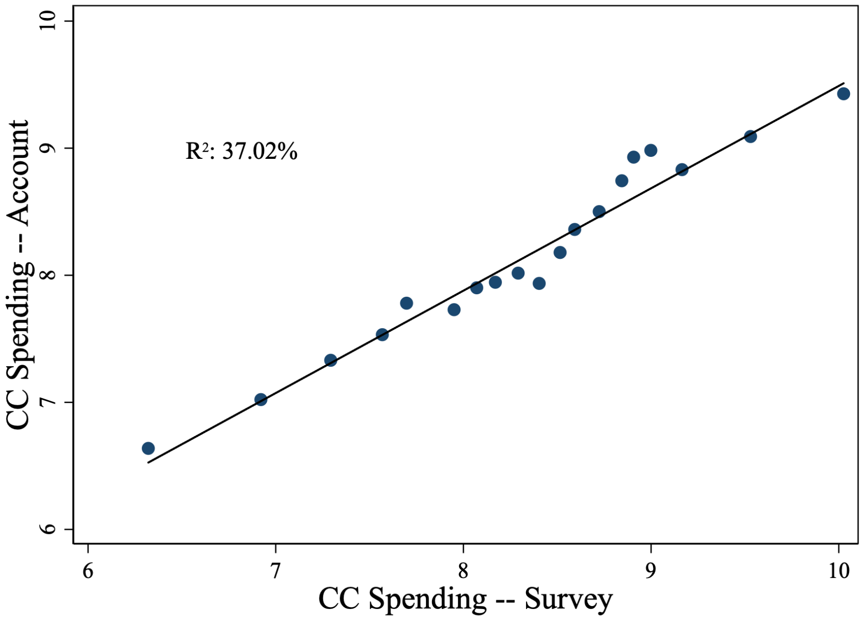
The annualized interest rate on credit card is around 20%. This rate is equivalent to a monthly interest rate of about 1.51%. If you carry over 8,000 CNY of debt on a credit card to the next billing cycle, then there will be an around 120.8 CNY in interest rate in the next month.[6]

1. *Suppose your billing cycle is at the end of the month. If you spend 6,000 RMB this month, and repay 3,000 RMB at the end of this month. How much interest in total would you incur at the end of the next month?*[7]
   (a) 15
   (b) 25
   (c) 35
   (d) 45
   (e) 55
   (f) 65
   (g) 75

[6] Sent in a new page to a random 40% of those who paid interest costs on credit card in 2020 before the experiment.
[7] All participants that paid interests in 2020 was reveal the information.

B: Additional Results

Figure B.1: Sanity Check of the Survey Data



Note: We use this figure to display a sanity checks for the measurement of spending from the credit card. The figure is a binned scatter plot of consumer spending from credit card in the bank last month based on the bank account data and that from survey question 1. Both measures are in log values.