Essays on Marketing Strategies for the Credit Card Market

By

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Abstract

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Credit cards are an important vehicle for spending and borrowing. Collaborating with a leading commercial bank in China, this dissertation consists of two chapters that explore how the design of credit card products can influence consumer behavior, alongside its implications for marketing strategies and consumer welfare.

The first chapter studies reward programs, often a prominent feature of credit cards. I combine proprietary consumer-level data and a survey to study the causal effect of rewards on consumption and consumers' subjective expectations. I leverage a fuzzy regression discontinuity (RD) design to show that a more generous reward design causes consumption increases across both reward-earning and non-reward-earning categories. Applying the fuzzy RD to the survey data, I find that consumers correctly understand the impact of reward design on reward-earning consumption but underestimate its effect on total consumption. Using a stylized model, I study the implications of this misperception for market structure and welfare. My calibration results show that consumer misperceptions incentivize banks to offer more generous rewards, which ultimately diminishes market efficiency and leads to a cross-subsidy from less to more sophisticated consumers.

The second chapter, coauthored with Xiao Yin, investigates the extent to which consumers misperceive the interest costs associated with credit card debt using a combination of administrative data and surveys. Through a randomized controlled trial with an information treatment, our results show that consumers are imperfectly informed about the interest cost of unsecured debt, and the resulting misperception induces excess debt-taking by 26%, mainly originating from spending on luxury goods. To understand the formation of interest rate misperception, we uncover selective information acquisition to be a potential channel. We demonstrate that consumers tend to actively seek information about their borrowing

status when they expect creditworthiness to be high, and they disproportionately pay more attention to favorable information when interest rates are low.

To my family

Contents

List of Figures

List of Tables

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Chapter 1

Rewards and Consumption in the Credit Card Market

1.1 Introduction

Reward programs are commonly seen as a prominent feature of credit cards. In 2022, the reward payment reached 67.9 billion US dollars and was rising among the top six credit card issuers in the United States.[1] Banks often craft these rewards strategically, advertising them as unique selling propositions for their credit card products. For example, credit cards issued by American Express in the United States (illustrated in Figure 1.1) incentivize consumers with an array of rewards tied to spending categories such as travel, groceries, and dining. While several business reviews (e.g., Santana et al., 2017) qualitatively address the role of such rewards in consumer acquisition, brand loyalty, and eventually profitability, there is a paucity of quantitative research on the causal effect of these rewards on consumer behavior in the credit card market. Besides, in spite of the prevalence of credit card rewards, it remains unclear why banks are willing to provide such generous offerings.

This paper steps to close the gap and addresses three key research questions. First, I explore the effect of credit card rewards on consumption. Notice that in many contexts, only a small fraction of transaction categories (such as flight tickets) can earn rich credit card rewards. For this reason, I further evaluate the spending changes in both reward-earning and non-reward-earning categories, respectively. It is plausible that consumers might curtail their spending in non-reward-earning categories by substituting purchases from these categories with ones that earn rewards. On the other hand, spending in non-reward-earning categories could also increase, leading to a rise in total consumption.

Second, I investigate whether consumers accurately understand how these rewards impact their consumption. In principle, reward programs should increase consumer welfare if consumers use these rewards and decide on consumption rationally. However, in practice, some deals can be so attractive that consumers may overreact to them. In this case, if

[1] See Schulz (2023) for an industry report.

consumers are not fully aware of their true expenditures, reward programs, on the contrary, may lure consumers into excess spending and decrease consumer welfare consequently. Rational expectations in this context, as a result, are crucial for consumers to make optimal consumption and saving decisions.

If consumers do not have rational consumption expectations, my third question explores the implications of such misperception for market structure and consumer welfare, focusing on the incentives that drive firms to offer reward programs and how firms might exploit consumer mistakes in their product designs and promotional strategies.

I partnered with a major commercial bank in China to make headway on these questions. For a reliable observation of consumption beyond mere spending within the bank, I follow the literature (e.g., Ganong and Noel, 2019) and confine my analysis solely to consumers who utilize the bank as their primary financial institution. I illustrate that my dataset will likely capture the majority of transactions conducted by the consumers in my sample.

To understand consumers' subjective expectations of spending, I deployed a survey instrument to elicit their perceptions. I constructed tailored questions that prompted consumers to estimate their total spending and the portion that would yield credit card rewards. I then integrated these perceptions with proprietary monthly administrative data detailing each consumer's financial decisions, including spending (through both checking and credit accounts), saving, and reward redemption behavior. This dataset, which juxtaposes consumer beliefs and revealed preferences, provides an ideal lab to study consumption patterns and consumer beliefs within the credit card market.

My conditional correlation analysis reveals positive associations between redeemed reward values and consumption. Moreover, consumers who underestimate their spending have higher consumption levels and redeem more rewards, suggesting that spending perceptions may be an important determinant of consumption. Despite these plausible and appealing correlations, identifying the causal effects can be particularly challenging. Indeed, a consumer can endogenously determine their consumption and reward redemption patterns, and these choices may be associated with unobserved confounding factors. For example, a consumer may opt for increased consumption due to their intent to redeem high-value rewards; as a result, such "reward chasers" and "non-chasers" may not yield an apples-to-apples comparison.

To provide causal evidence, I exploit the bank's two mutually exclusive credit card offerings: the Gold and Platinum cards. The Platinum card, in addition to offering all the benefits of the Gold card, features a more extensive and generous reward program. Aside from these rewards and their aesthetic differences, the two cards are essentially identical. I leverage the eligibility rule of the Platinum card to identify the causal effect of Platinum rewards on consumption and consumers' subjective expectations. The eligibility criteria mandate that consumers can only upgrade to a Platinum card if their total assets with the bank exceed 30,769 dollars (200,000 CNY). This rule results in a discontinuously upward jump in Platinum card adoption probability as soon as a consumer's assets surpass the stipulated threshold. Using a fuzzy regression discontinuity (RD) design (Imbens and Lemieux, 2008), I identify the local average treatment effect (LATE) for the compliers who narrowly cross the asset threshold and subsequently adopt the Platinum card.

I find that, on average, the availability of Platinum card rewards instigates an increase in total consumption by 118 dollars, representing an approximate surge of 10%. Reward-earning consumption rises by 64 dollars, resulting in a 15-dollar increase in the earned reward value. The Platinum rewards also trigger a 54-dollar increase in non-reward-earning consumption.

Additionally, my quasi-experiment design identifies the causal effect of rewards on consumers' perceived expenditure in reaction to the rewards. Consumers fail to accurately anticipate the total consumption change engendered by Platinum rewards: they predict a mere 17-dollar increase against the actual rise of 118 dollars. However, they correctly foresee a 63-dollar increase in reward-earning consumption. This suggests that consumers believed they could save 46 dollars from non-reward-earning expenditures through the utilization of credit card rewards. Misperception of spending in the non-reward-earning category emerges as the leading cause contributing to the overall underestimation of total consumption.

The majority of Platinum rewards consist of travel benefits and other high-end services that typically necessitate advance bookings. Mistakes in anticipating non-reward-earning expenditure suggest that when making reward-associated purchases, consumers neglect to consider their future demand for complementary products in non-reward-earning categories. As an illustrative example, a credit card reward offering discounted airfare might tempt a consumer to purchase a ticket to Hawaii, anticipating savings on the flight. However, this decision often neglects the cost of hotel rooms, car rentals, and other travel-related expenses in Hawaii. When the future comes, consumers realize the (surprisingly) high costs of these services in Hawaii, leading to an unplanned increase in non-reward-earning spending.

Motivated by the observed positive cross-elasticity of rewards on non-reward-earning consumption and that consumers overlook such *economic complementarity*, I introduce the term "complementarity ignorance" to encapsulate the phenomenon of neglecting non-reward-earning expenditures. My stylized model demonstrates the effect of complementarity ignorance on market structure. In period 0, the bank determines credit card reward offerings. Given the reward contract, consumers then solve a consumption and savings problem, distinguishing between reward-earning and non-reward-earning categories, such as flight tickets (reward-earning) and hotel rooms (non-reward-earning). Consumers decide whether to purchase flight tickets in period 1 and hotel rooms in period 2. My model predicts that if (naive) consumers overlook their demand for hotel rooms when booking flights, they will underestimate their consumption and consequently overspend. In contrast, (sophisticated) consumers with rational expectations of future demand will make optimal consumption and saving decisions. On the supply side, the bank faces a tradeoff between the revenue from transaction fees against the cost of reward disbursement and operational costs. In a perfectly competitive market, the bank profits from naive consumers while incurring losses from sophisticated consumers, suggesting a cross-subsidy from the former to the latter. The model further predicts that banks will offer more generous rewards for a higher level of complementarity between consumption categories. This explains why reward programs usually include purchases like travel but not essential services like utility payments. The presence of naive consumers also increases reward offerings, suggesting that naiveté exploitation incentivizes banks to offer generous rewards.

Lastly, my model highlights important implications of complementarity ignorance for consumer welfare. According to current credit card rewards, my numerical calibration illustrates that an average consumer faces a welfare loss of around 2.5% of their monthly consumption, equating to approximately 25 dollars. The decomposition of welfare effects reveals a disparity between naive and sophisticated consumers. Naiveté itself is very costly: naive consumers bear at least 80 dollars loss in welfare (around 7% of consumption), which can amplify with more naive consumers present in the market. On the contrary, sophisticated consumers derive benefits from credit card rewards, albeit at a smaller scale than the welfare loss experienced by naive consumers. Therefore, regulatory interventions for credit card rewards or strategies to debias complementarity ignorance may be beneficial from a welfare perspective.

Related Literature This research contributes to several strands of literature. First, it is closely related to "behavioral industrial organization" (Heidhues and Kőszegi, 2018) in numerous respects. The finding that consumers disregard complementary purchases resonates with the discussion on consumption behaviors of "behavioral agents" in prior literature, such as mental accounting (Thaler, 1985) and shrouded attributes (Gabaix and Laibson, 2006). Such negligence can be rationalized by a higher cognitive cost incurred on more complex objects, consistent with Gabaix (2014), Caplin and Dean (2015), and Caplin et al. (2019). Previous literature also considers contract design with naiveté exploitation. For instance, DellaVigna and Malmendier (2004), DellaVigna and Malmendier (2006), and Heidhues and Kőszegi (2010) demonstrate how firms can blend time-inconsistent preferences with immediate costs and deferred benefits by implementing back-loaded fees. In spite of these theoretical predictions, there is little empirical causal evidence, partially because of the difficulty of observing beliefs in practice. This paper contributes to the literature by unmasking a concrete behavioral bias using field data, i.e., complementarity ignorance. I also combine empirical results with a theoretical model to elucidate the effect of complementarity ignorance on conduct, market structure, and welfare within the realm of credit card rewards. Instead of focusing solely on financial decision-making processes, my findings underscore human behavior and hold relevance to other scenarios and contexts characterized by budget negligence.

Second, this paper contributes to the literature on reward credit cards and pricing strategies in marketing. In a review article, Hayashi et al. (2009) provide an exhaustive overview of reward schemes of credit cards in the U.S. market. Ching and Hayashi (2010) investigate how reward programs can encourage consumers to favor credit cards as their primary payment method. Agarwal et al. (2010) and Agarwal et al. (2022) discuss the funding sources of credit card rewards. To the best of my knowledge, this paper is the first to establish the causal effect of credit card reward design on consumption by applying a quasi-experiment to field data. The impact of rewards on associated consumption categories aligns with the advertising spillover effect, such as Seiler and Yao (2017), and offers a micro-founded explanation for the entrenched loss-leader pricing strategy as demonstrated in Hess and Gerstner (1987), Li et al. (2013), and others.

Lastly, my research joins the growing literature on the role of beliefs in consumer decisions. Related to household finance, Allcott et al. (2022) elicit consumers' perceived probability of getting payday loans, finding that consumers are surprisingly very aware of their time-inconsistent preferences and willing to pay a high premium for future borrowing avoidance. Zooming into the purchase funnel, Jindal and Aribarg (2021) elicit price beliefs and discuss their importance in consumer search processes. Armona et al. (2019) look at how price expectations affect purchase decisions and eventually the market structure. In the credit card market, a recent study by Han and Yin (2022) indicates that consumers bear excessive consumption loans due to interest rate misconceptions. From the bank's viewpoint, Yin (2022a) reveals that credit limit extensions can prompt consumers to harbor overly optimistic beliefs about future income, which significantly accounts for the boosting effect of credit limits on consumption and borrowing. My work builds upon this literature and integrates the survey tool with the proposed quasi-experiment; the discovered causal effect on consumer beliefs facilitates more nuanced scrutiny of incentives under decision-making processes.

Roadmap The rest of the paper proceeds as follows. Section 1.2 describes sample construction, survey design, and summary statistics. Section 1.3 provides a descriptive analysis of the interaction between reward redemption and consumer spending and borrowing behavior and discusses why the design of credit card rewards could be an important determinant. Section 1.4 details the empirical procedures to identify and estimate the causal effect of reward design on consumption. Section 1.5 uses a stylized model to reveal how complementarity ignorance affects equilibrium pricing and welfare. Section 1.6 concludes.

1.2 Data and Sample Construction

This section describes the data employed in my empirical analysis, as well as a discussion on the sample selection procedure to justify internal and external validity.

Data

The data for this study comes from a large commercial bank in China ("the bank," hereafter). The bank operates at a national level and ranks among the top 10 commercial banks in the country based on total assets. In 2020, the bank's total assets amounted to over 1 trillion US dollars. Given the extensive consumer base and comprehensive coverage of the whole demographics, the data collected from the bank can be considered representative of the broader population within the country.

Credit cards are widely used and accepted in China. According to a recent article,[2] credit card use in China has grown significantly since 2015, with the total volume of credit card

[2]See the article for a survey (in Mandarin Chinese) of the credit card market in China.

transactions across the top 14 Chinese commercial banks rising from 2.6 trillion US dollars in 2015 to 5.6 trillion in 2019. During the same period, the total number of credit cards increased from 0.47 billion to 0.78 billion.

Similar to the credit card products in other countries, an important feature of credit cards issued by the bank is the benefits offered. Through credit card spending, consumers can earn rewards and cashback on a variety of products and services, including but not limited to price discounts (e.g., 5% off on JD.com purchases, gas, restaurant, and grocery), coupons (e.g., 10 CNY off on movies, 9 CNY off on takeouts, and 20 CNY off on purchases over 200 CNY at KFC restaurants), and travel-related rewards (free buffet at selected hotels, free airport pickup services, and flight delay insurance). The available benefits and rewards are subject to variation depending on the bank's prevailing promotional strategies. At the end of each monthly billing cycle, redeemed rewards are automatically applied as a statement credit to the consumer's account.

Sample Restrictions

Due to my inability to capture consumer financial behavior outside the bank, I have imposed certain restrictions during the sample selection process. Given that consumers might have multiple bank accounts, single-provider transaction-level data raise concerns about the completeness of the data in covering the full extent of consumers' financial status. To alleviate this concern, I follow Ganong and Noel (2019) and impose two filters to ensure that consumers in my sample predominantly utilize the bank as their primary banking institution. First, I include only consumers whose accounts have at least 15 outflow transactions during the sampling period. An outflow is any debit from a checking, saving, or credit card account, including a cash withdrawal or electronic payment. This filter reduces the original sample by approximately 35%. The second restriction mandates that the bank should be able to directly identify and calculate consumers' income directly by observing regular inflows into checking accounts, resulting in a further drop of about 10% in observations.

Another concern pertains to cash transactions made by consumers. In fact, recent reports[3] show that consumers in China primarily use digital wallets (e.g., Alipay and WeChat Pay) for everyday transactions. In 2021, the penetration rate of mobile payment reached 87.6% and continued to rise.[4] If a digital wallet does not have sufficient balance, the digital wallet account has to be linked to a consumer's checking account or credit card to complete transactions. Given that consumers in my sample use the bank as their primary banking institution, the bank will be capable of recording most of a consumer's cash-equivalent transactions made through digital wallets. This capability, along with my aforementioned restrictions, allows the bank to provide a reliable observation of consumers' total consumption.

[3] See Ovide (2021) and Daxueconsulting (2022) for the reports that digital wallets on mobile phones are the main payment method in China.

[4] See Slotta (2022) for the statistics about mobile payments in China.

Observational Variables of Interest

First and foremost, transaction-level data enable direct measurement of consumer spending. The data record three types of spending: total spending, reward-earning spending, and non-reward-earning spending. Total spending comprises purchases of non-durable goods (as defined by the bank) from a consumer's checking account plus the repayment of linked credit cards over the last billing cycle, including but not limited to credit card purchases and transactions through digital wallets. Reward-earning spending refers to those credit card transactions that trigger rewards, whereas non-reward-spending is calculated as the difference between total and reward-earning spending. Accompanying reward-earning spending, the data also include information about the rewards, which is the monetary value of benefits or services earned by a consumer.[5]

The bank issues two types of mutually exclusive credit cards: Gold and Platinum. Except for their distinct colors and benefits, these two credit cards share identical features, including debt interest rates, annual fees,[6] and the method of redeeming credit card rewards. The Gold card has 13 benefits, while the Platinum card has all the Gold benefits plus 14 Platinum exclusive benefits (mostly related to travel and high-end services). Table 1.1 provides some example reward benefits. To understand how these designs affect consumption, I record the type of card that a consumer currently holds along with the corresponding holding period, defined as the number of days since the approval of a consumer's credit card application.

The dataset also records other related financial behavior. Debt is the outstanding interest-incurring balance on the credit card. A consumer's asset with the bank is the sum of savings, the total value of insurance, and financial investments, minus consumption loans. To measure income, the bank records a consumer's regular monthly income flow and bonuses if the customers declare that they are working as employees. The bank calculates this number in one of two alternative ways: if income is paid as a direct deposit from the consumers' employers to this bank, then this number is directly labeled as income 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.[7]

[5]For reward points, the bank has an internal metric to value points in dollars.

[6]The Platinum card has *prima facie* higher annual fees than the Gold card. However, annual fees will be waived if a credit card has over five transactions in a year. Given the selection restrictions, all consumers have *de facto* zero annual fees in my sample.

[7]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 bounded by an upper- and lower-percentile 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, I exclude the consumers in the capped region from the final sample. Removing customers whose incomes are capped drops the sample by 9.6%.

Table 1.1: Example of Credit Card Rewards

	Gold	Platinum
5% off JD.com purchases	Y	Y
50% Starbucks/KFC	Y	Y
5% off gas/groceries	Y	Y
$10 off movie tickets	Y	Y
Cashback on international flights		Y
Foreign airport pickup		Y
Travel insurance		Y
Hotel free buffet		Y
Travel medical insurance		Y

Note: This table provides an example of the reward benefits of the Gold and Platinum cards offered by the bank. These benefits can take the format of price discounts, coupons, cashback, and points (in this case, the bank has a metric to measure points in monetary values). The Platinum card includes all the Gold card benefits but also provides additional Platinum exclusive benefits, mostly travel-related. These benefits and rewards are subject to change depending on the bank's prevailing business goals.

To understand and control for heterogeneity, I also collect information on consumer age, gender, (self-reported) education, credit score, cities,[8] and industries.[9]

Survey Design for Perceived Consumption

Consumer beliefs can play a pivotal role in the financial decision-making process (e.g., Yin, 2022a; Han and Yin, 2022). Therefore, it is interesting and crucial to collect data on consumers' perceived level of consumption, both related and unrelated to credit card rewards. To elicit these perceptions, I collaborated with the bank to conduct a survey among a randomly selected group of customers who met the criteria specified in Section 1.2 in July 2022. Selected consumers received a link through text and WeChat messages to a mobile application where the survey was designed and delivered. Consumers were informed that their responses were for research purposes only and would not be used against their financial products, interest rates, or credit scores to any extent. Within a week of completion, each participant received a gift worth around 2 US dollars.

Appendix A.3 provides detailed information about the survey. In a nutshell, questions 1 and 2 elicit a consumer's perceived spending and perceived reward-earning spending, respectively.

[8]There are 48 cities (anonymous to the econometrician) across the nation in total.

[9]There are 14 industries (anonymous to the econometrician) in total, e.g., retail, health, banking, and public administration.

- *What was your average monthly spending in the past six months (excluding spending on fixed assets such as rent and various loans)?*
- *In the past six months, on average, how much money have you spent on your credit card that earns cashback and rewards each month? Cashback rewards include but are not limited to discounts, points, and services.*

Consumers were asked to fill in an integer as their best guess in the instruction. Since it may cause confusion to ask about spending that is unrelated to credit card rewards and cashback, I calculate the difference in answers to questions 1 and 2 and use it as a consumer's perceived spending in the non-reward-earning category.

1.3 Descriptive Analysis

I start the descriptive analysis of the data with some summary statistics and visualizations. This section also presents a correlation analysis of reward redemption, consumption, and spending perception errors.

Summary Statistics

The data contain survey responses from 4,565 credit card users (consumers, hereafter) in China and monthly averages of the observational variables of interest from December 2021 to June 2022. For simplicity and comparability, the currency unit used throughout the paper is converted to US dollars (1 USD $\approx$ 6.5 CNY).

Table 1.2 presents the summary statistics of the data. The mean total spending is approximately $1,133.6 with a standard deviation of $419. The spending within the bank is very close to the total spending, including elsewhere, which confirms that the spending data provided by the bank is a reliable measure of total consumption. On average, around 19% of the total spending is towards the reward-earning category, suggesting that the majority of spending categories do not generate credit card rewards. The average monetary value of credit card rewards is $43.4, corresponding to a reward rate of 20% of the reward-earning spending and 4% of total spending. Most consumers in the sample earn a nontrivial amount of benefits from credit card rewards, as suggested by the first quartile of reward value at $29.4.

In terms of card types, 37.8% of consumers hold a Platinum card, and the remaining 62.2% hold a Gold card. The mean holding period of a credit card is 282.8 days with a standard deviation of 66.2 days, allowing for comparison between newly converted and relatively established consumers.

Most consumers do not use credit cards for borrowing. This observation motivates the focus of the study on the product perspective of credit cards. The average income is $1,690.6 with a standard deviation of $1,088.9. The average total assets within the bank are $32,364.6,

Table 1.2: Summary Statistics

	mean	sd	p25	p50	p75	count
Total spending	1133.6	419.0	838.8	1024.3	1268.0	4564
Reward-earning spending	213.1	171.7	109.0	163.2	249.8	4564
Non-reward-earning spending	920.6	273.8	715.4	861.1	1037.0	4564
Rewards	43.40	30.14	29.46	34.35	42.80	4564
Platinum	0.378	0.485	0	0	1	4564
Holding period	282.8	66.18	232	283	334	4564
Debt	852.6	2549.1	0	0	422.3	4564
Asset	32364.6	21617.0	18462.3	26157.2	40337.5	4564
Income	1690.6	1088.9	964.5	1331.4	2200.4	4564
Female	0.585	0.493	0	1	1	4564
Age	37.32	10.60	28	36	46	4564
Education	2.878	0.859	2	3	3	4564
Credit score	55.11	5.403	51.39	54.57	58.11	4564
Total spend under-report	85.71	550.9	-248.5	89.47	399.1	4564
Reward spend under-report	6.560	30.06	-11.08	3.714	20.59	4564
Total spend under-report rate	0.0719	0.452	-0.237	0.0878	0.379	4564
Reward spend under-report rate	0.0354	0.157	-0.0598	0.0213	0.134	4564

Note: This table records the summary statistics of the data. Total spending is defined as the purchases of non-durable goods from a consumer's checking account plus the repayment of linked credit cards over the last billing cycle. Reward-earning spending is defined as a consumer's credit card transactions that can trigger rewards. Platinum is a dummy variable if a consumer holds a Platinum card (instead of a Gold card). Holding period is the number of days that a consumer has the current credit card product. Rewards are the dollar value of earned benefits. Debt is the outstanding interest-incurring balance on the credit card. A consumer's asset with the bank is the sum of savings, the total value of insurance, and financial investments, minus consumption loans. Under-reporting is the value of true spending minus reported spending.

about 20 times the monthly income. The high asset value within the bank indicates that the bank is indeed the primary banking institution for the consumers in the sample.

For demographics, the average age is 37.3, with a standard deviation of 10.6. Education is coded as follows: 1 - high school diploma and below, 2 - some college, 3 - bachelor's degree, and 4 - graduate school. Most consumers received some college education, and the median consumer holds a bachelor's degree.

Lastly, Figure 1.2 uses binned scatter plots to visualize survey responses of the perceived spending against the actual spending. The green diagonal curve is the 45-degree line, and the red curve is a quadratic fit. On average, consumers underestimate their total spending by 8% ($85.7); the underestimation wedge enlarges for larger spending. However, consumers seem to understand the spending related to rewards quite well; the underestimation rate is 3.5% ($6.7). This gap between the perception errors in total spending and reward-earning spending may be explained by consumers paying more attention to reward-related spending but having insufficient attention towards the more complex non-reward-earning category. For example, noticing an attractive discount on flights, consumers are aware of the expenditure on flights. However, consumers also have to make many travel-related miscellaneous purchases on lodging, car rentals, restaurants, etc., and they cannot recall each bill verbatim because of the large variety.

Despite the systematic downward perception errors, the perceived spending fits the trend of corresponding true spending fairly well, suggesting reasonable credibility of survey responses. The prevalence of spending underestimation also suggests that spending recorded by the bank covers total consumption quite well.

Conditional Correlations

The study next explores potential determinants behind reward redemption, fitting simple linear regressions of reward value as in Equation (1.1). Here, X_i represents total spending, reward-earning spending, non-reward-earning spending, assets (in thousand US dollars), debt, card type, total and reward-earning spending under-reporting, and covariates of demographics and financial literacy, respectively in each regression. For simplicity and interpretability, except for city and industry dummies, covariates are discretized and divided into two bins according to their median values.

$$Reward_i = \alpha + \beta X_i + \mathbf{Covariate}_i^T \gamma + \varepsilon_i \tag{1.1}$$

Table 1.3 shows the main regression results of Equation (1.1). Not surprisingly, rewards are positively correlated with total spending and reward-earning spending. In particular, credit card benefits can be lucrative: a \$1 increase in reward-earning spending corresponds to a \$0.16 increase in rewards. Interestingly, non-reward-earning spending also co-moves with rewards in the same direction, suggesting that consumers may not save money in the end by substituting reward-earning consumption for the non-reward-earning counterpart. Additionally, richer consumers (with higher asset values) tend to earn more rewards; despite a small correlation, higher reward value comes with higher credit card debt. All else equal, consumers with a Platinum card earn \$20 higher rewards than those with a Gold card; this is consistent with the fact that Platinum cards have more benefits than Gold cards. For spending perception error, I observe a higher reward value for larger spending under-reporting: a \$1 total spending under-reporting is associated with a \$0.004 reward value, while a \$1 reward-earning spending under-reporting is associated with a \$0.2 reward value.

In terms of consumption, I fit simple linear regressions of reward-earning spending as in Equation (1.2), where X_i denotes asset (in thousand US dollars), debt, card type, total and reward-earning spending under-reporting, respectively in each regression, with the covariates as previously described.

$$Total\_Spending_i = \alpha + \beta X_i + \mathbf{Covariate}_i^T \gamma + \varepsilon_i \tag{1.2}$$

Table 1.3: Descriptive Analysis: Reward Redemption

	(1) Rewards	(2) Rewards	(3) Rewards	(4) Rewards	(5) Rewards	(6) Rewards	(7) Rewards	(8) Rewards
Total spending	0.069***							
	(0.005)							
Reward spending		0.159***						
		(0.009)						
Non-reward spending			0.091***					
			(0.008)					
Asset (thousand $)				0.570***				
				(0.071)				
Debt					0.005***			
					(0.001)			
Platinum						20.189***		
						(2.483)		
Tot-spend under-repo							0.004***	
							(0.001)	
Rew-spend under-repo								0.192***
								(0.067)
Constant	-23.892***	12.684***	-31.274***	20.266***	27.818***	28.993***	28.722***	28.660***
	(3.537)	(1.313)	(5.209)	(1.721)	(1.183)	(1.314)	(1.317)	(1.366)
Observations	4564	4564	4564	4564	4564	4564	4564	4564
R^2	0.729	0.768	0.566	0.300	0.363	0.256	0.189	0.218

Note: This table shows the OLS fit of rewards on variables of interest. Omitted control variables include age, income, gender, education, and credit score. City and industry fixed effects are included. Standard errors in parentheses are clustered at city × industry level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.4 shows the main regression results of Equation (1.2). Similar to the observations in Table 1.3, reward-earning spending is positively correlated with total assets and debt. Furthermore, all else equal, consumers with a Platinum card have $410 higher total spending than those with a Gold card; the regression analysis suggests that a Platinum credit card product might not only help consumers earn higher rewards but also stimulate higher consumption. Similar to Table 1.3, higher spending under-reporting comes with higher consumption, while consumption appears to be more sensitive to the reward-earning perception error than the total spending perception error.

I continue a similar analysis of spending perception error by fitting simple linear regressions as in Equations (1.3) and (1.4), where X_i denotes asset (in thousand US dollars), debt, and card type, respectively in each regression, with the covariates as previously described.

Table 1.4: Descriptive Analysis: Consumption

	(1) Total spending	(2) Total spending	(3) Total spending	(4) Total spending	(5) Total spending
Asset (thousand $)	10.992***				
	(0.784)				
Debt		0.065***			
		(0.007)			
Platinum			409.934***		
			(28.207)		
Tot-spend under-repo				0.067***	
				(0.014)	
Rew-spend under-repo					1.742***
					(0.624)
Constant	594.693***	749.673***	762.961***	759.335***	761.279***
	(18.801)	(15.611)	(15.620)	(17.941)	(18.340)
Observations	4564	4564	4564	4564	4564
R^2	0.636	0.548	0.567	0.418	0.426

Note: This table shows the OLS fit of total spending on variables of interest. Under-reporting is the value of true spending minus perceived spending. Omitted control variables include age, income, gender, education, and credit score. City and industry fixed effects are included. Standard errors in parentheses are clustered at city × industry level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

$$Under\_Reporting_i = \alpha_1 + \beta_1 X_i + \mathbf{Covariate}_i^T \gamma_{\mathbf{1}} + \varepsilon_i \tag{1.3}$$

$$Reward\_Spending\_Under\_Reporting_i = \alpha_2 + \beta_2 X_i + \mathbf{Covariate}_i^T \gamma_{\mathbf{2}} + \nu_i \tag{1.4}$$

Table 1.5 shows the main regression results of Equations (1.3) and (1.4). Higher asset value is associated with larger under-reporting in total spending, possibly because richer consumers also spend more and hence have a larger perception error. On the other hand, asset value is not correlated with under-reporting in reward-earning spending. Debt does not appear to be an important factor behind spending misperception despite a modest but statistically significant correlation with reward-earning spending under-reporting. Opting in for Platinum cards is a strong predictor of total spending under-reporting: consumers with a Platinum card have a $120 larger underestimation than those with a Gold card; consistent with Table 1.4, Platinum card consumers have higher consumption, which is likely to be the cause of larger spending perception error. There is no statistically meaningful difference in reward-earning spending under-reporting between Platinum and Gold consumers, though.

Table 1.5: Descriptive Analysis: Spending Under-report

	Total spending under-reporting			Reward spending under-reporting		
	(1)	(2)	(3)	(4)	(5)	(6)
Asset (thousand $)	2.432***			-0.039		
	(0.609)			(0.049)		
Debt		0.004			0.002**	
		(0.006)			(0.001)	
Platinum			120.399***			-0.767
			(20.821)			(2.245)
Constant	53.263***	89.983***	90.321***	2.961**	1.825	2.367*
	(18.144)	(14.811)	(15.021)	(1.328)	(1.294)	(1.274)
Observations	4564	4564	4564	4564	4564	4564
R^2	0.024	0.018	0.026	0.051	0.082	0.051

Note: This table shows the OLS fit of spending perception error on variables of interest, where under-reporting is the value of true spending minus perceived spending. Omitted control variables include age, income, gender, education, and credit score. City and industry fixed effects are included. Standard errors in parentheses are clustered at city × industry level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Discussion

Preliminary analyses highlight the following important correlations. Firstly, compared to Gold cardholders, Platinum cardholders redeem more rewards, a phenomenon which is justified by the card's design. Concurrently, their total consumption also escalates appreciably. Secondly, my findings suggest that reward-earning and non-reward-earning purchases do not act as substitutes but rather as complements. This is supported by the observed synchronous increase in reward value and non-reward-earning consumption. Thirdly, Platinum card users exhibit considerably larger misperceptions in reported total spending than Gold users. Nevertheless, both consumer groups display a comparable level of perception error in reward-earning expenditures.

These results cast light on the impact of rewards on consumption. Motivated by the lure of credit card rewards, consumers are observed to increase purchases in the reward-earning category. Interestingly, spending in the non-reward-earning category also amplifies, which may occur inadvertently, as Platinum cardholders commit larger inaccuracies in total spending estimates but not in reward-earning spending. However, it should be noted that a simple linear regression may not accurately elucidate the causal effect due to potential confounders. In reality, the decision to opt for a Platinum card, as well as reward redemption, is endogenous. As such, Platinum and Gold cardholders may display profound differences and regression analysis may fail to disentangle whether the variation in consumption is a result of rewards per se or attributable to unmeasured selection.

1.4 Causal Effect of Reward Availability

To identify the causal effect of credit card rewards on consumption, the ideal data would involve randomizing rewards among consumers and assessing the subsequent consumption within each reward level group. However, this presents empirical challenges in two key respects. First, the definition of treatment is ambiguous: it could be interpreted as the value of redeemed rewards in dollars, as my data suggests, or as reward items such as travel benefits or movie ticket coupons. Secondly, randomization is impractical: if the treatment were to be defined as the reward value in dollars, it is unclear how a consumer's *choice* could be randomly assigned; if the treatment were benefit items, it would not be incentive incompatible for a bank to randomize as unstable reward designs could tarnish product images. The next best empirical approach is to employ observational data, albeit with certain assumptions and limitations.

Identification Strategy: Fuzzy Regression Discontinuity Design

Treatment Definition In my data, the variation in the reward design is based on the card type. A Gold card offers 13 benefits to consumers, while a Platinum card provides an additional 14 benefits exclusive to this tier (primarily associated with travel and high-end services), encompassing all the benefits of the Gold card. Except for the available rewards and color difference, the two cards are identical, sharing the same interest rate, annual fees, reward redemption methods, etc. Thus, I exploit this variation to identify the causal effect of the availability of Platinum rewards on consumption. In essence, my control group is the Gold cardholders, and I examine how consumers modify their behavior when Platinum benefits become available to them, even if they do not necessarily utilize these benefits. The exogenous variation I focus on is product design, which serves as a well-defined treatment.

This approach, admittedly, adopts an agnostic view of the reward, termed as the "Platinum benefits." It should be noted that the bank applies varying benefits to credit cards based on its seasonal business objectives. Considering the variation available in the data, I trade off the heterogeneous nature of rewards for a precise definition of the treatment effect.

To interpret the treatment effect, in a related paper, Bursztyn et al. (2018) discuss Platinum cards as a status good: consumers may seek the Platinum status to flaunt their social standing. This poses a potential challenge to the interpretation of the Platinum treatment: the effect could stem from a demand for status rather than the rewards themselves. However, they argue that the demand for status is only relevant if the transactions are "visible,"[10] i.e., when consumers physically present their Platinum cards to others. Given the prevalence of digital transactions discussed in Section 1.2, the bulk of transactions in my sample

[10] Bursztyn et al. (2018) do not find an effect of Platinum status on the usage of credit cards for online transactions as shown in Table II.

are invisible,[11] and the effect can, therefore, only be explained by the difference in reward designs.

Exogenous Variation The uptake of Platinum cards, however, still remains endogenous. Essentially, Gold and Platinum cardholders could inherently exhibit different behaviors. For example, if a consumer chooses the Platinum card due to their affinity for travel, the effect of the Platinum card on consumption is fundamentally through the preference for travel, not the rewards themselves.

To address the endogeneity issue, I utilize the eligibility condition for Platinum cards: a customer qualifies for a Platinum card only if their total assets within the bank exceed 200,000 CNY ($30,769). This eligibility condition composes a fuzzy regression discontinuity (RD) design: surpassing the asset threshold instigates a discontinuous jump in the probability of Platinum card adoption, while consumers are not obliged to opt for a Platinum card. In essence, exceeding the asset threshold serves as an instrumental variable (IV) for the uptake of Platinum cards, thereby helping identify the effect of the availability of Platinum rewards.

Design Validity Before an empirical estimation procedure, it is important to clarify the assumptions and consolidate the identifiable effect. Assumption 1 formalizes the setup à la Imbens and Angrist (1994).

Assumption 1. *For a consumer i, let y_i denote the outcome variable of interest, $T_i \in \{0,1\}$ denote the Platinum uptake decision, and $Z_i \in \{0,1\}$ denote whether a consumer's asset passes the Platinum threshold. Further define the potential treatment status $T_i(z)$, and the potential outcome $y_i(t,z)$ where $t \in \{0,1\}$ and $z \in \{0,1\}$, as in a Rubin causal model. Assume that*

1. *Independence.* $(y_i(1,1), y_i(1,0), y_i(0,1), y_i(0,0), T_i(1), T_i(0)) \perp\!\!\!\perp Z_i$
2. *First stage.* $\Pr(T_i = 1 \mid Z_i = 1) > \Pr(T_i = 1 \mid Z_i = 0)$
3. *Exclusion restriction.* $y_i(t,1) = y_i(t,0)$ *for all* (i,t).
4. *Monotonicity.* $T_i(1) \geq T_i(0)$ *for all* i.

The independence assumption ensures that the instrument, surpassing the asset threshold, is *as good as randomly assigned*. Empirically, the instrument is exogenous in the sense that when the running variable is near the eligibility threshold, falling just above or below the threshold is only a matter of coincidence. Given that the total asset consists of several inter-categorical items, including a consumer's savings, the present value of financial investments, and insurance, it can be uneasy to precisely manipulate the asset value. In particular, there might be concerns about a scenario where consumers intentionally push their assets

[11] An article (GoClickChina, 2022) indicates that consumers primarily complete transactions by scanning a QR code using a mobile app for the corresponding digital wallet.

beyond the threshold to qualify for a Platinum card for its benefits, as it could compromise the IV exogeneity. If this were the case, there would be bunching behavior above the asset threshold, as consumers just below the threshold would deliberately increase their asset value to qualify for a Platinum card. Figure 1.3a falsifies this hypothesis: the histogram does not show an upward jump on the right-hand side of the asset threshold (red vertical line). Concretely, a McCrary (2008) test does not show evidence that the density on the right-hand side is larger than the left-hand side, with a test statistic of -0.131 and a standard error of 0.109. Furthermore, a smooth kernel density estimate (green curve) around the threshold suggests no manipulations of the running variable around the threshold, which indicates the validity of the independence assumption.

The first stage, a standard IV assumption, is empirically testable. Figure 1.3b presents a binned scatter plot showcasing the probability of Platinum card adoption relative to the total assets, where a distinct upward leap emerges at the asset threshold (indicated by the vertical dashed line). It is worthwhile to note the positive probability of Platinum card uptake just below the threshold: this occurs when a consumer adopts a Platinum card, and their assets subsequently drop below the threshold. Nevertheless, the bank does not retract their Platinum card under these circumstances.

The exclusion restriction assumption stipulates that the IV itself does not directly affect the outcome of interest. In my scenario, it suggests that surpassing the asset threshold can only affect consumption via Platinum card rewards. This assumption, while plausible, remains untestable. Importantly, the asset threshold applies exclusively to Platinum card eligibility and has no bearing on other products within the bank. Consequently, it would be atypical for the threshold itself to alter consumption patterns. Finally, the monotonicity assumption precludes the presence of defiers; this assumption, although intuitive, is also untestable: it would indeed be illogical for a consumer to be discouraged from a Platinum card once their assets exceed the threshold.

Assuming the validity of Assumption 1, the fuzzy RD design enables the identification of the local average treatment effect (LATE) of Platinum reward availability. The LATE is local in two respects: 1) the effect applies to consumers near the asset threshold, and 2) the effect pertains to the compliers who opt for Platinum cards upon narrowly surpassing the asset threshold. Conceptually, Platinum consumers just above the threshold constitute the treatment group, while Gold consumers just below the threshold form the control group. Therefore, a non-zero Platinum card uptake probability below the threshold will not dilute the complier average treatment effect, as Platinum consumers below the threshold, i.e., the always-takers, will be excluded from the control group in the causal comparison.

Intention-to-Treat Analysis To ensure an apples-to-apples comparison, Figure 1.4 illustrates the intention-to-treat (ITT) effect of surpassing the asset threshold on various covariates: age, gender (female), education, income, and credit score. For each covariate, I have included a binned scatter plot against the total asset, with the vertical line indicating the asset threshold. Overall, none of the covariate variables display a discontinuous jump around the threshold. As a concrete robustness check, Table A2 confirms that rewards do not have an effect on any of the covariates. This balance in covariates implies that the IV (surpassing the asset threshold) does not induce observable selection and supports the validity of my Fuzzy RD design.

Examining the ITT effect on my primary outcomes of interest is also insightful, as illustrated in Figure 1.5: total spending, reward-earning spending, non-reward-earning spending, rewards, total spending under-reporting, and reward-earning spending under-reporting. Upon crossing the Platinum card eligibility threshold, total spending increases by approximately \$100, with around \$50 of this increase attributable to reward-earning spending for a reward value of \$10; these jumps are notably pronounced. Non-reward-earning spending also sees a less obvious rise of under \$50, denoted by a smaller yet distinct leap. Regarding the survey responses, an upward shift of \$80 occurs in the under-reporting of total spending, despite different trends on either side of the threshold. Conversely, the bins for under-reporting of reward-earning spending do not display any discontinuous change at the threshold. It is worth noting that debt has been excluded from my variables of interest as consumers with high asset values seldom hold consumption debts, making it challenging for the fuzzy RD design to identify any local effect on debt at the asset threshold.

Empirical Estimation and Results

While the ITT provides a valid causal effect, it reflects the effect of surpassing the asset threshold itself. This is not equivalent to the causal effect of rewards, given the presence of noncompliance, as demonstrated in Figure 1.3b. This makes the RD design "fuzzy" because not everyone who crosses the asset threshold opts for a Platinum card. To estimate the causal effect of Platinum rewards, I implement a two-stage least squares (2SLS) procedure.

Econometric Specification In general, there are two types of econometric specifications for fuzzy RD. Calonico et al. (2014) propose a local nonparametric estimator, which initially selects data points around the threshold based on an optimal bandwidth (Imbens and Kalyanaraman, 2012), and then carries out a weighted 2SLS using a triangle kernel. This method does not rely on the functional specification but discards many observations. Alternatively, one could execute a global 2SLS regression using all data points by assuming the true conditional expectation function (CEF) as a high-order polynomial of the running variable. This method is more data-efficient but can be sensitive to the functional form. Due to a modest sample size, the local nonparametric approach can be underpowered and hence challenging to conduct heterogeneity analysis. For this reason, I proceed with the global method.

Moreover, as Figure 1.5 suggests some nonlinearity, a linear model in the running variable is likely misspecified; meanwhile, Gelman and Imbens (2019) discourage high-order polynomials in RD designs due to potential overfitting issues. Considering both data efficiency and nonlinearity, I assume that the CEF is a quadratic function of the running variable. Table A1 in Appendix A.1 provides robustness checks showing that the RD results are stable and statistically significant for both the local and global approaches with the running variable's first to fifth polynomials.

Specifically, for consumer i, let T_i denote Platinum card uptake, s_i denote the total asset, and $S \approx 30{,}769$ denote the asset threshold. I also include the covariates to control for observed heterogeneity and increase estimation precision. These covariates include age, gender, education, income, credit score, city, and industry. Then, for an outcome of interest, y_i, the reduced form is

$$y_i = \alpha + \beta \widehat{T_i} + \gamma_1 s_i + \gamma_2 s_i^2 + \mathbf{Covariate}_i^T \lambda + \varepsilon_i \tag{1.5}$$

with the first stage as

$$T_i = a + b\,\mathbb{1}\left\{s_i > S\right\} + c_1 s_i + c_2 s_i^2 + \mathbf{Covariate}_i^T \mathbf{d} + \nu_i. \tag{1.6}$$

I execute the above 2SLS system on reward-earning spending, non-reward-earning spending, rewards, total spending under-reporting, and reward-earning spending under-reporting. For conciseness, the effect on total spending is deferred to Table A3 in Appendix A.1 as it is redundant. Given that the LATE on debt is negligible since consumers with large assets rarely hold debts, I also leave the results on debt in Table A4 in Appendix A.1: all results are statistically insignificant for polynomials from the first to fifth order using the global approach.

Main Results The main results are enclosed in Table 1.6, where the coefficient of Platinum, i.e., $\widehat{\beta}$ in the reduced form Equation (1.5), is the estimated effect of rewards. All standard errors are clustered at the city $\times$ industry level to account for within-group covariance. The estimates align with the discontinuous jumps in Figure 1.5. Focusing on the point estimates, opting for a Platinum card causes consumers to spend \$64.1 more in the reward-earning category, yielding a reward value of \$14.9. This observation implies reward-seeking behavior. In the meantime, non-reward spending increases by \$58.9: consumers do not appear to substitute away from non-reward-earning purchases; rather, reward-earning and non-reward-earning goods seem to be complementary due to the positive cross-elasticity of rewards on non-reward-earning consumption. Notably, this finding is in line with recent empirical work in other settings. For example, Di Maggio et al. (2022), where a higher level of liquidity (induced by "buy-now-pay-later" installment loans) in one expenditure category leads to additional same-category expenditure. Ding et al. (2022); Liu et al. (2021) also document a large stimulation of digital coupons on consumption, where there is no evidence of inter-categorical or intertemporal substitutions.

Looking at the covariates, it is interesting to note that consumers with higher income and higher credit scores spend more in both the reward-earning and non-reward-earning categories and earn more credit card rewards. Older consumers purchase more non-reward-earning but not reward-earning products.

Do consumers understand the spending changes when upgrading to the Platinum card? The answer is no regarding total spending: upon receiving Platinum rewards, consumers

Table 1.6: Effect of Platinum Reward Availability – Global Approach

	(1) Reward spending	(2) Non-reward spending	(3) Rewards	(4) Tot-spend under-repo	(5) Rew-spend under-repo
Platinum	64.153**	53.872**	14.853***	101.052***	0.982
	(27.725)	(22.195)	(4.354)	(29.903)	(4.392)
Asset (thousand \$)	0.542	13.180***	-0.154	0.853	-0.109
	(1.256)	(1.116)	(0.234)	(1.610)	(0.176)
Asset (thousand \$)^2	0.004	-0.038***	0.004***	0.000	0.000
	(0.006)	(0.007)	(0.001)	(0.010)	(0.001)
Male	-0.820	7.159	-1.309	-54.422***	2.469
	(10.619)	(7.979)	(1.909)	(14.645)	(1.618)
Age: elder	6.522	17.333**	1.160	-40.820**	1.080
	(8.861)	(7.336)	(1.641)	(18.555)	(1.553)
Edu: high	14.042	10.169	-2.238	-1.941	2.554
	(14.099)	(10.453)	(2.524)	(20.249)	(1.980)
Income: high	41.992***	37.418***	4.368**	6.631	0.752
	(9.944)	(7.501)	(1.702)	(15.508)	(1.448)
Credit score: high	87.190***	81.515***	7.390***	-8.552	4.108**
	(12.050)	(9.539)	(1.935)	(17.044)	(1.603)
Observations	4564	4564	4564	4564	4564
R^2	0.268	0.812	0.256	0.012	0.008

Note: This table shows the 2SLS fit of outcomes of interests on Platinum card takeup where the eligibility asset threshold is an IV in the first stage. I follow a global approach with a quadratic specification of the running variable. Table A1 in Appendix A.1 shows that the estimates, nonetheless, are robust regardless of different specifications or approaches. Under-reporting is defined as the value of true spending minus perceived spending. City and industry fixed effects are included. Standard errors in parentheses are clustered at city $\times$ industry level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

become more unaware of their expenditure – the total spending under-reporting increases by \$101.1. For covariates, male and older consumers have larger misperceptions about total spending. On the other hand, consumers have the same level of accuracy in perceiving reward-earning spending: the under-reporting only rises by an imprecise \$1.

It is worth examining the actual and perceived spending together. The effect on total spending under-reporting is equivalent to consumers' underestimation of the spending impacted by Platinum rewards, as indicated by the derivation below, where the hatted terms denote consumer perceived values:

$$
\begin{aligned}
&\Delta Under\_Reporting \\
&\quad = \left(Spending_{Plat} - \widehat{Spending}_{Plat}\right) - \left(Spending_{Gold} - \widehat{Spending}_{Gold}\right) \\
&\quad = (Spending_{Plat} - Spending_{Gold}) - \left(\widehat{Spending}_{Plat} - \widehat{Spending}_{Gold}\right) \\
&\quad = \Delta Spending - \Delta\widehat{Spending}
\end{aligned}
$$

Notice that the actual total spending increases approximately by \$118 (of which \$64 is from the reward-earning category and \$54 is from the non-reward-earning category). The estimated effect of \$101 on underestimation implies that consumers perceive their total spending to increase by only \$17 in response to Platinum rewards – just around 10% of the actual increase. Meanwhile, consumers are almost correct about the rise in the reward-earning category (imprecise \$1 under-reporting). This implies that consumers thought they could substitute away from the non-reward-earning purchases and *save* \$46 from credit card rewards, while in reality, the non-reward-earning spending also winds up increasing, unexpectedly, in the end.

Interpretation: Complementarity Ignorance

In summary, empirical results show that consumers, on average, underestimate the increase in total spending by about 90% when opting for Platinum rewards, and the misperception mainly originates from the unexpected additional expenditure in the non-reward-earning category. These observations suggest that consumers pay relatively more attention to the consumption associated with rewards but fail to adequately notice other forms of consumption.

Such relative inattention to non-reward-earning consumption versus rewards is not uncommon. Rewards are the main appeal of Platinum cards, and it is natural for consumers to concentrate on rewards but neglect other aspects. This phenomenon can also be explained through a rational inattention model: in comparison to the reward-earning consumption, the non-reward-earning category is far more complex, comprising daily consumption of groceries, transportation, and so on; inattention to non-reward-earning consumption looms larger because consumers have to bear higher cognitive costs.

The reward design offers further insights into the under-reporting of non-reward-earning expenditures. Platinum rewards primarily concern travel benefits and other high-end services, which typically necessitate reservations and upfront payments. When booking these rewards-related goods and services, consumers see them as appealing deals because of high reward values but are unaware of the associated consumption in the non-reward-earning category.

As an illustrative example, consider a new coupon of 10% off on flights added to the reward category when upgrading to the Platinum card. Those flights may become more attractive than before: compared to a Gold card holder, Platinum consumers attentively pay $90 for a $100-worth ticket and expect to save $10 through rewards. However, when the travel itinerary is realized, unplanned additional expenses occur for hotel rooms, restaurants, tickets for tourist attractions, and so forth, which are non-reward-earning. This unexpected complementary consumption contributes to the misperception of total spending increase.

The effect of credit card rewards on consumption, as well as the magnitude of consumption misperception, are economically interesting and important. Prior literature, in fact, documents consumer behavior in a similar vein. In particular, those complementary goods in the non-reward-earning category can be thought of as a shrouded attribute, as per Gabaix and Laibson (2006), with a subtle difference. In the context of Gabaix and Laibson (2006), firms intentionally charge and shroud an unusually high price on complementary *products* (e.g., toner cartridges for printers) to achieve abnormal markups. While credit card issuers can earn higher revenue through card usage (including transaction fees and a higher likelihood of accruing high-interest debt), they do not have direct control over products per se; instead, they can design a *contract* where rewards are applied to certain products with various (and implicit) complementary consumption, such as flight and hotel rooms, or movie tickets and popcorn.

Given the observed positive cross-elasticity of rewards on non-reward-earning consumption and that consumers overlook such *economic complementarity*, I introduce the term "complementarity ignorance" to describe the phenomenon of neglecting non-reward-earning expenditures. Complementarity ignorance can eventually lead consumers to overlook the existence of related complementary spending upfront and ultimately increase total consumption, similar to the budget negligence behavior as seen in Augenblick et al. (2022). A naive consumer, unprepared for such complementary consumption, ends up spending more than anticipated; a sophisticated consumer, aware of the complementary purchases in the non-reward-earning category, is less likely to buy as many reward-earning goods. The distortion in the non-reward-earning consumption among naive consumers, caused by complementarity ignorance, can help banks earn extra profit, leading the market to exhibit de-commoditization as per Bordalo et al. (2015). Online Appendix A.4 provides an illustration using a structural model with numerical simulations. Essentially, the competition for attention to rewards drives consumers to focus more on quality, consequently softening price competition.

Beyond complementarity ignorance, my findings pertain to human behavior and can apply to other contexts characterized by budget negligence. Several interpretations exist for the phenomenon of neglected budget on such complementary consumption, including mental accounting (Thaler, 1985) and limited attention to complex objects (e.g., Morrison and Taubinsky (2021)'s discussion on opaque taxes). Regardless of the interpretation, the misperception of non-reward-earning consumption increase in response to rewards eventually leads consumers to make suboptimal consumption decisions. This effect can also be generalized to contexts broader than the credit card market, providing insights into advertising and product design strategies for firms.

Heterogeneous Effects

My empirical results conclude with a discussion of heterogeneous effects. Ideally, in a stratified randomized experiment, heterogeneous treatment effects can be estimated through the interaction between the treatment variable and covariates in a pooled regression. However, while the asset threshold can still interact with covariates and serve as the IVs for the interactions between Platinum card uptake and the covariates, the LATE interpretation may not be valid since it is not clear how Assumption 1 holds for multiple instruments. As a result, the 2SLS fits in Equations (1.5) and (1.6) are obtained separately on different subsamples, stratified covariates. Assuming no interference between strata, the standard error for the difference in point estimates can be computed as the square root of the sum of the corresponding variances.

Table 1.7: Heterogeneous Effect of Platinum Reward Availability

	(1) Reward spending	(2) Non-reward spending	(3) Rewards	(4) Tot-spend under-repo	(5) Rew-spend under-repo
Holding-period: long	49.230**	42.476**	12.306***	82.239	1.769
	(23.661)	(19.730)	(3.985)	(51.097)	(4.033)
Holding-period: short	78.780**	66.163**	17.374***	126.571***	0.186
	(36.742)	(28.677)	(5.511)	(45.924)	(5.413)
Debt-to-income: high	113.191***	83.491**	21.914***	151.193***	-10.995
	(41.316)	(33.642)	(7.229)	(51.759)	(6.813)
Debt-to-income: low	-2.813	3.479	4.622	52.966	1.829
	(16.827)	(14.257)	(3.479)	(37.613)	(3.412)
Credit score: high	111.582**	71.803**	23.892***	102.109**	0.812
	(44.748)	(34.197)	(6.741)	(44.580)	(6.683)
Credit score: low	15.164	43.683**	2.573	130.177***	0.814
	(23.743)	(21.698)	(4.089)	(46.670)	(3.433)
Education: high	46.475	21.543	12.876**	120.221	-2.187
	(32.602)	(22.407)	(5.409)	(82.654)	(7.735)
Education: low	69.053*	64.601**	15.352***	89.716***	-0.232
	(37.631)	(29.342)	(5.715)	(33.808)	(5.645)
Gender: Male	55.199	45.294	12.209**	94.156**	-0.197
	(35.725)	(29.066)	(5.847)	(40.191)	(6.230)
Gender: Female	27.327	42.990*	10.720**	36.886	-0.058
	(29.250)	(25.100)	(4.903)	(56.345)	(4.789)
Age: elder	97.569**	88.465***	19.889***	60.929	0.431
	(40.515)	(32.175)	(6.547)	(43.779)	(6.884)
Age: young	20.824	23.480	5.554	113.261**	0.317
	(25.510)	(22.485)	(4.403)	(51.405)	(4.909)

Note: This table shows the 2SLS fit of outcomes of interests on Platinum card takeup where the eligibility asset threshold is an IV in the first stage, using different subsamples of covariate strata. Only the coefficients on Platinum takeup are reported. I follow a global approach with a quadratic specification of the running variable. Holding period is defined as the number of days that a consumer holds the current credit card product. Under-reporting is defined as the value of true spending minus perceived spending. Omitted control variables include age, income, gender, education, and credit score. City and industry fixed effects are included. Standard errors in parentheses are clustered at city × industry level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.7 presents the estimated heterogeneous treatment effect of rewards on consumption and perceived consumption. Specifically, this paper investigates differences among consumers based on their credit card experience (holding period), wealth (debt-to-income ratio), credit availability (credit score), financial literacy (education), and demographics (gender and income). The covariates are split into two groups by median values for comparability. Due to a small sample size, the analysis of the heterogeneous treatment effect is underpowered; many of the differences, although sizable in point estimates, are statistically insignificant. Nevertheless, the point estimates can still provide some insights into heterogeneity.

Newly converted Platinum card users are more responsive to rewards than established users. Platinum rewards trigger an increase of \$78.1 in reward-earning spending among consumers with a short holding period, versus \$49.2 for those with a longer holding period. Interestingly, the effect on non-reward-earning spending aligns proportionately with that on reward-earning spending. New consumers manifest a larger total spending underestimation (\$125.6), while experienced users have a smaller (and imprecise) underestimation of \$82.2. These effects suggest that consumers may learn about the overlooked complementary consumption associated with rewards over time, subsequently exhibiting reduced spending misperception. The spending increase spurred by Platinum rewards also diminishes as a result. However, these differences are not statistically significant due to the limited sample size.

In terms of wealth, it seems that only consumers with a high debt-to-income ratio significantly respond to rewards and exhibit substantial underestimation of total spending. Conversely, for consumers with a low debt-to-income ratio, there is no effect on spending and only a modest and imprecise effect on total spending underestimation. Most of these differences between consumers with high and low debt-to-income ratios are significant at a 5% level. This comparison suggests that rewards may exacerbate self-control issues among less affluent consumers: with the availability of Platinum rewards, debt-incurring consumers spend more to redeem rewards without recognizing the true expenditure, potentially leading to a further accumulation of debt.

Consumers with high credit scores expend more on reward-earning products and earn higher reward values than those with lower credit scores, at approximately a 10% significance level. No economically or statistically significant difference is observed in comparisons between high education vs. low education and male vs. female. Although underpowered, for older consumers, the reward effects are more substantial on both reward-earning and non-reward-earning consumption. In contrast, younger consumers display more substantial spending under-reporting.

1.5 The Economics of Complementarity Ignorance

In this section, I use a stylized model of consumption and saving, incorporating credit card rewards, to examine how the ignorance of complementary purchases can affect market equilibrium and consumer welfare.

Consumers decide on *reward-earning purchases* upfront, such as flights or movie tickets. These reward-earning products are often associated with *add-on complementary purchases* that occur later on. For example, consumers may need to pay for hotel rooms *after arriving* at the destination, or they desire to purchase popcorn *upon reaching* the theater. These complementary purchases, such as hotel rooms and popcorn, are not covered by credit card rewards.

Credit card rewards can lure *naive* consumers into booking reward-earning goods and services while overlooking the complementary purchases that will be necessary in the future. As a result, naive consumers end up with excessive spending. On the other hand, *sophisticated* consumers are aware of the impending complementary consumption, so they do not incur excess spending. For example, they might not react as strongly to credit card rewards on flights or movie tickets if they knew ex-ante that hotels or popcorn are expensive.

The proposed model and mechanism share similarities with Gabaix and Laibson (2006), except for two key distinctions: 1) In Gabaix and Laibson (2006), firms choose whether to shroud the existence of add-on products. In my model, since the bank does not directly sell products but profits from transactions, it designs credit card rewards to include consumption categories that are likely to induce complementary purchases, such as flights, hotel breakfasts, and movie tickets. 2) The *distortion* in Gabaix and Laibson (2006) arises from a costly effort to avoid expensive add-on purchases. In contrast, in my model, the distortion triggered by behavioral bias is directly due to suboptimal choices.

To illustrate the model, I will repeatedly refer to the example of flights (as part of reward-earning consumption) and hotel rooms (as part of non-reward-earning consumption) in the ensuing discussion. However, the model applies broadly to any other products that are associated with complementary purchases.

Utility and Timeline

I use a parsimonious model to depict the static problem of consumption and saving. A consumer decides on the reward-earning consumption CR, non-reward-earning consumption CN, and saving S. Normalize the price index for non-reward-earning consumption to 1. Consumers receive cashback on reward-earning products. Let $p < 1$ denote the price index for reward-earning consumption, which is equivalent to saying that the reward rate is $1 - p$. Let y denote a consumer's total wealth.

For simplicity, I ignore the income effect on consumption and assume a quasi-linear utility function of natural logarithms. Saving is normalized to a numeraire. Then, a consumer solves the following problem

$$\max_{CR,CN,S} \alpha \log(CR) + \beta \log(CN - mCR) + S \quad \text{subject to} \quad pCR + CN + S \leq y. \tag{1.7}$$

There are three primitive parameters in this model. α and β control the relative preference over CR and CN. The complementarity between CR and CN is represented by a latent parameter m. A larger m represents a higher level of complementarity, and $m = 0$ represents an additively separable preference.

Below I describe the timeline à la the shrouding game in Gabaix and Laibson (2006).

- **Period 0.** The bank decides on the reward-earning categories with a corresponding m. Given m, the bank then decides on the price index p pertaining to credit card rewards.
- **Period 1.** Consumers decide on the reward-earning consumption CR since these products usually require advance bookings and payments. At the same time, consumers generate expectations of non-reward-earning consumption $\widehat{CN}$ and saving $\widehat{S}$.
  - *Naive* consumers overlook the add-on complementary consumption related to reward-earning bookings and have a misperception of $\widehat{m} = 0$. As a result, naive consumers overspend on CR, and the expected non-reward-earning consumption $\widehat{CN}_{naif}$ is too low.
  - *Sophisticated* consumers have a correct m perception and are fully aware of the upcoming complementary consumption. As a result, sophisticated consumers have a rational expectation $\widehat{CN}_{soph}$.
- **Period 2.** Consumers decide on the non-reward-earning consumption CN according to the reward-earning consumption CR decided in period 1. Naive consumers will increase CN unexpectedly, while sophisticated consumers do not need to adjust as they formed a rational expectation $\widehat{CN}_{soph}$ in period 1.

Demand Side: Naiveté vs. Sophistication

On the demand side, I first analyze the first best, i.e., *sophisticated* consumption and saving decisions of the problem in Equation (1.7). Utility maximization gives that

$$\begin{aligned} CR_{soph} &= \frac{\alpha}{p+m} \\ CN_{soph} &= \beta + \frac{\alpha m}{p+m} \\ S_{soph} &= y - \frac{1+m}{p+m}\alpha - \beta \end{aligned} \tag{1.8}$$

Notice that sophisticated consumers have a rational expectation of add-on complementary consumption, i.e., $\widehat{CN}_{soph} = CN_{soph}$, so period 2 does not make a difference here.

For naive consumers with $\widehat{m} = 0$, in period 1, they decide on CR_{naif} purchases and expect to have $\widehat{CN}_{naif}$ and $\widehat{S}_{naif}$. Utility maximization with $m = 0$ yields that

$$\begin{aligned} CR_{naif} &= \frac{\alpha}{p} \\ \widehat{CN}_{naif} &= \beta \\ \widehat{S}_{naif} &= y - \frac{\alpha}{p} - \beta \end{aligned} \tag{1.9}$$

In period 2, the true m realizes, and naive consumers re-optimize CN_{naif} given CR_{naif} decided in period 1 using according to the corresponding marginal rate of substitution and the price ratio. Intuitively, after purchasing the flight (the reward-earning purchase) and planning a trip, it is preferable for the consumer to book a hotel room at the destination (the complementary, non-reward-earning purchase). Utility "re-optimization" yields the final consumption and saving decisions by naive consumers

$$\begin{aligned} CR_{naif} &= \frac{\alpha}{p} = \underbrace{\frac{p+m}{p}}_{\text{overspending}} CR_{soph} \\ CN_{naif} &= \underbrace{\beta}_{=\widehat{CN}_{naif}} + \underbrace{\frac{m(\alpha+\beta)}{p}}_{\text{under-reporting}} = \underbrace{\frac{p+m}{p}}_{\text{overspending}} CN_{soph}. \\ S_{naif} &= y - \frac{\alpha}{p} - \beta - \frac{m(\alpha+\beta)}{p} \end{aligned} \tag{1.10}$$

The expressions CR_{naif} and CN_{naif} illustrate excess consumption compared to sophisticated (optimal) consumers. Specifically, complementarity ignorance will scale up consumption by a multiplier of $\frac{p+m}{p}$. In other words, reward-earning consumption becomes more elastic to rewards with complementarity ignorance. It is interesting to note that if the bank imposes rewards on the products that do not come with complements (when $m = 0$), then naive consumers would not suffer from excess and unexpected spending. Moreover, recall that consumers do not correctly understand the increase in non-reward-earning consumption caused by credit card rewards as discussed in Section 1.4, and this corresponds to the $\frac{m(\alpha+\beta)}{p}$ term in Equation (1.10). Proposition 1 summarizes the effect of complementarity ignorance on naive consumers through credit card rewards. The formal proof is left in Appendix A.2.

Proposition 1. *For naive consumers, complementarity ignorance scales up consumption by* $\frac{p+m}{p}$ *compared to the first best. Complementarity ignorance also incurs* $\frac{m(\alpha+\beta)}{p}$ *unexpected spending on non-reward-earning products in period 2.*

Supply Side

Turning to the supply side, given the reward-earning categories, i.e., the parameter m, the bank decides on the price index p for reward-earning purchases to maximize profit. The bank charges merchants an (exogenously determined) interchange fee through consumption. In the meantime, the bank also bears the cost of cashback disbursement to consumers for reward-earning consumption as well as the cost of operation.

Assume that the bank has a common constant operational c, per consumer, regardless of the naiveté type. Let r denote the exogenous interchange fee rate on consumption, then the profit per consumer is the revenue from interchange fees minus reward payout and an operational cost

$$\begin{aligned}\pi_{naif}(p) &= r(CR_{naif} + CN_{naif}) - (1-p)CR_{naif} - c \\ &= r\left[\frac{\alpha}{p} + \beta + \frac{m(\alpha+\beta)}{p}\right] - \alpha\frac{1-p}{p} - c \\ \pi_{soph}(p) &= r(CR_{soph} + CN_{soph}) - (1-p)CR_{soph} - c \\ &= r\left[\frac{\alpha}{p+m} + \beta + \frac{\alpha m}{p+m}\right] - \alpha\frac{1-p}{p+m} - c\end{aligned}. \tag{1.11}$$

The profit functions sketch out the tradeoff between increased consumption and reward disbursement.[12] If the bank imposes more lucrative rewards, i.e., a lower p, then the interchange fee revenue becomes higher through higher consumption. On the other hand, the bank also bears a higher cost because of the higher reward payout. Note that the net revenue (interchange fees minus reward payout) from naive and sophisticated consumers are co-linear due to the same over-spending multiplier, i.e., $CR_{naif} = \frac{p+m}{p}CR_{soph}$ and $CN_{naif} = \frac{p+m}{p}CN_{soph}$. The comparison of these profit functions shows that firms can receive higher net revenue from naive consumers through ignorance of complementarity m

$$\frac{\pi_{naif} + c}{\pi_{soph} + c} = \frac{m+p}{p}. \tag{1.12}$$

When the net revenue is positive, Equation (1.12) implies a positive profit from naive consumers and a negative profit from sophisticated consumers in a perfectly competitive equilibrium. The next subsection sheds light on equilibrium pricing and profits.

Market Equilibrium

For the market equilibrium, I use a perfectly competitive market as an illustrative case. Let q denote the fraction of naive consumers, and thus $1-q$ denote the fraction of sophisticated

[12] See Schulz (2023) for an industry report.

consumers. Then zero-profit condition gives that

$$\pi = q \underbrace{\left(r \left[\frac{\alpha}{p} + \beta + \frac{m(\alpha+\beta)}{p} \right] - \alpha \frac{1-p}{p} - c \right)}_{\equiv \pi_{naif}} + (1-q) \underbrace{\left(r \left[\frac{\alpha}{p+m} + \beta + \frac{\alpha m}{p+m} \right] - \alpha \frac{1-p}{p+m} - c \right)}_{\equiv \pi_{soph}} = 0. \quad (1.13)$$

Cross-Subsidy First and foremost, Equation (1.13) yields the equilibrium profits from naive and sophisticated consumers, respectively,

$$\begin{aligned} \pi_{soph} &= -\frac{cmq}{p+mq} \leq 0 \\ \pi_{naif} &= \frac{cm(1-q)}{p+mq} \geq 0 \end{aligned} \quad (1.14)$$

where the equality holds if $m = 0$. When $m > 0$, i.e., when rewards-earning and non-reward-earning are not additively separable, the opposite signs in Equations (1.14) illustrate *cross-subsidization* from naive consumers to sophisticated consumers. Excess spending will not occur on sophisticated consumers because they are perfectly aware of the spending on hotel rooms in the future, and they can benefit from credit card rewards on flights so that the bank earns a negative profit from them. Such benefits, in fact, come at the expense of naive consumers through complementarity ignorance and the induced consumption increase; indeed, the bank can earn a positive profit from naive consumers. Proposition 2 summarizes this finding. The formal proof is left in Appendix A.2.

Proposition 2. *With complementarity ignorance, the equilibrium profit from naive consumers is* $\pi_{naif} = \frac{cm(1-q)}{p+mq} \geq 0$ *whereas the profit from sophisticated consumers is* $\pi_{soph} = -\frac{cmq}{p+mq} \leq 0$*. The opposite signs indicate cross-subsidization from naive consumers to sophisticated consumers: credit card rewards increase the welfare of sophisticated consumers at the expense of naive consumers through complementarity ignorance and induced excess consumption.*

The negative profit from sophisticated consumers, $-\pi_{soph}$, can be interpreted as the welfare gain for them. The model gives two interesting predictions. First, $-\pi_{soph} \to 0$ when $m \to 0$: when the consumption categories are additively separable, there is no complementarity ignorance for the bank to exploit, and therefore the welfare gain for sophisticated consumers becomes zero. Second, $-\pi_{soph} \to 0$ when $q \to 0$: when all consumers become sophisticated in the market, there are no consumers for the bank to exploit complementarity ignorance, and therefore the welfare gain for sophisticated consumers becomes zero.

Comparative Statics In addition, Equation (1.13) gives the equilibrium price index p for reward-earning products, and it is important to understand how naiveté determines the contract design of credit card rewards. The analytical solution to the equilibrium price p is cumbersome, so I apply the implicit function theorem on Equation (1.13) to obtain the partial derivatives. Assume a reasonable[13] interchange fee rate such that $r < \frac{\alpha}{\alpha+m(\alpha+\beta)}$, one can show that

$$\frac{\partial p}{\partial m} = -\frac{\partial \pi/\partial m}{\partial \pi/\partial p} = -\frac{q\frac{\partial \pi_{naif}}{\partial m} + (1-q)\frac{\partial \pi_{soph}}{\partial m}}{q\frac{\partial \pi_{naif}}{\partial p} + (1-q)\frac{\partial \pi_{soph}}{\partial p}} < 0 \tag{1.15}$$

Equation (1.15) predicts that the price index for reward-earning goods p is decreasing in complementarity m. In other words, the bank will provide more generous rewards for a higher complementarity in consumption categories in equilibrium. Intuitively, if the consumption categories exhibit a higher level of complementarity, ignoring the complementary purchases later on plays a more important role in naive consumers' decision-making processes; as a result, the bank is incentivized to provide more credit card rewards to capture more surplus from naive consumers. Proposition 3 summarizes this result. The formal proof is left in Appendix A.2.

Proposition 3. *Assume that the bank faces a reasonable interchange fee rate such that* $r < \frac{\alpha}{\alpha+m(\alpha+\beta)}$. *The equilibrium price index for reward-earning goods p is decreasing in complementarity m. When the consumption categories exhibit a higher level of complementarity, the bank can earn a higher profit through naiveté exploitation and therefore has the incentive to provide more generous credit card rewards and exploit complementarity ignorance.*

The fraction of naive consumers, q, is also an important determinant of the equilibrium price index p. Again, assume a reasonable interchange fee rate such that $r < \frac{\alpha}{\alpha+m(\alpha+\beta)}$, Equation (1.13) yields that

$$\frac{\partial p}{\partial q} = -\frac{\partial \pi/\partial q}{\partial \pi/\partial p} = -\frac{\pi_{naif} - \pi_{soph}}{\partial \pi/\partial p} < 0. \tag{1.16}$$

Equation (1.16) predicts that the price index for reward-earning goods p is decreasing in the fraction of naive consumers q. Equivalently, in equilibrium, the bank will provide more generous rewards if more naive consumers are present in the market. Intuitively, if there are more naive consumers, the bank has the incentive to offer more lucrative credit card rewards and exploit complementarity ignorance. Proposition 4 summarizes this result. The formal proof is left in Appendix A.2.

Proposition 4. *Assume that the bank faces a reasonable interchange fee rate such that* $r < \frac{\alpha}{\alpha+m(\alpha+\beta)}$. *The equilibrium price index for reward-earning goods p is decreasing in the*

[13] In the data, reward-earning consumption is about one-fifth of the non-reward-earning consumption, so $\alpha/\beta \approx 0.25$. A plausible complementarity parameter, m, should range in $(0, 1)$. This implies that the interchange fee rate is less than 14.3%. In reality, the average interchange fee rate imposed by the bank is about 5.25%.

fraction of naive consumers q. For a larger pool of naive consumers, the bank is incentivized to provide more credit card rewards and exploit complementarity ignorance.

Propositions 3 and 4 essentially give two rationales for the abundant credit card rewards in practice. First, my model predicts that reward-earning categories have to come with (shrouded or implicit) complementary consumption. This hypothesis is consistent with the fact that credit card rewards usually include travel or entertainment purchases but not essential services such as utility bills. Second, the provision of credit card rewards is incentivized by naiveté exploitation. Given the current reward offerings in my data, my model predicts that the market should have a non-negligible proportion of naive consumers who neglect complementary consumption that will occur later on. This hypothesis is consistent with my empirical finding in Section 1.4 that consumers underestimate the impact of reward design on non-reward-earning consumption.

A Welfare Analysis: Naiveté's Effect on Efficiency Cost

This subsection sheds light on the efficiency cost caused by complementarity ignorance. I analyze how the inefficiency varies in q, i.e., when more naive consumers are present in the market.

For an interesting analysis, I assume a positive complementarity parameter $m > 0$ in the discussion hereafter. To evaluate the efficiency cost, I define the benchmark as the scenario of no naiveté, i.e., $q = 0$, and all consumers make consumption and saving decisions according to Equations (1.9). On the demand side, consumers respond to credit card rewards, p, and decide on consumption and savings. Denote $u_{naif}(p) \equiv u\left(CR_{naif}(p), CN_{naif}(p), S_{naif}(p)\right)$ and $u_{soph}(p) \equiv u\left(CR_{soph}(p), CN_{soph}(p), S_{soph}(p)\right)$. On the supply side, the bank decides on rewards, p, to maximize profit. Let the star notations represent the equilibrium without naiveté. In a perfectly competitive market, let p^* denote the zero-profit equilibrium price, and the corresponding utility of sophisticates is $u^* \equiv u_{soph}(p^*)$. Then, the benchmark, i.e., the first best of welfare, is u^*.

In the quasi-linear utility specification, since savings are treated as the numeraire in dollars, the utility (in utils) is equivalent to a monetary measure of welfare (in dollars). With the presence of naiveté, i.e., when $q > 0$, the average efficiency cost per consumer is given by

$$inefficiency = q \underbrace{\left[u^* - u_{naif}(p)\right]}_{>0} + (1-q) \underbrace{\left[u^* - u_{soph}(p)\right]}_{\leq 0} \tag{1.17}$$

where $inefficiency > 0$ means that the total welfare is below the benchmark. It is worth noting the difference between u^* and $u_{soph}(p)$: u^* is the optimal utility evaluated at p^* (without naiveté presence) whereas $u_{soph}(p)$ are evaluated at p. The comparative statics in Equation (1.16) shows that $p < p^*$ with naiveté presence (when $q > 0$).

The efficiency cost has two components. On the one hand, $u^* > u_{naif}(p)$: naive consumers make suboptimal decisions so that their utilities are smaller than the optimum. On the other hand, $u^* \leq u_{soph}(p)$ where the equality holds when $p = p^*$: the lower price caused by the naiveté presence enables sophisticated consumers to have higher consumption and savings so that their utilities become larger. As a result, the fraction of naive consumers, q, has two channels to affect welfare:

- Directly through q: fixing the price index p, efficiency cost increases in q. Intuitively, the more naive consumers, the higher the efficiency cost is.
- Indirectly through p: a larger q lowers p as shown in Equation (1.16).
  - Via $u_{naif}(p)$: within an individual naive consumer, a lower p implies a larger multiplier for naifs $\frac{m+p}{p}$ and then implies a lower u_{naif} because the decisions are further away from the optimum.
  - Via $u_{soph}(p)$: within an individual sophisticated consumer, a lower p implies higher u_{soph}. This effect resonates with the cross-subsidy discussed earlier: sophisticated consumers also spend "too much" compared to the first-best outcome u^* because of the lower price caused by the presence of naiveté.

Welfare Effect Decomposition: Numerical Calibration It is interesting to understand the size of the efficiency cost as well as the relative importance of these channels. Since the closed-form solution to the equilibrium price p is intractable, in a calibration exercise, I numerically solve for the equilibrium and compute the efficiency cost for different values of q. I set $\alpha = 170.5$ and $\beta = 841.5$ to reflect the average consumption in Table 1.2. The average interchange fee rate is about $r = 0.0525$. To calibrate the complementarity parameter, m, notice that the model gives an under-reporting value $\frac{m(\alpha+\beta)}{p}$ in Equation (1.10). Table 1.2 shows the average reward rate ($p \approx 0.8$) and average under-reporting (\$85). Then, $m \approx 0.063$ given chosen values of α and β. The cost of operation is set to be $c = 20$ given the zero-profit condition and the back-of-the-envelope calculation[14] according to the summary statistics in Table 1.2.

Figure 1.6 shows how the equilibrium price index p and efficiency cost evolves in the fraction of naive consumers q, with p stretching out from around 0.82 to around 0.74 as q increases from 0 to 1. Consistent with Equation (1.16), a larger fraction of naive consumers will incentivize the firm to impose more credit card rewards for the purpose of naiveté exploitation. This corresponds to the upward trend of average efficiency cost per consumer as q increases: the economy is less efficient as a whole if it has more naive consumers. The current reward-earning price index $p \approx 0.8$ shown in Table 1.2 implies that the fraction of naive consumers $q \approx 0.3$, where the average efficiency cost is around \$25, which is about 2.5% of the monthly consumption.

It is also interesting to observe the negative association between price and inefficiency caused by q. The existence of highly rewarding credit card benefits indicates a large proportion of naive consumers in the market. This observation seems different from the prediction

[14] The average total consumption is about \$1,100, among which the bank receives a 5.25% interchange fee. The average reward payout, in the meantime, is about \$40. Then, the cost of operation is roughly \$20.

of the negative relationship between price and efficiency cost (deadweight loss) in classical economic theory. In fact, in the current setup, a lower price is not driven by competition; instead, it is endogenized by higher naiveté presence, which is a sign of inefficiency.

The decomposition of the effect of the presence of naiveté, represented by q, on efficiency cost is graphically represented in Figure 1.7. The blue solid line demonstrates the direct channel by varying q, keeping the price index fixed at $p = 0.8$, which reflects the current reward-earning price index in the data. Not surprisingly, the average efficiency cost escalates with an increasing proportion of naive consumers in a nearly linear fashion, echoing the representation in Figure 1.6.

Focusing on the indirect channels, I show the impact of the fraction of naive consumers q on the efficiency cost through the equilibrium price index p. The orange dashed curve shows how $u^* - u_{naif}(p)$ changes in q. Interestingly, naiveté itself is very costly: a naive consumer suffers from at least \$80 of welfare loss (7% of average monthly consumption) due to complementarity ignorance. When q expands, the efficiency cost per naive consumer further magnifies because of a lower p and the larger overspending multiplier $\frac{p+m}{p}$. The green dotted line demonstrates how $u^* - u_{soph}(p)$ varies in q. Expectedly, the “efficiency cost” is below zero because sophisticated consumers do not suffer from complementarity ignorance and instead benefit from a lower price p when $q > 0$. Since q lowers p, $u^* - u_{soph}(p)$ departs further away from zero with a larger q.

Holistically, illustrated by the steeper slope of the blue curve, the direct effect of q contributes more to the efficiency cost than the indirect effects. This is because q only has a small second-order effect on p as illustrated in Figure 1.6. These indirect effects also expose a disparity between naive and sophisticated consumers. Although sophisticated consumers enjoy some benefits, the magnitude of such welfare gains is considerably smaller than the welfare loss incurred by naive consumers. Therefore, it may be deemed worthwhile to implement policy instruments to regulate credit card rewards or to correct the misconceptions of naive consumers from a social welfare standpoint.

Discussion

Lastly, a question may arise whether these impacts of complementarity ignorance are sustainable. Essentially, would naive consumers become sophisticated in the long run? This is unlikely to happen for several reasons. First, aligning with Gabaix and Laibson (2006), competition will not help here. A “transparent” bank lacks the incentive to debias consumers. While it possesses the ability to transform naive consumers into sophisticated ones, the newly converted sophisticated consumers would not defect to a transparent bank, as they stand to make a positive welfare gain, as outlined in Equation (1.14).

Furthermore, the adaptive reward design by the bank impedes consumers from sufficient learning of their consumption habits. Consumers are constantly faced with the need to reassess relevant complementary consumption aligned with the current reward category, similar to the results found in Augenblick et al. (2022). Empirical evidence from recent studies in the credit card market, such as Han and Yin (2022), indicates that consumers forget newly gained information quickly, making it fundamentally challenging to debias complementarity ignorance completely. Putting these considerations aside, even if a fraction of the *current consumers* manage to transition from naiveté to sophistication, the marketplace will always be replenished with new behavioral entrants. This enables banks to perpetually exploit complementarity ignorance and offer credit card products with appealing reward schemes in the long run.

1.6 Conclusion

In this paper, collaborating with a large commercial bank, I utilize a fuzzy RD design based on the eligibility rule of the bank's Platinum card to empirically identify the causal effect of credit card rewards on consumption. I first find that the bank's Platinum card rewards work effectively: it stimulates a 10% total spending increase relative to consumers without Platinum rewards. The effectiveness is largely contributed by the positive spillover effect of reward programs on other (non-reward) consumption categories.

On the other hand, consumers are not fully aware of such a spillover effect, uncovered by the application of the fuzzy RD design on the combination of survey responses and actual financial behavior provided by the bank. Consumers understand the consumption changes related to rewards well but vastly underestimate the changes in total consumption. This misperception can be explained by *complementarity ignorance*, where consumers overlook their *future* expenditures on relevant *complementary* purchases when deciding on reward *upfront*. For example, consumers cannot resist booking flight tickets when they receive high reward values, but at the moment of flight booking, they do not consider their future demand for hotel rooms and car rentals, which are not included in the reward program.

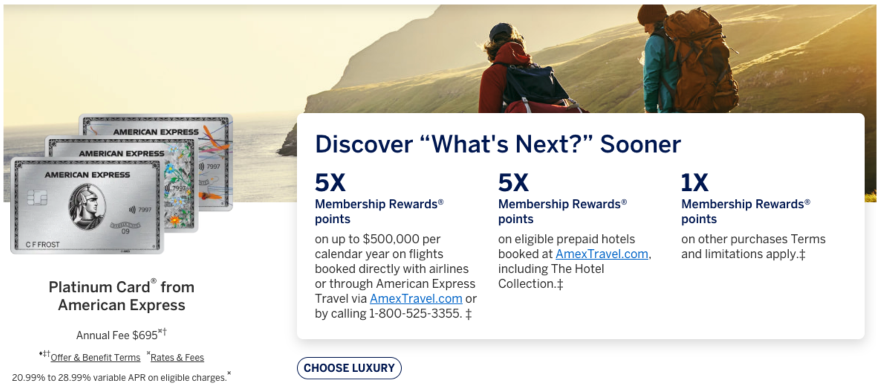
I employ a stylized model to demonstrate the implications of complementarity ignorance for market structure and consumer welfare. The bank sets credit card reward offerings in period 0. Given rewards, consumers choose reward-earning bookings (such as flights) in period 1 and non-reward-earning bookings in period 2 (such as hotel rooms). My model shows that naive consumers will overspend if they oversee hotel room expenditures in period 2 when booking flights in period 1, and this excess spending generates extra revenue from interchange fees for the bank. In a perfectly competitive market, the equilibrium outcome predicts that naive consumers cross-subsidize sophisticated consumers: sophisticated consumers indeed benefit from credit card rewards at the cost of naive consumers' welfare loss. The equilibrium rewards are increasing in level of complementarity between consumption categories, which explains why rewards are typically imposed on travel but not utility bills. Additionally, a larger fraction of naive consumers also incentivizes the bank to offer more rewards to exploit complementarity ignorance. This explains why abundant credit card rewards exist in reality.

Using a numerical calibration with the model, given the current reward rate in the data, an average consumer incurs a monthly cost of \$25 (around 2.5% of consumption). Welfare effect decomposition reveals that naiveté itself leads to at least \$80 of welfare loss (around 7% of consumption), and the loss looms larger if more naive consumers are present in the market due to more substantial rewards. Sophisticated consumers, in contrast, can benefit from these rewards, but the size of welfare gain is much smaller than the welfare loss of naive consumers. As a result, from a welfare perspective, regulations and debiasing devices shall be established to counteract complementarity ignorance.

Due to the data variations, unavoidably, this paper discusses only the local average treatment effect of consumers at a relatively wealthy level and does not explicitly consider the details of reward designs, such as introductory offers and other commonly used promotions. In the stylized model, I only consider the extensive margin of the naiveté level under the setup of perfect competition.

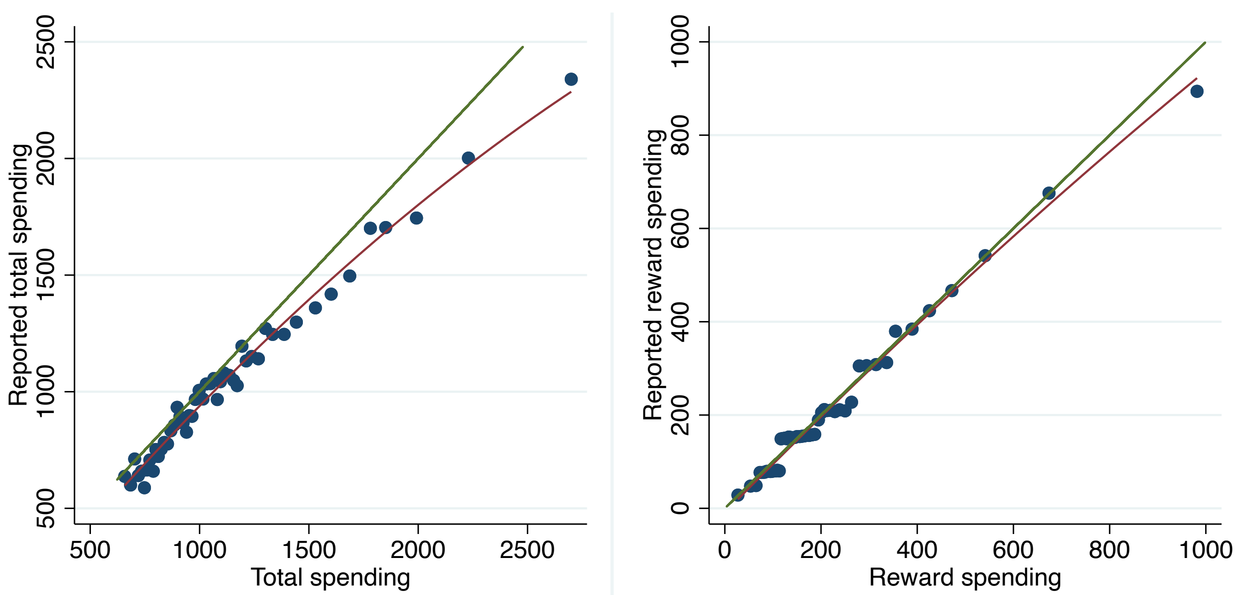
Several potential directions warrant exploration in future research. It would be interesting to examine the intensive margin of naiveté, especially with debiasing regulations i.e., the time-varying treatment effect of rewards on consumption and consumer beliefs. It is also worthwhile to investigate how complementarity ignorance would interplay with market dynamics and competition, as these findings may provide crucial insights into competitive strategies and market interventions.

Figure 1.1: An Example of Credit Card Ads by American Express



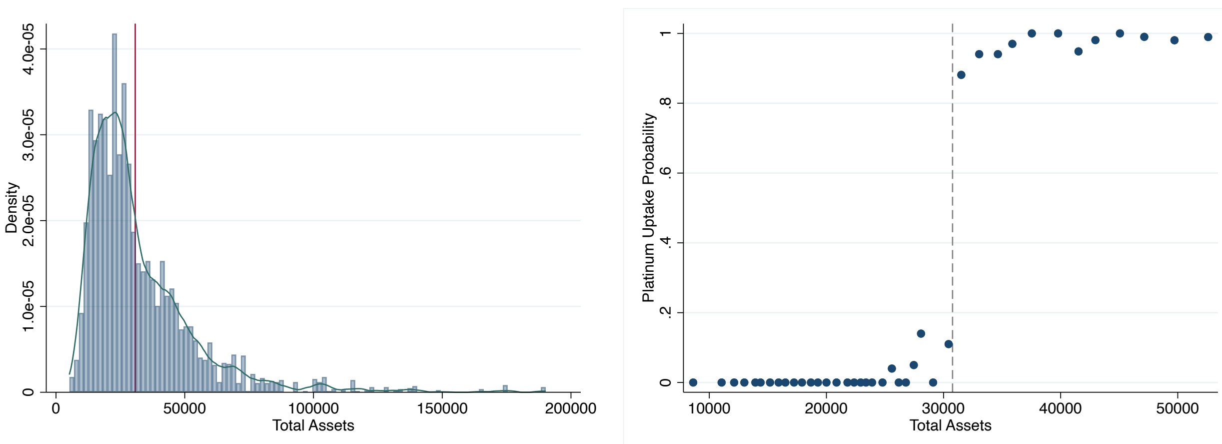
Note: This figure shows an example of credit card advertisements. Notice the abundant rewards associated with these cards. Source: American Express Platinum Card, captured on June 15, 2023.

Figure 1.2: Spending and Perceived Spending



Note: This figure shows the binned scatter plots of perceived spending against true spending. Reward-earning spending is defined as the consumption that can earn credit card rewards. The green curve is the 45-degree line, and the red curve is a quadratic fit. Consumers, in general, under-report their total spending; the underestimation looms larger for larger spending. In contrast, consumers seem to understand reward-earning spending fairly well.

Figure 1.3: Fuzzy RD: Design Validity Check

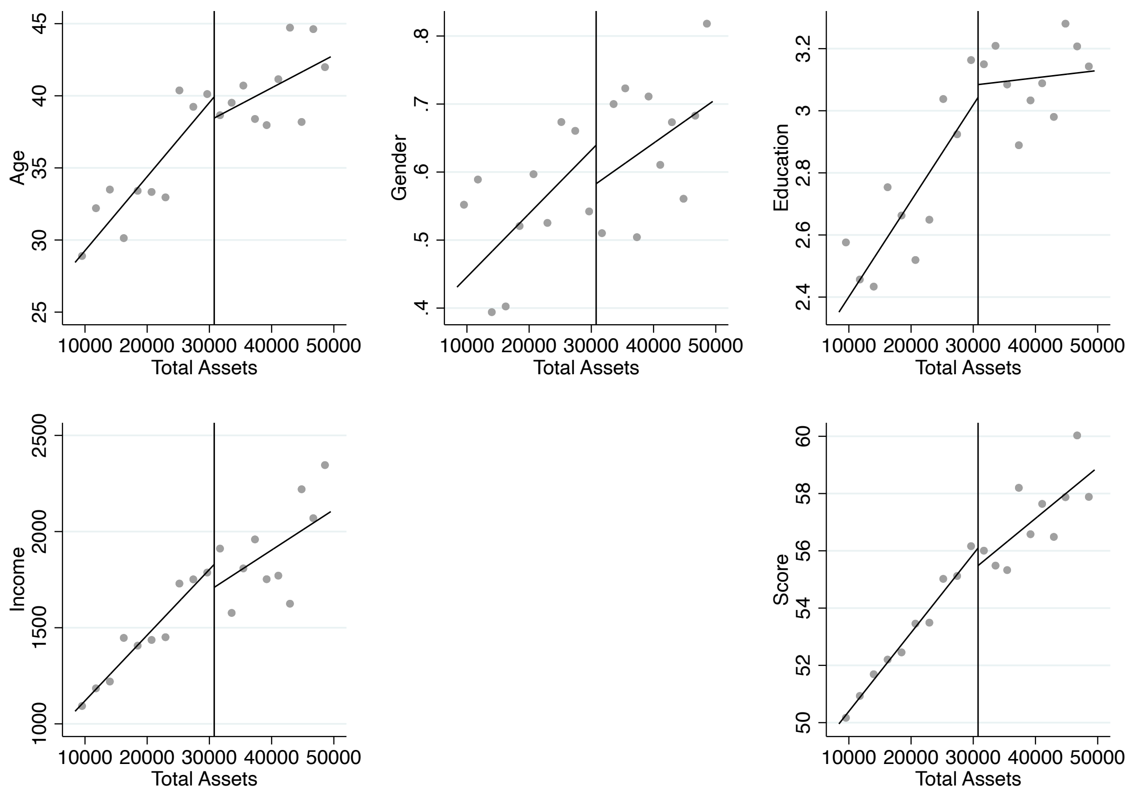


(a) Running Variable

(b) Fuzzy RD: First Stage

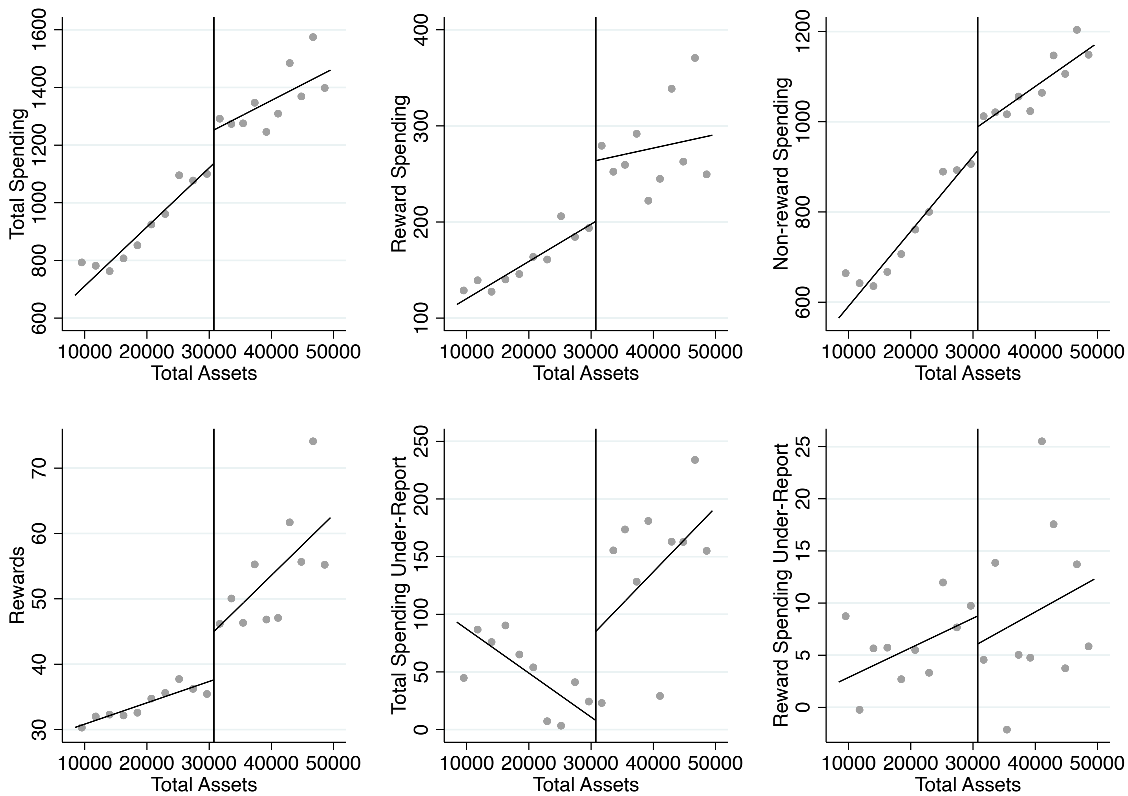
Note: Panel (a) in this figure includes a histogram plot of the total asset values where the red vertical line is the asset threshold for Platinum card eligibility, and the green curve is a kernel density estimate (KDE). The right-hand side of the threshold is the advantageous side, but there is no evidence of bunching, which does not support the hypothesis that consumers intentionally increase their asset value in order to get qualified for a Platinum card. Panel (b) in this figure shows a binned scatter plot of Platinum uptake probability against asset values, where the vertical dashed line is the asset threshold for Platinum card eligibility. Notice the upward jump when passing the asset threshold, which shows a strong first stage of the fuzzy RD design.

Figure 1.4: Fuzzy RD: Covariate Balance Check



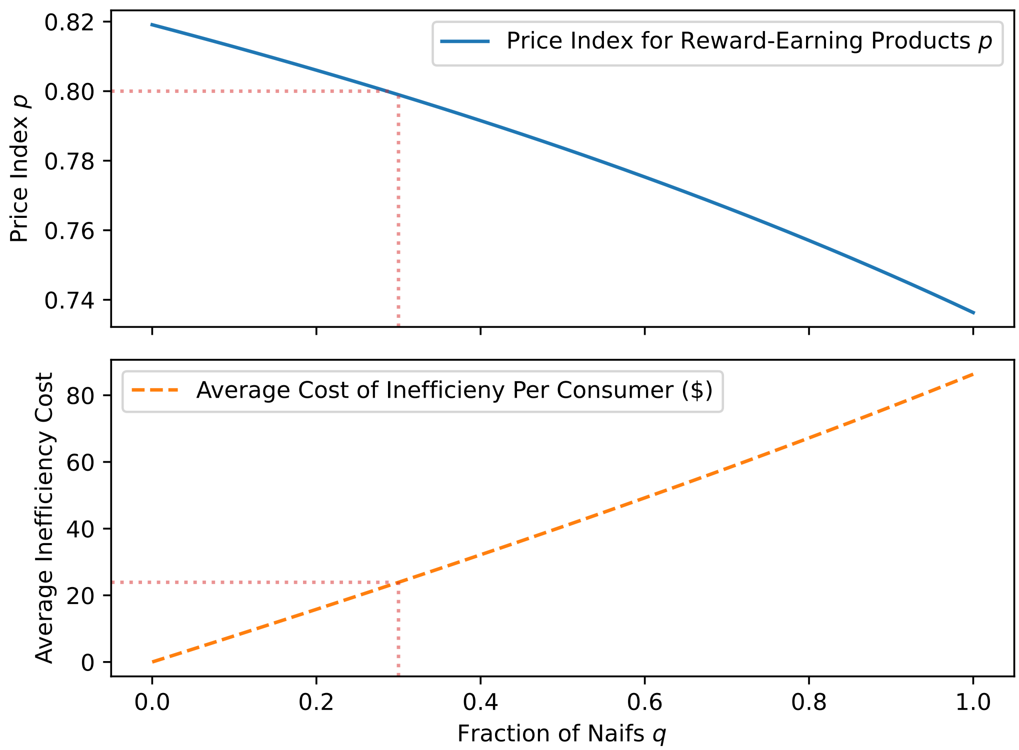
Note: This figure provides a covariate balance check at the asset threshold (vertical line). Notice that no discontinuity happens to any of the covariates. From the observed selection point of view, the fuzzy RD design provides an apples-to-apples comparison at the asset threshold.

Figure 1.5: Fuzzy RD: Intention-to-Treat Visualization



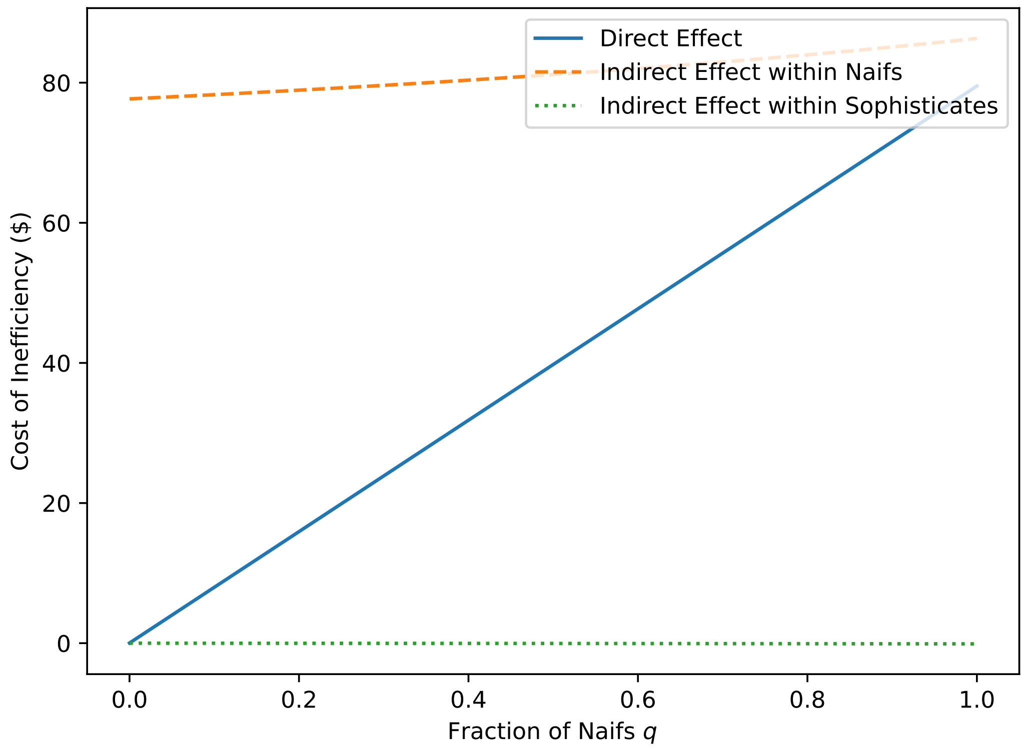
Note: This figure illustrates the fuzzy RD for the main outcome variables of interests where the vertical lines are the asset threshold. Notice the upward jumps happening in total spending, reward-earning spending, non-reward-earning spending, and reward values. For perception errors, despite different trends (because of the noise in the survey data), it appears that opting for a Platinum card enlarges consumers' total spending underestimation. No discontinuity occurs in the perception error of reward-earning spending.

Figure 1.6: Welfare Effect of Naivete Presence



Note: This figure illustrates the connection between naiveté presence, rewards, and welfare loss, implied by the model. Using the upper panel, given the reward-earning price index $p \approx 0.8$ in the data, the fraction of naive consumers q is around 30%. Given $q \approx 0.3$, the lower panel estimates that the average inefficiency cost per consumer is around \$25, which is about 2.5% of the monthly consumption.

Figure 1.7: Welfare Effect Decomposition



Note: This figure illustrates the decomposition of the effect of naiveté presence q on welfare. First, q has a direct effect on welfare loss: the average efficiency becomes lower when there are more naive consumers. Second, q has an indirect effect through p: the equilibrium reward-earning price index is lower for a larger q; the changed price index also changes the decisions of naive and sophisticated consumers. Within a naive consumer, notice that naiveté itself is very costly: the welfare loss is around \$80 and looms larger for a larger q. Within a sophisticated consumer, despite some welfare gain, the size is much smaller than the welfare loss of a naive consumer.

Chapter 2

Interest Rate Misperception in the Credit Card Market

2.1 Introduction

Consumers often accumulate significant debt to smooth their consumption over time, and the optimal level of debt critically depends on the associated interest costs. Recent literature has documented various behavioral biases among consumers, leading them to make suboptimal leverage decisions (Meier and Sprenger, 2010; Stango and Zinman, 2009; Bertrand and Morse, 2011). While there is a rich body of literature explaining excess debt-taking based on consumers' non-traditional preferences or varying levels of financial literacy, there has been limited direct study on how consumer *beliefs* about the marginal cost of debt causally affect borrowing. This paper concentrates on the credit card market and investigates consumers' perceptions of the costs of unsecured debts.

Credit cards and similar financial products serve as essential tools for households to acquire debts. Across many advanced economies, at least one-third of consumers carry positive credit card balances.[1] Understanding borrower incentives in credit card markets is crucial for analyzing household debt-taking behaviors. A notable characteristic of credit cards is their often opaque pricing structure. Figure 2.1 illustrates an advertisement for applying for a credit card from Chase Bank. Despite prominently highlighting benefits, the price, the annual percentage rate (APR) of the debt, is ambiguously presented as "low" in small font. This selective disclosure strategy may lead consumers to misunderstand the true costs of credit card debt, potentially resulting in suboptimal debt levels. For example, a recent survey by Bank Rate[2] found that over 40% of U.S. credit card holders are unaware of their cards' interest rates. Therefore, it is crucial to evaluate whether consumers misperceive the interest-related costs associated with their credit cards and, if so, how such misperception

[1]See Gross and Souleles (2002), Zinman (2009), Fulford (2015) for examples in the U.S., Vihriälä (2020) for Finland, Gathergood and Olafsson (2022) for Iceland, and Yin (2022b) for China.

[2]See Johnson (2022) for details.

Figure 2.1: Application Landing Page of Chase Credit Cards

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

affects their borrowing decisions.

In this paper, we mainly address three research questions. First, do consumers understand the interest rates associated with credit card debts? Second, if interest misperception exists, how does it affect consumers' financial behavior? Third, what factors contribute to such misperceptions?

Studying the effects of perceived interest rates on debt decisions is challenging as it necessitates simultaneous observations of realized debt decisions and beliefs about current interest rates on debt. To address this challenge, we collaborated with a major commercial bank in China to elicit consumer perceptions regarding the marginal costs of credit card debts. Analyzing these perceived interest rates directly, we find that consumers exhibit a wide range of perceptions regarding the interest rates associated with credit card borrowing. Despite an average APR of 19%, the perceived interest rates obtained from the survey question span from 5% to 35%, with an interquartile range of 9% to 20%.

We then 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 debt-takers. The straightforward information treatment yielded substantial instantaneous effects on perceived interest rates. Specifically, following exposure to the information, the perception errors of borrowers in the treatment group shifted from -4.3 to 0.6 percentage points. Conversely, for those in the control group, the perception errors before and after the experiment were -4.4 and -4.7 percentage points, respectively. These findings suggest an average treatment effect (ATE) of 5.2 percentage points on perception errors. Furthermore, the experiment significantly changed the absolute value of perception errors among treated borrowers. Post-exposure to the information treatment, the absolute perception errors of the treatment group decreased from 6.9 to 4.8 percentage points, whereas the control group experienced an insignificant change from 7.3 to 8.2 percentage points. This indicates an ATE of 3.0 percentage points on the absolute perception errors.

While having a noisy perception of the interest cost may seem inconsistent with consumers possessing full information, these noisy perceptions could stem from rational inattention due to limited demand for borrowing. In such cases, the noisy perceptions about interest costs might have trivial real effects, as only borrowers with limited needs for debt might experience significant misperceptions. To investigate whether interest rate misperceptions have a real stake in debt-taking, 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 $446.9 three months after the experiment compared to the control group, representing a 19% reduction. Since our measure of debt is derived from the credit registry, this estimate is not confounded by intra- or inter-bank fund transfers. Furthermore, we employ two-stage least squares in a Bayesian learning framework and find that a one percentage point decrease in the perceived interest rate results in an increase in borrowing by $138.9. Given the average perceived interest misperception of -4.4 percentage points, the results suggest that interest rate misperception on average induces an average excess credit card debt borrowing of $608.5, which accounts for around 26% of the current borrowing level.

It is important to understand how consumers adjust their debt after learning the true cost of borrowing. Two possibilities exist: 1) consumption remains unchanged, with borrowers shifting from debt-financed spending to liquidity-financed spending, and 2) consumers reduce spending, leading to lower borrowing. Leveraging our granular measure of spending and assets, we test these hypotheses and find results consistent with the latter. In particular, consumers reduced spending by 16% in the three months following the treatment, primarily by cutting back on luxury purchases. At the same time, we observe evidence that consumers opt for illiquid assets, such as certificates of deposit, over liquid assets after learning about their interest rate misperceptions. These findings suggest that rather than facing liquidity constraints, excess borrowing reflects excess consumption. Moreover, consumers may utilize illiquid assets as an implicit commitment device (Laibson, 1997) to prevent suboptimal spending and borrowing behavior.

Our findings reveal that borrowers possess noisy information regarding the interest costs of credit cards, and interest rate misperception exerts a large effect on borrowing behavior. This prompts a natural question: why do borrowers harbor such misperceptions? Despite initially encountering evasive perceived interest rates when acquiring credit cards, effective interest rates can be retrieved by logging into debt accounts. Over time, expectations shall converge to the correct level through Bayesian learning.

To explore borrowers' information acquisition behavior, we examine their decisions on logging into debit card and credit card accounts (Sicherman et al., 2015). A unique feature of our setup is the existence of two separate mobile apps, one for debit card accounts and the other for credit card accounts, facilitating the analysis of attention on savings and debts separately. We first demonstrate that the average number of credit card account logins, at 3.8 times per month, is approximately 40% lower than the average of 6.4 times per month for debit card account logins. This indicates that borrowers tend to allocate less attention to their debts compared to their assets. Furthermore, we observe that only credit card account logins exhibit a positive correlation with credit scores. In other words, borrowers tend to asymmetrically pay less attention to their debt when their creditworthiness is expected to be lower – a phenomenon reminiscent of the ostrich effect introduced by Karlsson et al. (2009). Consequently, information tends to carry more weight on positive news, leading borrowers to maintain an average negative perception bias even over the long term.

We then test such a mechanism of selective information acquisition. Specifically, since the true interest rate exceeds the average perceived interest rate, the information treatment serves as exogenous bad news to an average borrower. If borrowers attempt to avoid information when confronted with bad news, then treated borrowers should exhibit reduced logins to their credit card accounts but not to their debit card accounts. Consistent with this hypothesis, we find that while there is no significant change in debit card account logins, the number of monthly credit card account logins decreased by 0.75 times for the treatment group compared to the control group. This reduction is approximately 20% smaller relative to the pre-treatment average. Moreover, we observe that consumers with variable APR increased their perceived interest rates and decreased debts twice as much as those with fixed APR. This indicates that consumers with variable APRs possess a larger negative perception error and therefore excess borrowing ex-ante. These observations suggest that, despite having the same average APR, consumers tend to prioritize favorable news, i.e., a low cost of borrowing, when presented with information on both low and high APRs, resulting in an overall underestimation of interest costs.

We conclude our study by examining the long-run effects of the information treatment on interest rate perception and borrowing. Given that our experiment represents a one-time shock, we anticipate that the misperception will revert if consumers persist in focusing on good news while avoiding bad news post-treatment. To test this hypothesis, we surveyed consumers about their perceived interest rates nine months after the treatment and tracked their debt trajectories accordingly. Our findings reveal that the intention-to-treat effect of the information treatment on perceived interest rates depreciated by 42% after nine months.

Furthermore, debt began to increase again four months post-treatment. In light of these findings, to mitigate biases associated with selective information acquisition, we recommend implementing repeated policies such as periodic reminders or interventions that directly influence consumers' information acquisition processes.

Related Literature This paper intersects with three main strands of literature. First, it contributes to the literature on how consumer behavioral biases influence 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, etc.).[3] While most existing studies focus on non-traditional preferences or financial literacy, we enrich this literature by integrating survey data, transaction-level data, and an RCT to examine the impact of biased beliefs on consumer borrowing. The studies most closely related to ours are those by Ferman (2016) and Seira et al. (2017), where RCTs were employed to assess the effectiveness of information disclosures in the credit card market in enhancing consumers' awareness of credit card attributes and their financial decision-making. In line with prior literature indicating limited impact of such information disclosures, our survey on interest rate *perceptions* directly observes the evolution of consumer beliefs in the decision-making process. Additionally, our inquiries regarding the one-month costs of debt contribute to the findings that borrowers often misperceive the costs of debt, even for short durations of repayment. Thus, our setting contrasts with the previously documented exponential bias (Stango and Zinman, 2009; Bertrand and Morse, 2011) caused by the negligence of compounding, which relies on longer loan maturities to induce excess borrowing.

Our study also contributes to the literature on information acquisition in scenarios characterized by complex or obscured information. For example, Ellison (2005), Gabaix and Laibson (2006), and Bordalo et al. (2015) have delved into firm pricing strategies when consumers pay less attention to non-salient features at a theoretical level, particularly in contract designs with shrouded attributes. Empirical investigations in this domain primarily rely on revealed preferences, examining consumer demand following alterations in the salience of product attributes. Studies by Hossain and Morgan (2006), Chetty et al. (2009), Dertwinkel-Kalt et al. (2019), and Blake et al. (2021) illustrate how prices on shrouded attributes can influence product demand. Furthermore, regarding information acquisition, research by Karlsson et al. (2009); Eil and Rao (2011); Di Tella et al. (2015); Huffman et al. (2022); Möbius et al. (2022) reveals that consumers often focus on favorable signals or form positively motivated beliefs while avoiding or forgetting disadvantageous information. Our contribution lies in directly observing how consumer beliefs evolve through information acquisition and identifying the causal effect of belief changes on decision-making.

Lastly, this paper contributes to a growing literature that examines the role of beliefs in shaping consumer spending and saving decisions (see DellaVigna, 2009; Benjamin, 2019, for a review). For instance, Manski (2004), Ameriks et al. (2020), and Giglio et al. (2021) have investigated the relationship between investor beliefs and stock investment, while Bucks

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

and Pence (2008), Bailey et al. (2019), and Kuchler et al. (2022) have analyzed how beliefs influence mortgage leverage choices. Our work extends this literature by employing a quantitative survey matched to transaction-level data on consumer borrowing decisions. Through the integration of our survey with an RCT, we are able to causally explore the channels that influence consumer borrowing behavior.

Roadmap The remainder of the paper proceeds as follows. Section 2.2 outlines the sample construction, survey design, and provides summary statistics, along with a descriptive analysis of the interaction between perceived interest rates and borrowing behavior. Section 2.3 elaborates on the information treatment and the estimation of the effect of interest rate misperceptions on borrowing. In Section 2.4, potential reasons for the formation of interest rate misperceptions are discussed. Finally, Section 2.5 concludes.

2.2 Research Design, Sample Collection, and Descriptive Analyses

Data

The data utilized in this study originate from a top-10 national commercial bank in China ("the bank" hereafter), ranking among the country's top ten banks based on total assets. As of 2023, the bank reported assets exceeding 1 trillion US dollars, 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 consumers 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, akin 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 consumers to accumulate balances up to this limit each month and utilize the card as a payment method. Consumers 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, usually equating to 10% of the current outstanding balance. Consumers have the option to repay any proportion of the outstanding balance exceeding this minimum requirement. Those who repay all accrued balances within the billing cycle avoid incurring interest costs and can benefit from cashback rewards and transaction discounts. Unpaid balances are carried over to the subsequent billing cycle, accruing daily interest at a rate of around five basis points.

Credit card usage in China has witnessed remarkable growth since 2016. Over the period from 2016 to 2022, the total outstanding balance on credit cards surged from 3.6 trillion to 8.7 trillion CNY. Meanwhile, the aggregate credit limits rose from 9.1 trillion to 22.3 trillion CNY. Credit cards, along with other forms of personal credit offered by commercial banks in China, continue to be the predominant method for obtaining consumption-based unsecured debt. Despite the emergence of similar products from FinTech platforms and consumer lending companies, such as Alibaba's Huabei, the market share held by these entities remains relatively modest. As of 2023, these companies collectively accounted for approximately 20% of all consumption-based credit debt.[4]

Experimental and Survey Design

In November 2020,[5] we collaborated with the bank to administer surveys to a randomly selected group of customers who had incurred positive debt in 2020. Our primary outcome variable of interest is the total unsecured debt. Debt information was sourced from the Credit Reference Center of the People's Bank of China, the official credit registry, utilizing credit reports obtained by the bank. The Credit Reference Center aggregates personal credit data from all financial institutions, capturing the overall borrowing outlook of the consumers.

The survey was implemented through a mobile application, with survey links disseminated to customers via text messages. To incentivize participation, each participant received a gift valued at approximately $3 upon survey completion within a week. The key variable of interest in our study is consumers' perceived interest rate of credit card debt. Recognizing that consumers may not intuitively understand percentage values, we directly elicited participants' beliefs regarding the interest cost associated with borrowing a certain amount from a credit card, with only a portion repaid before the expiration of the interest-free period. Question 2 in the survey (outlined in detail in Online Appendix A) outlines our approach. Specifically, for each participant, we asked 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.*
>
> *a: You spend ¥5,000 this month and repay ¥3,000 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 ¥0 at the end of this month.*
>
> - 0 • 10 • 20 • 30 • 40 • 50 • 60

[4] Refer to International (2020) for the source in Mandarin Chinese.

[5] In China, the COVID-19 lockdowns became much fewer in late 2020, and consumers started to resume normal lives.

To mitigate 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.[6] 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 consumers' beliefs regarding credit card interest rates using the following formula:

$$Perceived\ r = \frac{1}{3}\left(\frac{x_1}{2000} + \frac{x_2}{4000} + \frac{x_3}{5000}\right), \tag{2.1}$$

where x_1, x_2, and x_3 represent the choices for the three values of repayment. 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.

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.

A novelty of our approach lies in the high-frequency nature of our question. Specifically, consider a consumer who borrows a present value P at a periodic interest rate r over a time horizon T, with periodic compounding. The future value F is given by the formula:

$$F = P(1 + r)^T. \tag{2.2}$$

From Equation (2.2), a consumer's biased perception of F could stem from three components: P, r, and T. Similar to Stango and Zinman (2009) and Bertrand and Morse (2011), consumers could exhibit exponential bias if they perceive the functional form of $(1 + r)^T$ as $(1 + r)^{(1-\theta)T}$, where $\theta \in (0, 1)$ represents a consumer's errors in compounding interest rate payments. Therefore, an exponentially biased consumer would underestimate T. Additionally, an inattentive consumer who is unaware of the true level of debt in their account might misperceive P. For instance, they could miscalculate their total consumption or total assets, leading to 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 the interest rate r.

In our survey, when eliciting the consumer's belief about the total payment of a consumption debt, we directly inquire about the required total payment in the next billing

[6] We utilized survey question 1 to assess the integrity of the responses. This question inquired about the participants' total spending via credit cards with the bank in the preceding month. Figure B.1 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.

Table 2.1: Summary Statistics

	Mean	Std. Dev.	25 pct	Median	75 pct	Count
Debt	2329.8	2940.2	243.9	1057.5	3347.4	1219
Perceived r	15.15	6.929	9.164	14.25	19.56	1219
Interest rate	19.51	1.117	18.60	19.61	20.70	1219
Spending	1539.2	1028.2	829.2	1310.8	1993.3	1219
Credit limit	10122.5	6252.8	5422.5	8544.6	13685.4	1219
Credit score	54.93	7.737	49.85	54.59	59.67	1219
Income	2345.4	1403.0	1438.8	2097.5	2837.5	1219
Assets	26537.6	25380.8	9724.9	18774.7	34143.8	1219
Age	38.20	10.77	28	38	47	1219
Female	0.569	0.495	0	1	1	1219
Education	1.778	0.858	1	2	2	1219
Credit logins	3.823	1.872	2.667	3.333	4.667	1219
Debit logins	6.747	4.014	4	5.333	8.667	1219

Note: This table provides the summary statistics of our sample, with all variables measured on a monthly basis. Monetary values are expressed in US dollars. Perceived r represents the perceived interest rate obtained from our survey. 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. Credit logins refer to the monthly frequency of logins to the dedicated credit card app, while debit logins indicate the monthly frequency of logins to the regular mobile banking app (distinct from the credit card app).

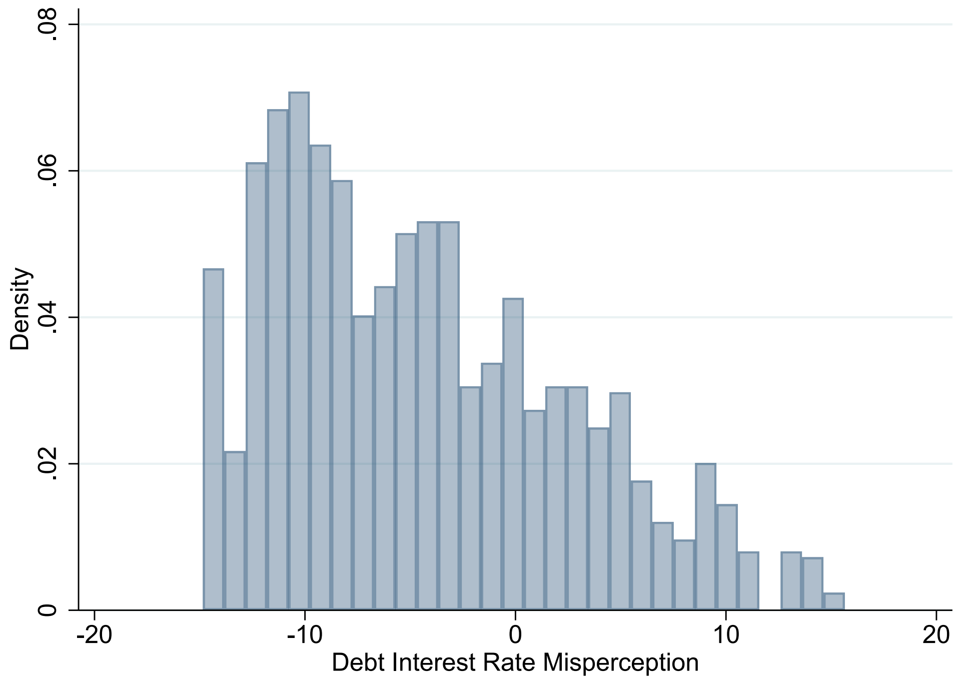
cycle. Therefore, we effectively fix $T = 1$ and vary P with hypothetical values. By doing so, we control for any misperception in T or P. Based on the answered F, we can directly measure the perceived value of r.

Summary Statistics

Our sample includes a total of 1,219 consumers with positive outstanding unsecured debt. Table 2.1 shows the summary statistics. A 99% winsorization is applied to all variables onward to reduce noises from outliers. The currency unit is converted to US dollars (1 USD = 7.1 CNY) hereafter for comparability. A consumer's highest degree information 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. We elicit consumer-perceived interest rates as described in Section 2.2 and denote them as *Perceived r* in Table 2.1.

Debt, in this study, refers to the unpaid balance on credit cards that incurs interest, calculated on a monthly basis. 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 every consumer also maintains positive savings. This phenomenon aligns with the puzzling trend observed in consumer finance literature, where individuals simultane-

Figure 2.2: Debt Interest Rates Misperception



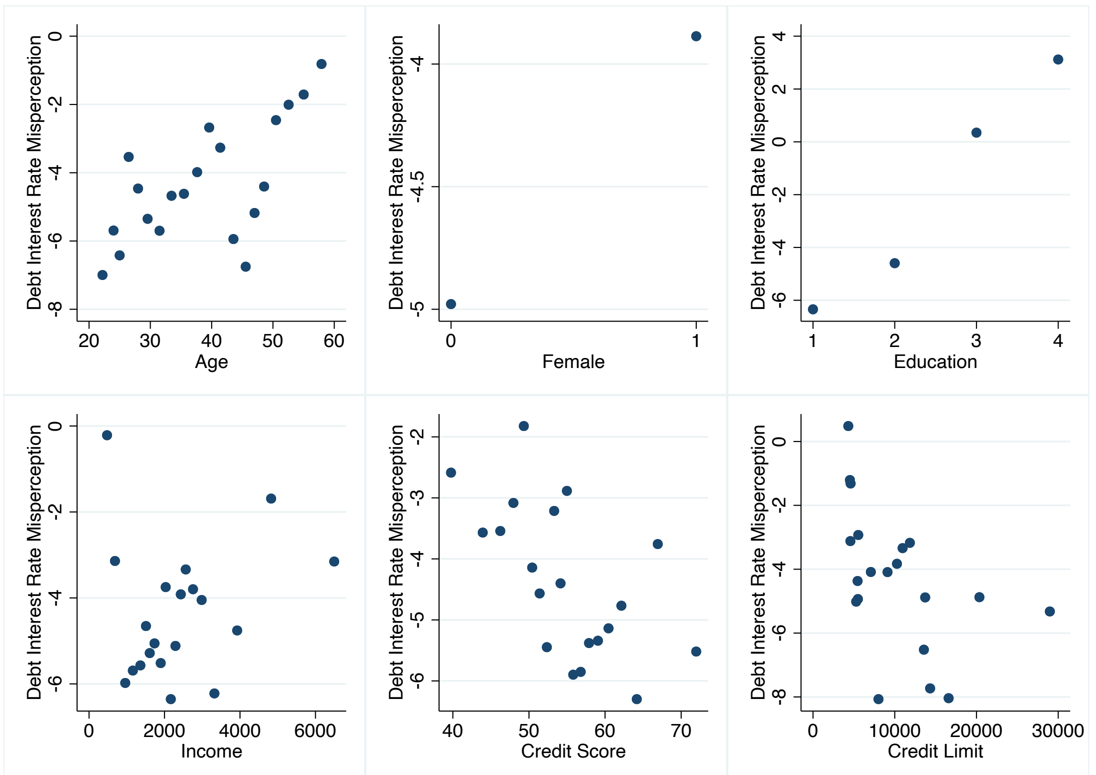
Note: This figure illustrates the distribution of debt interest rate misperception among survey respondents. Debt interest rate misperception is computed as the perceived interest rate minus the true interest rate, expressed in percentage points.

ously hold low-interest savings and high-interest credit card debts (Gross and Souleles, 2002; Telyukova, 2013; Gorbachev and Luengo-Prado, 2019; Gathergood and Olafsson, 2022). Approximately 57% of the consumers 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.

Consumers exhibit varying debt interest rates, with a mean of 19.6% and an interquartile range spanning from 18.6% to 20.7%. Interestingly, consumers tend to underestimate the interest rates associated with their credit card debt, with the mean perceived rate standing at 15.2%. Despite the true interest rates exhibiting a relatively narrow distribution, the perceived rate distribution is notably wider, with a standard deviation six times greater than that of the true interest rates.

The heterogeneous nature of perceived interest rates is further illustrated in Figure 2.2 through the distribution of perception errors $Bias_i$. The majority of perception errors fall within the range of approximately -15 to 15 percentage points. Moreover, the distribution exhibits a right-skewed pattern, suggesting that more individuals tend to underestimate rather than overestimate debt interest rates.

Figure 2.3: 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.

Debt Interest Rate Misperception Heterogeneity

We begin by examining how interest rate misperception co-varies with other factors using binned scatter plots depicted in Figure 2.3. Regarding demographics, younger and male borrowers tend to perceive lower interest rates and exhibit larger perception errors. Consumers 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 consumers with higher debt levels (facilitated by high credit scores and limits) may tend to underestimate the cost of borrowing. These associations are further detailed in Table B1 in the Online Appendix, which presents the results of a linear regression analysis.

Interest Rate Misperception and Borrowing Behavior

Our analysis of perceived interest rates reveals that consumers generally lack accurate knowledge of the true cost of borrowing. It is well-documented in recent literature that heterogeneous beliefs are sometimes only weakly correlated with corresponding actions (Ameriks et al., 2020; Giglio et al., 2021). We proceed to investigate whether interest rate misperception influences consumer borrowing behaviors.

We examine the relationship between interest rate misperception (defined as the perceived interest rate subtracted from the true interest rate) and debt accumulation using a binned scatter plot displayed in Figure 2.4. Interestingly, we observe a distinct pattern where only downward bias exhibits a negative correlation with debt accumulation, while the relationship conditional on upward bias appears to be flat.

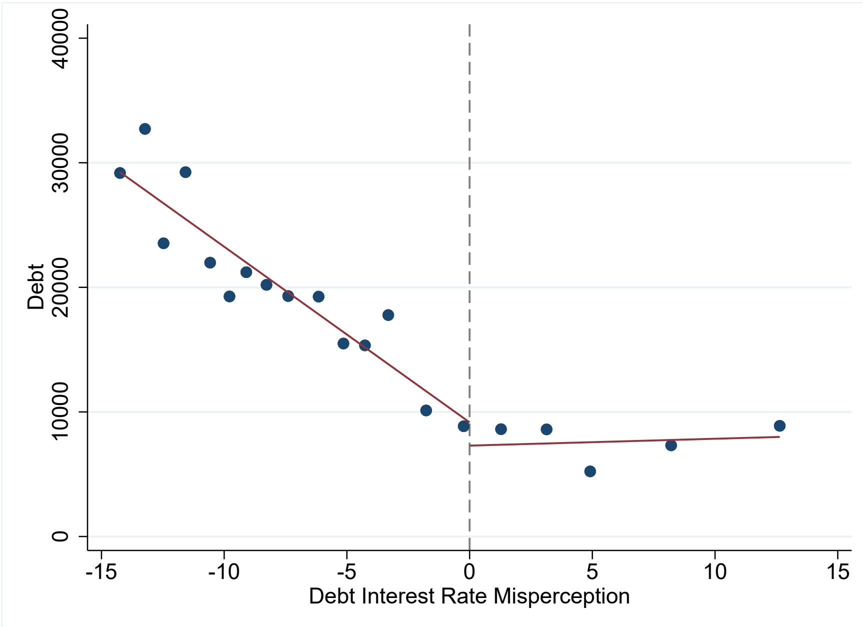
The asymmetric effects of positive and negative misperceptions carry important implications. In a market characterized by consumers' inaccurate perceptions of interest costs, even if the errors average out to near zero, interest rate misperception could lead to significant inefficiencies. Specifically, excess debt may be accumulated at the aggregate level due to the first-order inefficiency induced by interest rate misperception, despite any second-order inefficiencies arising from misallocation. Further details are provided in Table B2 in the Online Appendix, which presents the results of a linear regression analysis demonstrating a large negative correlation between negative interest rate misperception and debt, while the association between positive misperception and debt remains modest.

2.3 Information Treatment on Debt Interest Rate

The previous section highlights that consumers exhibit heterogeneous perceptions of the true interest rate associated with credit card borrowing. Those with a negative perception error tend to accumulate more debt, while the relationship between misperception and debt remains flat when consumers overestimate the interest rate. Taken together, these findings suggest an excess of credit card borrowing at the aggregate level. However, the ordinary least squares (OLS) estimates may be subject to potential endogeneity issues. For instance, unobserved heterogeneity could bias the regression results via omitted variable bias if debt-taking is influenced by latent preference variables not orthogonal to the perceived interest rates, although the direction of bias is uncertain. Additionally, debt-taking behavior and 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. Conversely, motivated reasoning could be another channel: consumers holding excessive debt may intentionally disregard or project a lower interest rate to justify suboptimal borrowing behavior. To mitigate these potential endogeneity concerns, we leveraged a randomized controlled trial (RCT) to identify the effect of perceived interest rates on borrowing behavior.

Several factors may contribute to consumers' lack of accurate interest rate perception.

Figure 2.4: 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.

One possibility is the obscure presentation of interest rates in practice, as illustrated in Figure 2.1. Additionally, consumers may not pay sufficient attention to interest rates because credit card borrowing represents a small or infrequent aspect of their overall financial activities. In light of these possibilities, we devised an information treatment aimed at enhancing the salience of true interest rate-related costs and, consequently, consumers' attention to interest rates.

Identification Strategy: Information Treatment

Identifying the causal effect of interest rate perception on borrowing behavior is challenging due to the impracticality of randomizing consumer beliefs. To address this issue, we surveyed the consumers for a second round, wherein we implemented an information treatment for a randomly chosen subset of participants, as outlined in Section 2.2.

Information Treatment Design For a random 40% of the participants, we revealed the following information at the end of the survey on a new page

> *The annualized interest rate on credit cards 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 APR, monthly interest rate, and CNY amount of interest payment incurred given carrying over ¥8,000 for a month. Then, all the participants regardless of the treatment status 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? Choice: _____.*

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

The order of the choices was randomized to mitigate the anchoring effect. Then, we compute the implied perceived interest rate again using Equation (2.1). Essentially, our information treatment increased the salience of the interest rate by explicitly presenting the true cost of borrowing in an exogenous manner. 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 B3 in the Online Appendix presents the means 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.

Intention-to-Treat Effect of Information Treatment on Interest Rate Perceptions

Our information treatment engendered substantial responses from consumers. Figure B2 in the Online Appendix illustrates the distributions of perception revisions for the control and treatment groups, respectively. For a detailed analysis, Table 2.2 reports the means and standard errors of the bias and absolute bias of the perceived interest rates grouped by treatment status. In the control group, consumers exhibited minimal changes in their perceptions, with little revision observed between the perceived interest rates in our two elicitation processes (*Bias* changes from -4.4 to -4.7 percentage points, while $|Bias|$ moves from 7.3 to 8.2 percentage points). In contrast, in the treatment group, consumers predominantly adjusted their perceived interest rates upwardly (*Bias* rises from -4.3 to 0.7 percentage points), and their revised interest rates moved closer to the true rates ($|Bias|$ drops from 6.9 to 4.8 percentage points). The distributions of interest perception revision between the

Table 2.2: Perceived Interest Rate Revision

	Control		Treatment	
	Before	After	Before	After
Bias	-4.39	-4.72	-4.32	0.62
	(0.27)	(0.31)	(0.29)	(0.26)
$\|Bias\|$	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, 20%, whereas $|Bias|$ is the absolute value of the difference. Standard errors are reported in parentheses.

treatment and control groups, as depicted in Figure B2 in the Online Appendix, underscore the effectiveness of the information treatment.

To evaluate the intention-to-treat (ITT) effect of our information treatment, we employ a difference-in-differences (DID) design. 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 following regression equation:

$$y_i = \alpha + \beta_1 Treated_i + \beta_2 After_i + \gamma(Treated_i \times After_i) + \mathbf{X}_i'\theta + \varepsilon_i \tag{2.3}$$

where $Treated_i$ 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.

We present the ITT effects of the information treatment on perceived interest rates, absolute perception errors, and debt in Table 2.3. Consistent with the descriptive observations from Table 2.2, and controlling for covariates, consumers increased their perceived interest rates by 5.2 percentage points following the information treatment, while their misperception errors decreased by 3.0 percentage points. Furthermore, in line with the average underestimation of interest rates by consumers, the information treatment resulted in a reduction in credit card debt by $446.9, representing a 19% decrease relative to the pre-treatment level.

Effect of Interest Rate Misperception on Debts

Next, we evaluate the effect of interest rate misperception on credit card borrowing using a two-stage least squares (2SLS) framework similar to the approach of Coibion et al. (2021) and Coibion et al. (2024). Since perceived interest rates are endogenous, we employ the information treatment as an instrumental variable (IV) for perceived interest rates.

Table 2.3: ITT Effect of Information Treatment

	(1) Perceived r	(2) $\lvert Bias \rvert$	(3) Debt
After × Treated	5.206***	-3.011***	-446.864**
	(0.519)	(0.329)	(210.678)
After	-0.455	0.874***	199.420
	(0.368)	(0.226)	(152.044)
Treated	0.353	-0.443**	-268.330*
	(0.358)	(0.223)	(157.718)
Constant	9.915***	11.569***	2338.693***
	(1.120)	(0.722)	(489.619)
Observations	2438	2438	2438
R^2	0.231	0.133	0.117
Controls	Yes	Yes	Yes

Note: This table presents the OLS estimates of a DID framework. 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In the first stage, we estimate the relationship between the perceived interest rates elicited in the second round ($Perceived\ r_i$) and their counterparts elicited in the first round ($Perceived\ r_i^{prior}$), along with treatment status and their interaction:

$$Perceived\ r_i = a + bPerceived\ r_i^{prior} + cTreated_i + dPerceived\ r_i^{prior} \times Treated_i + \mathbf{X}_i' e + \nu_i, \quad (2.4)$$

where $\mathbf{X}_i$ includes controls for demographics, financial status, and credit availability at the pre-treatment level. The reduced-form equation is then specified as:

$$y_i = \alpha + \beta \widehat{Perceived}\ r_i + \gamma Perceived\ r_i^{prior} + \mathbf{X}_i' \theta + \varepsilon_i \quad (2.5)$$

where $\widehat{Perceived}\ r_i$ is the predicted perceived interest rate from the first stage regression.

In this framework, the excluded instruments are $Treated_i$ and $Perceived\ r_i^{prior} \times Treated_i$, while $Perceived\ r_i^{prior}$ is treated as an included instrument as it is not randomly assigned. The coefficients $b + d$ in the first-stage regression indicate the weight assigned to the prior relative to the signal provided in the information treatment, ranging from 0 to 1. Table B4 in the Online Appendix presents the results of the first-stage regression, where $b + d \approx 0.37$ suggests that our information treatment substantially revised consumer perceptions of interest rates, indicating a strong first stage. This implies that consumers did not have a precise understanding of the debt interest rate ex-ante.

Table 2.4: 2SLS Estimates of Effect of Perceived Interest Rate on Debts

	(1) Debt	(2) Debt (Downward Bias)	(3) Debt (Upward Bias)
Perceived r	-138.921***	-131.617***	-107.536***
	(22.566)	(21.155)	(32.495)
Constant	3263.870***	3758.525***	-1363.562
	(630.925)	(765.435)	(945.702)
Observations	1219	899	320
R^2	0.175	0.159	0.223
First-Stage F	532.886	781.324	47.494
Controls	Yes	Yes	Yes

Note: This table presents the 2SLS estimates of a Bayesian learning framework expressed in Equation (2.4), where the treatment status is used as an IV for the perceived interest rate in the first stage. The results in column (1) correspond to the entire sample, while columns (2) and (3) represent subsamples comprising only consumers 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. 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.4 presents the results of the 2SLS estimation. The first-stage F statistics in all columns are well above the 10% critical value, indicating that weak instruments are not a concern. Column (1) reports the results of Equation (2.5) where perceived interest rates from the second-round elicitation are instrumented using Equation (2.4). The debt-taking decision conforms to the law of demand: a one percentage point increase in the perceived interest rate decreases debt by $138.3. Given an average APR of 19.5% and an average debt of $2,325.7, this corresponds to an elasticity measure of -1.2.

Considering an average interest rate misperception of -4.4 percentage points, the estimated effect of perceived interest rate on debt suggests an excess borrowing of $608.5 on average, representing approximately 26% of the current debt level. For external validity, 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).[7]

Additionally, considering the asymmetric correlations between interest rate misperception and credit card debt around 0 as illustrated in Figure 2.4, Table 2.4 columns (2) and (3) estimate the same 2SLS system using subsamples of consumers who underestimate and overestimate the interest rate, respectively. Unlike the OLS results, we find a significant

[7]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.

effect of perceived interest rate on borrowing regardless of the direction of misperception. The sensitivity estimates, -130.4 for consumers with negative perception errors and -107.5 for those with positive perception errors, do not exhibit significant differences. These results suggest that the endogeneity of the perceived interest rate is more pronounced for consumers with positive perception errors, underscoring the importance of instrumental variables in the estimation process.

Alternative to Bayesian learning, in the Online Appendix, we show a "model free" 2SLS framework reported in Table B5, where the perceived interest rate sensitivity of debt is equivalent to the ITT effect of the information treatment on debt divided by the ITT effect of the information treatment on perceived interest rates. Since consumers tend to adjust their interest rate perceptions toward the true information we provided as shown in Table 2.3, subsampling them into groups with positive and negative perception errors is likely to satisfy the monotonicity assumption in the local average treatment effect (LATE) framework (Angrist and Imbens, 1995). Therefore, the results in columns (2) - (3) can be interpreted as the LATE of perceived interest rates on debt. We yield similar estimates to those in Table 2.4.

Excess Borrowing Reflects Excess Spending

We have shown that consumers often have noisy perceptions of their credit card interest rates, and an information treatment that provides them with accurate information helps to correct these misconceptions. This indicates that consumers recognize, to some extent, the errors in their beliefs about debt interest rates and consider our provided accurate information to be valuable.

What steps do consumers take to reduce credit card borrowing once they become aware of their interest rate misperceptions? We posit two possibilities: 1) Consumers 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 individuals may 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 2.5 columns (1) - (4). Note that 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.

The results align with the first hypothesis. Compared to the control group, treated consumers reduced their monthly spending by \$254.9, representing a 16% decrease in the three months post-treatment. With debt decreasing by \$446.9, this translates to an asset increase of \$320.8, which falls within one standard error (689.5) of the actual ITT effect of the information treatment on total assets (\$136.6), presenting no evidence of post-treatment inter-bank transfers.

Table 2.5: Three-month ITT Effect of Information Treatment on Spending and Savings

	(1) Spending	(2) Liquid assets	(3) Illiquid assets	(4) Necessities spending	(5) Luxuries spending	(6) Other spending
After × Treated	-254.911***	-1224.612*	1361.193***	-56.804	-184.318***	-13.789
	(53.096)	(740.003)	(345.800)	(44.553)	(51.282)	(45.143)
After	152.129***	668.494	-32.407	12.958	38.727	100.444***
	(33.083)	(491.885)	(221.342)	(29.869)	(33.825)	(28.697)
Treated	-28.861	-306.258	413.501*	44.690	-46.300	-27.251
	(27.411)	(273.235)	(233.579)	(32.615)	(33.277)	(29.114)
Constant	-144.633	-915.115	-1059.842	344.935***	-598.081***	108.513
	(120.436)	(1737.108)	(750.564)	(98.669)	(124.855)	(105.928)
Observations	2438	2438	2438	2438	2438	2438
R^2	0.659	0.775	0.691	0.085	0.462	0.077
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. 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We further show the anatomy of asset changes in columns (2) - (3). Consumers reduced liquid assets by $1,224.6 and increased illiquid assets by $1,361.2. 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, consumers 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 (predefined by the bank). We find that around 72% of consumption reduction originates from a decrease of $184.3 in luxury purchases.

Despite no evidence of inter-bank transfers, a potential concern about incomplete measures of consumption may arise, 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 consumers 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? Answer: _____.

As enclosed in Table B6 in the Online Appendix, this procedure yields similar estimates to those in Table 2.5.

These findings together indicate that excessive borrowing corresponds to excessive spending. 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, consumers began to settle high-interest credit card debt by curtailing (seemingly unnecessary) luxury expenditures. Juxtaposed to credit card debt payoff, it is an interesting observation that consumers opted out of liquid assets for inflexible certificates of deposit in nearly a one-to-one ratio. This behavior aligns with the insights of Laibson (1997), suggesting that consumers view illiquid assets as an implicit commitment device to mitigate excessive consumption induced by interest rate misperceptions.

2.4 Selective Information Acquisition and Interest Rate Misperception

In this section, we examine the potential reasons for the interest rate misperception. The literature has considered various factors contributing to biased belief formation. One potential channel is selective information acquisition in the presence of beliefs in utility. That is, when beliefs about individuals' status have hedonic values, consumers tend to pay more attention to favorable information, while ignoring unpleasant information, causing a phenomenon known as the ostrich effect (Karlsson et al., 2009; Oster et al., 2013).

To access information about credit card borrowing, such as current APR and interest payments, consumers typically log in to a mobile app provided by the bank. Although credit card accounts and other bank accounts (such as checking and savings accounts) are often linked to the same mobile app, the bank in our study utilizes a separate mobile app specifically for credit cards. Therefore, we can analyze the frequency of logins to this card-specific mobile app each month to investigate attention allocation toward interest rate payments. This analysis allows us to test whether selective information acquisition could contribute to the formation of interest rate misperception, similar to the approach taken by Sicherman et al. (2015).

The summary statistics of login frequencies provided in Table 2.1 show that, on average, consumers log into their credit card accounts approximately 3.8 times per month. In contrast, logins to debit card accounts occur around 6.4 times per month, representing a roughly 40% difference. This observation suggests that individuals tend to pay less attention to their debts compared to their assets.

Suggestive Evidence of Selective Information Acquisition

We begin with descriptive findings concerning the association between login frequency and creditworthiness (as indicated by credit scores), employing a regression represented by Equation (2.6). Here, $Logins_i$ denotes the monthly login frequency of consumer i into their credit card account, while $High\ Credit\ Score_i$ is a dummy variable indicating whether consumer i possesses a credit score above the sample median. The regression equation is formulated as follows:

$$Logins_i = \alpha + \beta High\ Credit\ Score_i + \mathbf{X}_i'\theta + \varepsilon_i. \tag{2.6}$$

Table 2.6: Creditworthiness, Logins, and Interest Rate Perceptions

	(1) Credit logins	(2) Debit logins	(3) Perceived r
Credit score: high	0.303***	0.151	-0.617*
	(0.082)	(0.205)	(0.325)
Credit logins			-3.211***
			(0.239)
Debit logins			1.334***
			(0.112)
Constant	4.305***	7.673***	16.439***
	(0.098)	(0.250)	(0.488)
Observations	2575	1897	1897
R^2	0.031	0.020	0.185
Controls	Yes	Yes	Yes

Note: This table presents the OLS estimates. Credit score: high is a dummy variable that takes the value of 1 when a consumer's credit score is above the sample median, reflecting their creditworthiness. Credit logins refer to the monthly frequency of logins to the dedicated credit card app, while debit logins indicate the monthly frequency of logins to the regular mobile banking app (separate from the credit card app). White robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Column (1) of Table 2.6 shows a positive correlation between creditworthiness and the frequency of logins to credit card apps: consumers with credit scores above the sample median log in approximately 0.3 times more per month (roughly 8% higher than the average login frequency) compared to their counterparts. This finding is consistent with selective information acquisition, suggesting that individuals tend to pay closer attention to their debt status when they possess higher creditworthiness. In contrast, column (2) presents a similar regression fit for debit card logins with respect to creditworthiness, where we do not observe a statistically significant positive correlation.

In addition, column (3) presents the results of the following regression, examining the relationship between perceived interest rates and credit card app login frequency:

$$Perceived\ r_i = \alpha + \beta Logins_i + \mathbf{X}_i'\theta + \varepsilon_i \tag{2.7}$$

where creditworthiness and debit card logins are included in the control variables $\mathbf{X}_i$. We find that with each increase in monthly login frequency to the credit card app, a consumer's perceived interest rate decreases by 3.2 percentage points. This negative correlation is consistent with two hypotheses: 1) When individuals perceive a poor financial status due to high debt resulting from a high interest rate, they may be less inclined to log in to their

Table 2.7: Evidence of Selective Information Avoidance

	(1) Credit logins	(2) Debit logins	(3) Perceived r (Fixed r)	(4) Debt (Fixed r)	(5) Perceived r (Variable r)	(6) Debt (Variable r)
After × Treated	-0.747***	-0.259	3.319***	-269.478	6.178***	-539.119**
	(0.162)	(0.330)	(1.032)	(362.421)	(0.546)	(259.313)
After	0.266**	0.364	-0.148	181.881	-0.592	207.235
	(0.110)	(0.229)	(0.757)	(266.792)	(0.366)	(184.669)
Treated	0.077	0.115	-0.088	-112.010	0.325	-334.809*
	(0.105)	(0.229)	(0.730)	(273.922)	(0.358)	(193.701)
Constant	4.651***	9.359***	9.911***	2277.073***	10.435***	2255.054***
	(0.370)	(0.766)	(2.331)	(875.760)	(1.173)	(592.966)
Observations	2438	2438	792	792	1646	1646
R^2	0.066	0.036	0.290	0.123	0.258	0.117
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents the OLS estimates of a DID framework. Columns (1) and (2) correspond to the entire sample. Columns (3) and (4) represent subsamples comprising only consumers with variable interest rates (e.g., those who received reduced APR offers) in the past three years, while columns (5) and (6) comprise those with fixed interest rates. 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

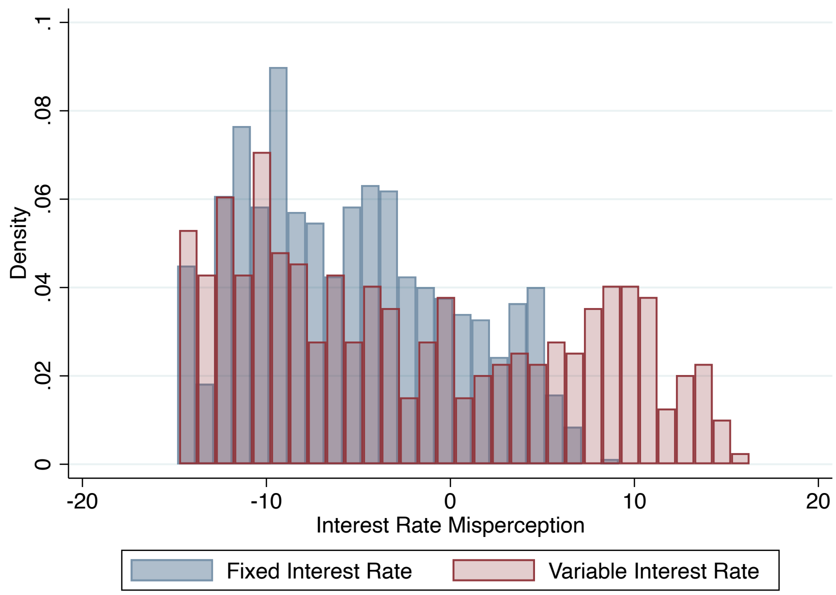
credit card app and review their borrowing status; 2) Consumers may selectively focus on information related to lower interest rates, such as when receiving offers for reduced APR, resulting in lower perceived interest rates.

Low Creditworthiness Discourages Information Acquisition

We next leverage the experiment to test these hypotheses of selective information acquisition. Table 2.7 columns (1) - (2) show the ITT effect of information treatment on login behavior using Equation (2.3). Recall that consumers on average underestimated the debt interest rate. This indicates that the revelation of the true cost of borrowing through our information treatment served as unfavorable news by an average consumer.

Consistent with selective information acquisition, a negative shock to creditworthiness dissuades consumers from logging into their credit card accounts: the information treatment led to a decrease in login frequency by 0.7 times, representing a 20% reduction. However, there is no evidence indicating that consumers refrained from logging into their debit accounts. These findings suggest that selective information acquisition may contribute to interest rate misperception: consumers tend to pay asymmetrically more attention to their financial status when their creditworthiness is high, while dodging information otherwise, resulting in an aggregate underestimation of the interest rate.

Figure 2.5: Interest Rate Variability and Misperception



Note: This figure plots the distributions of interest rate misperceptions for consumers with variable interest rates (represented by red bins) and those with fixed interest rates (represented by blue bins).

Asymmetrically More Attention to Low Interest Rates

Another interesting aspect of selective information acquisition to investigate is the variation in interest rates. Supposedly, when interest rates vary more, if consumers indeed pay more attention to low interest rates but less attention to high interest rates, a convex combination of these signals engendered by selective information acquisition will consequently amplify interest rate misperceptions.

From this perspective, we divide the sample into two groups: one comprising consumers with variable interest rates (e.g., those who received periodical reduced APR offers) in the past three years, and the other comprising those with fixed interest rates. It is worth noting that the true average APR for both groups is nearly identical, at 19.5% and 19.4%, respectively. The histogram plots of interest rate misperceptions for the variable and fixed interest rate groups, depicted in Figure 2.5, support the notion of asymmetric attention to positive news: when interest rates fluctuate over time, consumers tend to pay more attention to low interest rates than high interest rates. As a result, they exhibit a larger negative perception error compared to those with less variability in interest rates.

We can further investigate this hypothesis using our experiment. Columns (3) to (6) of Table 2.7 present the heterogeneous ITT effects of the information treatment on the perceived interest rate and debt three months post-treatment for the variable and fixed interest rate groups, respectively. Comparing columns (3) and (5), it is apparent that our

Table 2.8: Perceived Interest Rate Revision in the Long Run

	Control		Treatment		9m ITT
	Before	9 Months Later	Before	9 Months Later	
Bias	-4.39	-4.28	-4.32	-1.11	3.08**
	(0.27)	(0.27)	(0.29)	(0.26)	(0.55)
$\|Bias\|$	7.29	7.23	6.92	4.95	-1.89***
	(0.16)	(0.15)	(0.18)	(0.15)	(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, 20%, whereas $|Bias|$ is the absolute value of the difference. ITT denotes the corresponding DID estimates as in Equation (2.3). Standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

information treatment has a more pronounced positive effect on the perceived interest rate for consumers with variable interest rates, suggesting that these consumers initially had a larger negative perception error. Correspondingly, columns (4) and (6) demonstrate that our information treatment causes consumers with variable interest rates to reduce borrowing by $537.7, whereas the effect on borrowing for consumers with fixed interest rates is less than half and statistically insignificant. These findings collectively imply that, despite having the same average interest rate, consumers may selectively focus on their financial status only when the interest rate is low, leading to underestimation of interest rates and excess borrowing overall.

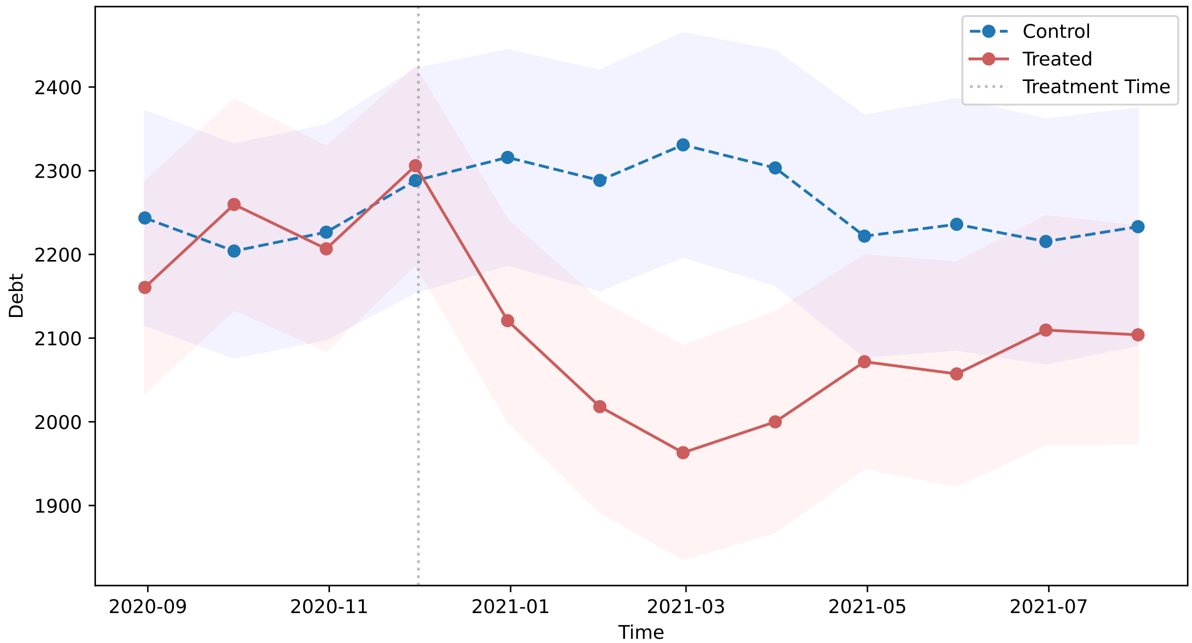
Reversal of Misperception and Debt in the Long Run

Our findings indicate that providing information about the true costs of debt helps correct misperceptions of interest rates instantaneously. However, since our information treatment offers a one-time signal regarding the cost of borrowing without influencing consumers' long-run information acquisition process, we posit that interest rate misperceptions and borrowing behavior may revert over time as consumers' financial circumstances change.

To test this hypothesis, we conducted a follow-up survey in late August 2021, eliciting the perceived interest rates of the same consumers for a third round using the same design described in Section 2.2. Table 2.8 presents the results along with the corresponding ITT effect estimate using Equation (2.3). Consistent with our hypothesis predicted by selective information acquisition, compared to Table 2.3, the effect on the perceived interest rate decreases from 5.3 to 3.1 percentage points, while the effect on the absolute perception error decreases from -3.0 to -1.9 percentage points.

Correspondingly, Figure 2.6 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

Figure 2.6: Long-Run Effect of Information Treatment on Debts



Note: This figure illustrates the credit card debt trajectories of consumers 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.

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 (such as the illustration in Figure 2.1). While the information treatment effectively corrected misperceptions initially, consumers are still exposed to varying levels of debt and interest rates over time. If their information acquisition behavior remains unchanged, interest rate perception and borrowing patterns will revert to pre-treatment levels. This finding aligns with existing literature, such as Seira et al. (2017), indicating that information disclosures may have modest effects on behavior. Our study provides suggestive evidence that this limited effect could stem from asymmetric attention in sequential information acquisition and decision-making.

In summary, a one-time information treatment might not be adequate to prevent consumers from selectively gathering or avoiding information over time, resulting in observed bias reversal. Given the presence of selective information acquisition, we propose employing repeated information treatments or implementing policies directly targeting information acquisition, such as periodic reminders, to help address misperceptions and enhance consumers' decision-making processes.

2.5 Conclusion

In this paper, we conducted a randomized controlled trial (RCT) to examine consumer perceptions of the cost of credit card borrowing and manipulate the salience of interest rates. Our findings reveal that, despite noisy perceptions, consumers tend to underestimate the interest rate associated with credit card debt.

Our information treatment aimed to enhance the salience of interest rates among a randomly selected group of consumers by explicitly presenting them with the true cost of borrowing in monetary terms. This intervention yielded significant responses from consumers: compared to the control group, those in the treatment group substantially adjusted their perception of interest rates, increasing them by an average of 5.2 percentage points and reducing absolute perception errors by 3.0 percentage points. Using treatment status as an instrumental variable for perceived interest rates within a Bayesian learning framework, we estimated the interest rate sensitivity of credit card borrowing. Our analysis indicates that for every percentage point increase in perceived interest rates, consumers, on average, reduced debt by $138.9, corresponding to an elasticity of -1.2. These findings suggest an excess borrowing of 26% at the current debt level on average.

Instead of liquidity constraints, our research suggests that excess borrowing is more closely linked to excess spending. Upon learning the true cost of borrowing, consumers reduced debt by cutting back on luxury purchases and turned to illiquid assets as an implicit commitment device to prevent suboptimal consumption induced by interest rate misperception.

Exploring potential reasons for interest rate misperception, we examined consumers' attention to their borrowing status, such as current APR and interest payments, using data on banking app login behavior. Our analysis uncovered evidence of selective information acquisition: consumers with lower creditworthiness were less likely to engage with their credit accounts, while those facing varying interest rates paid disproportionately more attention to favorable news (i.e., low interest rates) than adverse information, leading to overall underestimation of interest rates.

Although our information treatment provided an immediate shock, it did not directly alter information acquisition behavior. As a result, we anticipated that interest rate misperceptions will gradually revert to pre-treatment levels over time, despite the significant initial effect observed. Our follow-up survey conducted nine months after the intervention is consistent with this hypothesis, showing a reduction in perceived interest rate revisions between the treatment and control groups to 3.1 percentage points, equivalent to around 60% of the instantaneous effect. A similar pattern was observed in consumer debt trajectories, which initially decreased rapidly post-treatment but gradually rebounded thereafter.

In light of these findings, we propose that to counter biases stemming from selective information acquisition, one should consider implementing repeated interventions, such as periodic reminders or policies directly targeting consumers' information-seeking behavior. By consistently reinforcing the true costs of borrowing or actively shaping consumers' information acquisition habits, policymakers can mitigate misperceptions and foster more informed decision-making regarding debt. Such interventions have the potential to counteract the tendency to focus selectively on favorable news while overlooking unfavorable information, thereby fostering greater financial literacy and responsible borrowing habits among consumers over time.

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Appendix A

Appendix for “Rewards and Consumption in the Credit Card Market”

A.1 Additional Tables

Table A1: Effect of Platinum Reward Availability – Alternative Specifications

	(1) Reward spending	(2) Non-reward spending	(3) Rewards	(4) Tot-spend under-repo	(5) Rew-spend under-repo
Global: first-order	56.017***	129.690***	6.767*	101.009***	0.092
	(20.537)	(21.553)	(3.902)	(25.562)	(3.490)
Global: third-order	74.014***	62.345***	14.400***	114.937***	0.097
	(26.946)	(21.296)	(4.023)	(28.759)	(4.271)
Global: fourth-order	70.690**	70.851***	13.773***	110.786***	-0.152
	(29.261)	(23.002)	(4.692)	(31.630)	(4.522)
Global: fifth-order	79.316**	60.773**	10.117*	96.364***	-0.867
	(34.190)	(26.847)	(5.348)	(36.249)	(5.054)
Global observations: 4564					
Local: nonparametric	102.026***	67.108**	14.084***	67.597*	-5.675
	(39.068)	(27.163)	(4.773)	(36.114)	(5.207)
Local observations: 1112					

Note: The upper panel of this table shows the global 2SLS fit of outcomes of interests on Platinum card takeup where the eligibility asset threshold is an IV in the first stage, using a polynomial of the running variables in the first to fifth order. Only the coefficients on Platinum card takeup are reported. The lower panel of this table shows the corresponding local 2SLS fits using a triangle kernel with optimal bandwidth (Calonico et al., 2014). The estimates are robust regardless of the choice of specification or approach. Omitted control variables include age, income, gender, education, and credit score. City and industry fixed effects are included. Standard errors in parentheses are clustered at city × industry level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2: Effect of Platinum Reward Availability on Covariates – Global Approach

	(1) Age	(2) Male	(3) Education	(4) Income	(5) Credit score
Platinum	-0.853	0.024	0.085	-135.367	-0.183
	(1.348)	(0.069)	(0.099)	(95.502)	(0.595)
Asset (thousand \$)	0.460***	0.004	0.013**	17.298***	0.189***
	(0.065)	(0.003)	(0.005)	(5.042)	(0.033)
Asset (thousand \$)^2	-0.002***	-0.000	-0.000**	-0.028	-0.001**
	(0.000)	(0.000)	(0.000)	(0.028)	(0.000)
Age: elder		0.018	-0.132**	-26.274	0.148
		(0.038)	(0.058)	(52.933)	(0.284)
Male	0.138		0.132**	-36.288	-0.134
	(0.727)		(0.062)	(50.184)	(0.306)
Edu: high	-1.402*	0.053		191.168***	1.263***
	(0.820)	(0.044)		(65.703)	(0.349)
Income: high	-0.340	-0.020	0.169***		2.394***
	(0.493)	(0.024)	(0.038)		(0.224)
Credit score: high	0.475	-0.006	0.398***	525.886***	
	(0.735)	(0.039)	(0.063)	(50.857)	
Observations	4564	4564	4564	4564	4564
R^2	0.159	0.023	0.143	0.162	0.374

Note: This table shows the 2SLS fit of covariates on Platinum card takeup where the eligibility asset threshold is an IV in the first stage. I follow a global approach with a quadratic specification of the running variable. The are no statistically significant effects of rewards on covariance, implying covariate balance and apples-to-apples comparison. City and industry fixed effects are included. Standard errors in parentheses are clustered at city × industry level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3: Effect of Platinum Reward Availability – Global Spending

	(1) Spending	(2) Spending	(3) Spending	(4) Spending	(5) Spending
Platinum	185.423***	117.752**	136.104***	141.252***	139.782**
	(38.864)	(49.014)	(47.471)	(51.479)	(60.165)
Male	7.433	6.367	7.879	7.780	7.788
	(18.021)	(18.145)	(18.134)	(18.158)	(18.137)
Age: elder	34.038**	23.761	26.054	25.761	25.646
	(16.363)	(15.793)	(15.907)	(15.917)	(16.022)
Edu: high	28.678	24.340	27.652	27.191	27.098
	(24.621)	(23.946)	(23.823)	(23.917)	(23.640)
Income: high	79.357***	79.437***	79.303***	79.063***	79.113***
	(17.155)	(17.120)	(17.107)	(16.977)	(16.834)
Credit score: high	179.430***	168.893***	172.819***	172.341***	172.385***
	(20.586)	(21.158)	(21.527)	(21.521)	(21.454)
Asset (thousand \$)	8.448***	13.724***	8.353***	11.178**	10.524
	(0.940)	(2.284)	(2.831)	(4.461)	(8.855)
Asset (thousand \$)^2		-0.034***	0.049	-0.033	-0.005
		(0.012)	(0.036)	(0.136)	(0.379)
Asset (thousand \$)^3			-0.000**	0.000	0.000
			(0.000)	(0.001)	(0.006)
Asset (thousand \$)^4				-0.000	0.000
				(0.000)	(0.000)
Asset (thousand \$)^5					-0.000
					(0.000)
Observations	4564	4564	4564	4564	4564
R^2	0.613	0.618	0.620	0.620	0.620

Note: This table shows the 2SLS fit of total spending on Platinum card takeup where the eligibility asset threshold is an IV in the first stage. I follow a global approach with polynomials of the running variable from the first to fifth order. The coefficients of Platinum card takeup are consistent with the main results in Table 1.6. City and industry fixed effects are included. Standard errors in parentheses are clustered at city × industry level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A4: Effect of Platinum Reward Availability – Global Debt

	(1) Debt	(2) Debt	(3) Debt	(4) Debt	(5) Debt
Platinum	505.866	713.709	794.904	777.651	906.107
	(403.836)	(584.566)	(600.875)	(634.370)	(756.874)
Male	102.729	106.004	112.693	113.028	112.314
	(159.061)	(160.093)	(159.983)	(159.632)	(159.249)
Age: elder	262.162*	293.728*	303.874*	304.855*	314.893*
	(151.547)	(159.070)	(160.218)	(160.336)	(163.509)
Edu: high	96.652	109.977	124.630	126.175	134.244
	(248.056)	(242.242)	(240.199)	(242.088)	(239.134)
Income: high	-117.244	-117.490	-118.084	-117.278	-121.670
	(150.165)	(149.682)	(149.533)	(148.368)	(146.106)
Credit score: high	778.472***	810.836***	828.206***	829.808***	825.958***
	(216.978)	(227.365)	(230.972)	(230.855)	(229.929)
Asset (thousand $)	-7.061	-23.267	-47.028	-56.493	0.642
	(7.004)	(24.157)	(34.113)	(41.373)	(79.310)
Asset (thousand $)^2		0.103	0.470	0.744	-1.644
		(0.117)	(0.351)	(1.076)	(3.616)
Asset (thousand $)^3			-0.001	-0.004	0.034
			(0.001)	(0.010)	(0.056)
Asset (thousand $)^4				0.000	-0.000
				(0.000)	(0.000)
Asset (thousand $)^5					0.000
					(0.000)
Observations	4564	4564	4564	4564	4564
R^2	0.039	0.040	0.040	0.040	0.040

Note: This table shows the 2SLS fit of debt on Platinum card takeup where the eligibility asset threshold is an IV in the first stage. I follow a global approach with polynomials of the running variable from the first to fifth order. Since the LATE is identified around a high asset value, consumers rarely hold debt here. For this reason, the coefficients of Platinum card takeup are statistically insignificant regardless of the choice of specification. City and industry fixed effects are included. Standard errors in parentheses are clustered at city × industry level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A.2 Proofs for Propositions in Section 1.5

Proof for Proposition 1. The marginal utilities are

$$\begin{aligned} MU_{CR} &= \frac{\alpha}{CR} - \frac{\beta m}{CN - mCR} \\ MU_{CN} &= \frac{\beta}{CN - mCR} \\ MU_S &= 1 \end{aligned}$$

Utility optimization yields that

$$\begin{aligned} CR_{soph} &= \frac{\alpha}{p+m} \\ CN_{soph} &= \beta + \frac{\alpha m}{p+m} \\ S_{soph} &= y - \frac{1+m}{p+m}\alpha - \beta \end{aligned}$$

When $t = 0$, a naif with $\widehat{m} = 0$ decides on CR_{naif} purchases expects to have $\widehat{CN}_{naif}$ and $\widehat{S}_{naif}$

$$\begin{aligned} CR_{naif} &= \frac{\alpha}{p} \\ \widehat{CN}_{naif} &= \beta \\ \widehat{S}_{naif} &= y - \frac{\alpha}{p} - \beta \end{aligned}$$

When $t = 1$, true m realizes, and the naive consumer adjusts CN_{naif} according to CR_{naif} using the following equation

$$\frac{\frac{\alpha}{CR} - \frac{\beta m}{CN - mCR}}{\frac{\beta}{CN - mCR}} = p$$

which yields

$$\begin{aligned} CR_{naif} &= \frac{\alpha}{p} = \underbrace{\frac{p+m}{p}}_{\text{overspending}} CR_{soph} \\ CN_{naif} &= CR_{naif}\left[\frac{\beta(m+p)}{\alpha} + m\right] = \underbrace{\beta}_{=\widehat{CN}_{naif}} + \underbrace{\frac{m(\alpha+\beta)}{p}}_{\text{under-reporting}} = \underbrace{\frac{p+m}{p}}_{\text{overspending}} CN_{soph} \\ S_{naif} &= y - \frac{\alpha}{p} - \left(\beta + \frac{m(\alpha+\beta)}{p}\right) \end{aligned}$$

□

Proof for Proposition 2. The revenue per consumer is the *interchange fees* minus the cost of *reward payout*

$$
\begin{aligned}
Rev_{naif} &= r(CR_{naif} + CN_{naif}) - (1-p)CR_{naif} \\
&= r\left[\frac{\alpha}{p} + \beta + \frac{m(\alpha+\beta)}{p}\right] - \alpha\frac{1-p}{p} \\
Rev_{soph} &= r(CR_{soph} + CN_{soph}) - (1-p)CR_{soph} \\
&= r\left[\frac{\alpha}{p+m} + \beta + \frac{\alpha m}{p+m}\right] - \alpha\frac{1-p}{p+m}
\end{aligned}
$$

Then, the profit functions of sophisticated and naive consumers can be written as

$$
\begin{aligned}
\pi_{soph} &= r\left[\frac{\alpha}{p+m} + \beta + \frac{\alpha m}{p+m}\right] - \alpha\frac{1-p}{p+m} - c \\
&\equiv Rev_{soph} - c \\
\pi_{naif} &= r\left[\frac{\alpha}{p} + \beta + \frac{m(\alpha+\beta)}{p}\right] - \alpha\frac{1-p}{p} - c \\
&= \frac{p+m}{p}Rev_{soph} - c
\end{aligned}
$$

The zero-profit condition gives that

$$
\pi = q(\underbrace{Rev_{naif}}_{=\frac{p+m}{p}Rev_{soph}} - c) + (1-q)\left(Rev_{soph} - c\right) = 0
$$

which yields that

$$
Rev_{soph} = \frac{cp}{p+mq}.
$$

Therefore, the equilibrium profits from naifs and sophisticates are

$$
\begin{aligned}
\pi_{soph} &= Rev_{soph} - c = -\frac{cmq}{p+mq} \leq 0 \\
\pi_{naif} &= \frac{p+m}{p}Rev_{soph} - c = \frac{cm(1-q)}{p+mq} \geq 0
\end{aligned}
$$

Since $m \geq 0$, $c \geq 0$, $q \geq 0$, and $p > 0$,

$$
\pi_{soph} \leq 0 \quad \text{and} \quad \pi_{naif} \geq 0.
$$

□

Proof for Proposition 3. Since the analytical solution p is intractable, I use the implicit function theorem to analyze the partial derivatives. In terms of complementarity m,

$$
\frac{\partial p}{\partial m} = -\frac{\partial \pi/\partial m}{\partial \pi/\partial p} = -\frac{q\frac{\partial \pi_{naif}}{\partial m} + (1-q)\frac{\partial \pi_{soph}}{\partial m}}{q\frac{\partial \pi_{naif}}{\partial p} + (1-q)\frac{\partial \pi_{soph}}{\partial p}}
$$

Notice that $\beta > \alpha > 0$, $m \geq 0$, $c \geq 0$, $r > 0$, and $q \geq 0$, then

$$\begin{aligned}
\frac{\partial \pi_{naif}}{\partial m} &= \frac{r(\alpha+\beta)}{p} > 0 \\
\frac{\partial \pi_{soph}}{\partial m} &= \frac{\alpha(1-p)(1-r)}{(m+p)^2} > 0 \\
\frac{\partial \pi_{naif}}{\partial p} &= \frac{\alpha(1-r(m+1)) - mr\beta}{p^2} > 0 \quad \text{if} \quad r < \frac{\alpha}{\alpha + m(\alpha+\beta)} \\
\frac{\partial \pi_{soph}}{\partial p} &= \frac{\alpha(1+m)(1-r)}{(m+p)^2} > 0
\end{aligned}$$

so

$$\frac{\partial \pi}{\partial m} > 0 \quad \text{and} \quad \frac{\partial \pi}{\partial p} > 0$$

and therefore

$$\frac{\partial p}{\partial m} < 0.$$

□

Proof for Proposition 4. In terms of the naive fraction q, by the implicit function theorem,

$$\frac{\partial p}{\partial q} = -\frac{\partial \pi / \partial q}{\partial \pi / \partial p} = -\frac{\pi_{naif} - \pi_{soph}}{\partial \pi / \partial p}.$$

Notice that $\pi_{naif} - \pi_{soph} > 0$ and $\frac{\partial \pi}{\partial p} > 0$ (assuming $r < \frac{\alpha}{\alpha+m(\alpha+\beta)}$) as previously shown. Therefore,

$$\frac{\partial p}{\partial q} < 0.$$

□

A.3 Survey

Credit Card Usage Survey

Please read the following information carefully.

To better understand the impact of credit cards on people's lives, we randomly selected a certain number of active credit card users from our bank to complete this survey. We hope to use this survey to study the consumption behaviors and preferences of the residents generally. Therefore, we will focus only on highly summarized information for scientific research purposes, such as average values. We will not disclose the personal information of the participants in any respect. We will not, in any way, change the types of financial products we provide, including those regarding credit scores, credit limits, deposit rates, etc., based on the participants' individual answers.

1. What is the highest level of school you have completed or the highest degree you have received?

    a) High School degree or less

    b) Some college or associate degree

    c) Bachelor's degree

    d) Graduate school and/or degree

2. What is the total amount of savings you currently have?

3. Why do you use credit cards (please rank)?

    a) Convenience

    b) Promotion and Cash Return

    c) Building up Credit Score

    d) Not Enough Income

    e) Other reasons

4. What was your average monthly spending on non-durable in the past six months (excluding expenditure on durable goods such as housing, rent, and vehicle)?

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).

6. For the consumption you have incurred over the past six months, on average, how much do you think are from the categories of goods that can earn rewards from your credit cards from XXX bank.
   For example, suppose your average monthly spending is 4,000 RMB. For 2,000 of the 4,000 RMB you have spent, you can earn cash back or enjoy a discount due to using your credit cards from XXX bank, then please enter 2,000.

7. Suppose someone similar to you borrows 1 million for a year for general purposes (spending, business, mortgage, etc.). What would be the most likely level of the total repayment in a year?

8. How many hours do you usually work per week?

A.4 A Structural Model of Complementarity Ignorance

Empirical results show that credit card rewards do not help consumers save money; those rewards will increase total consumption instead. Of greater economic interest, the causal effect on perceived spending reveals the channel behind consumption increase – complementarity ignorance, which is a type of behavioral bias: consumers plan to save money by utilizing rewards and substituting away from the non-reward-earning category, but they fail to anticipate the reward's complementary consumption and wind up spending more in the non-reward-earning category.

It is still important to evaluate the importance of such behavioral bias. 1) How much does complementarity ignorance explain the effect of rewards on consumption increase? In other words, how would consumers adjust their consumption if there were no complementary ignorance? 2) How can banks leverage the behavioral bias of complementarity ignorance and increase profitability? 3) What happens to the welfare behind naifs (who have complementarity ignorance), sophisticates (who do not have complementarity ignorance), and firms?

To conduct these analyses, I build and estimate a structural model of the financial decision-making process of an average consumer. The comparison between naifs and sophisticates is constructed through counterfactual exercises.

Modeling Strategy

The model has to incorporate the following three stylized facts from my previous analysis. First, consumers decide on continuous values of lifetime reward-earning consumption, non-reward-earning consumption, and savings. Second, consumers overestimate the substitutability between reward-earning and non-reward-earning consumption. Lastly, consumers only underestimate the consumption in the non-reward-earning but not the reward-earning category.

I follow Telyukova (2013) and allow a different marginal utility for each consumption category. Consumers decide on reward-earning consumption, CR, and non-reward-earning consumption, CR, in their lifetime. Suppose a consumer's preference can be represented by a utility function with constant elasticity of substitution (CES). Formally, the instantaneous utility is written by

$$u(CR, CN) = \frac{1}{1-\gamma}\left(\alpha CR^{\hat{\rho}} + (1-\alpha) CN^{\hat{\rho}}\right)^{\frac{1-\gamma}{\hat{\rho}}} \tag{A.1}$$

where α is a parameter to control for relative preference over consumption categories and $\gamma > 1$ represents the concavity of the utility function to generate incentive of savings. The substitutability parameter, $\rho \in (-\infty, 1]$, determines the changes in consumption when consumers are treated by Platinum rewards. Notice that the substitutability parameter $\hat{\rho} = \rho + m$ is hatted in the decision-making process: consumers mistakenly think they could substitute CR for CN from Platinum rewards and therefore spends too much CR.

The mechanism of how rewards impact consumption is a crucial component. For tractability, I model the rewards as price discounts for tractability, where κ denotes the reward rate. Furthermore, let t denote the current timing, a denote asset value, y denote income, and r denote the interest rate. The intertemporal budget constraint is written as

$$a_{t+1} = (1+r)\left(a_t + y_t - (1-\kappa)CR_t - CN_t\right). \tag{A.2}$$

where $\kappa_{Plat} > \kappa_{Gold}$ is the incentive of higher CR when upgrading to a Platinum card because the prices in the reward-earning category become lower.

Putting together, a consumer in an infinite horizon solves the following problem

$$\max_{CR_t, CN_t} \sum_{t=0}^{\infty} \frac{\delta^t}{1-\gamma} \left[\alpha CR_t^{\hat{\rho}} + (1-\alpha) CN_t^{\hat{\rho}}\right]^{\frac{1-\gamma}{\hat{\rho}}} \tag{A.3}$$

subject to Equation A.2, where δ is a discount factor.

To incorporate the discrepancy between real and perceived spending, motivated by the fact that reward-earning products/services usually need reservations and payment in advance, I follow Gabaix and Laibson (2006) and set up the RD data-generating process in Section 1.4 as follows.

- Period 0. Consumers stay at the status quo, Gold cards, with CR_{Gold} and CN_{Gold}.
- Period 1. Consumers opt in for Platinum cards so that the reward rate changes from κ_{Gold} to κ_{Plat}. Consumers make CR_{Plat} purchases (e.g., book flights or movie tickets) and plan $\widehat{CN}_{Plat}$ according to $\hat{\rho}$. There is no hat on CR_{Plat}: consumers know the expenditure because it has to be pre-determined. $\widehat{CN}_{Plat}$ is hatted because the true CN_{Plat} realizes afterwards. Notice that a naif (with $m > 0$) only pays attention to CR_{Plat} itself, such as flights and movie tickets, whereas a sophisticate (with $m = 0$) is also aware of complementary purchases, such as tickets for tourist attractions and popcorn at movie theaters.
- Period 2. $\rho = \hat{\rho} - m$ and CR_{Plat} are realized, and consumers readjust CN_{Plat} given reward-earning consumption CR_{Plat}, reward rate κ_{Plat}, and true preference parameters α and ρ. During this period, naifs will purchase, for example, (unexpected) tickets for tourist attractions when traveling or popcorn at the movie theater. Sophisticates do not have to make adjustments because they already foresaw these complementary purchases and took them into consideration when deciding on CR_{Plat}.

Notice that the spending distortion incurred by complementarity ignorance is generated in period 2. In other words, a naif will no longer spend as much if they correctly anticipate those expensive complementary purchases related to rewards.

Identification and Estimation

Four structural parameters need to be identified and estimated: preference α, curvature γ, substitutability ρ, and behavioral bias m. The behavioral bias m, or complementarity ignorance, and the substitutability ρ, are the main parameters of interest, whereas the other two parameters are auxiliary in the modeling process.

I focus on the identification of parameters for an average consumer. In a lifetime consumption-saving problem with CES utility, consumers decide on the total consumption in each period and then allocate the budget for different goods according to preference. Therefore, the preference parameter α is identified through the CR/CN ratio, and the curvature parameter is identified through the ratio of $(CR + CN)/asset$.

The perceived substitutability parameter is identified through the comparative statics of reward rate changes from κ_{Gold} to κ_{Plat}. I use the model to simulate the corresponding CR_{Gold}, CN_{Gold}, CR_{Plat}, and $\widehat{CN}_{Plat}$ given κ_{Gold} and κ_{Plat}. Then, $\rho+m$ is identified through the $\Delta CR/CR$ where $\Delta CR = (CR_{Plat} - CR_{Gold})$. Lastly, I simulate CN_{Plat} given the true substitutability ρ and the reward-earning consumption CR_{Plat}. Then, the behavioral bias m is identified through the $\Delta Under\_Reporting/CN$ ratio where $\Delta Under\_Reporting = (\Delta CR + \Delta CN) - (\Delta CR + \widehat{\Delta CN}) = \Delta CN - \widehat{\Delta CN}$.

I follow the generalized method of moments (GMM) procedure and estimate the model empirically. Following Telyukova (2013), I use a month as the model frequency as it is natural for consumers to decide and reflect on financial choices on a monthly basis. I assume the intertemporal discount factor δ is 0.99 to match the monthly frequency. Given a set of structural parameters, I numerically solve the relative CR and CN on a discretized asset grid using Bellman iteration. Then, following the identification argument, I match the CR/CN and $(CR+CN)/asset$ ratios with the corresponding data for an average consumer to recover preference α and curvature γ. I also match the $\Delta CR/CR$ and $\Delta Under\_Reporting/CN$ ratios with the data for an average consumer to pin down substitutability ρ and behavioral bias m, where ΔCR and $\Delta Under\_Reporting$ for the data version are the fuzzy RD estimands in Section 1.4. The GMM system is therefore just-identified.

Table A5 shows the results of structural estimation along with the moment values that are used in the GMM procedure. It is worth noting that all four moments generated by the model are almost equal to the data counterparts in three decimal points, and the GMM criterion value is practically zero, so my model does a fairly good job of capturing the decision-making process of consumers in the data.

I provide some intuitions of the point estimates, albeit it is difficult to interpret these parameters precisely. The preference parameter over reward-earning consumption, α, is 0.377, which is consistent with the data that consumers spend a larger proportion of their budget on non-reward-earning goods where the CR/CN ratio is less than one. A curvature parameter $\gamma > 1$ suggests a concave utility function, which corresponds to the fact that consumers leave a significant amount of wealth as saving where $(CR + CN)/asset < 1$.

I next shed light on the main parameters of interest. Notice that a substitutability $\rho = 1$ represents perfect substitutes, $\rho = 0$ represents Cobb-Douglas preference (where the

Table A5: Structural Estimates

	Point Estimate	Standard Error
Preference α	0.377***	0.002
Curvature γ	1.198***	0.001
Substitutability ρ	0.755***	0.005
Behavioral bias m	0.026***	0.005
	Data	Model
CR/CN	0.216	0.216
$(CR+CN)/asset$	0.501	0.501
$\Delta CR/CR$	0.487	0.487
ΔUnder-report$/CN$	0.117	0.117
GMM criterion value	0.00001	

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

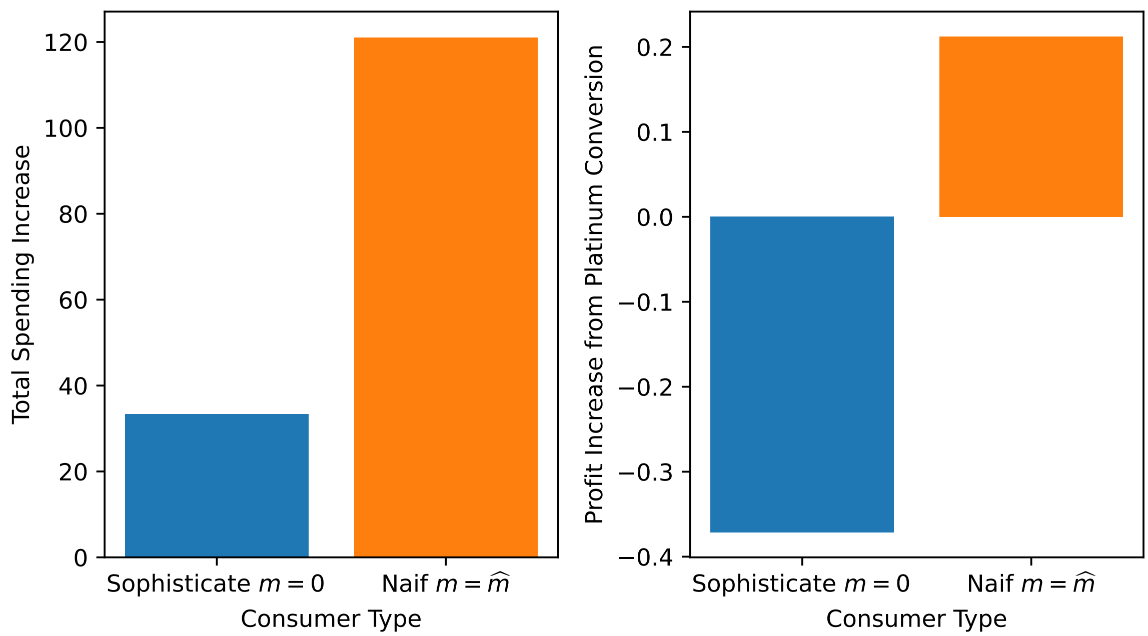
substitution and income effects cancel off), and $\rho \to -\infty$ means perfect complements. The point estimate for the true substitutability ρ is 0.755, suggesting that the reward-earning and non-reward-earning purchases are indeed quite substitutable. A positive behavioral bias $m = 0.026$ point estimate reveals complementarity ignorance: reward-earning and non-reward-earning goods, however, are less substitutable than what consumers expect, so they spend too much on reward-earning consumption when Platinum rewards are present.

Welfare Analyses from Counterfactuals

The model with the point estimates obtained in Section A.4 allows me to analyze the impact of complementarity ignorance on welfare. Concretely, I simulate the counterfactual decisions of *sophisticates* where the behavioral bias $m = 0$ and compare them with the *naifs*' counterparts where $m = \hat{m} = 0.026$ that is estimated previously.

Excess Spending I first evaluate consumer welfare by simulating the counterfactual total spending if there were no complementarity ignorance. Figure A1a illustrates excess spending by the naifs: if consumers had a correct understanding of the shrouded complementary consumption as a sophisticate, they would no longer be willing to spend as much, and total spending increase from Platinum rewards would drop to around \$37 instead of the factual \$ 118. This comparison shows that complementarity ignorance has a first-order effect on

Figure A1: Counterfactual: Naifs vs. Sophisticates



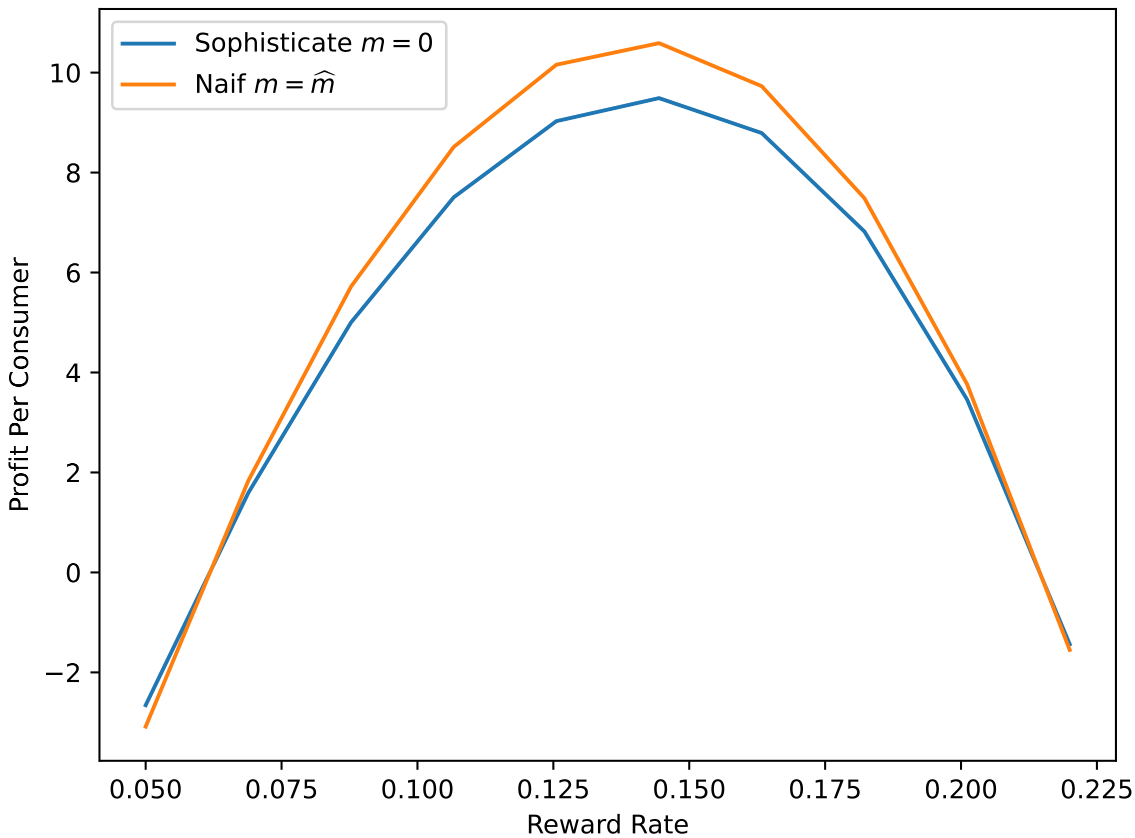
consumer welfare: Platinum credit card rewards will generate a distortion of \$81 excess spending on naifs.

Cross-Subsidization The spending distortion may incentivize the design of a high reward rate by the bank. Essentially, it is a tradeoff between costs from reward payback and gains from excess spending: a higher reward rate implies higher reward payout toward consumers; on the other hand, spending generates profit for the bank from interchange fees, consumer acquisition, higher debt-taking probability, and so on. Assume that the bank earns 5.25 cents for each dollar consumption,[1] I calculate the profit from each consumer as the difference between profit from spending and reward payout (reward-earning consumption multiplied by the reward rate).

Figure A1b shows the changes in profit per consumer upon upgrading to the Platinum card. The bank can earn 20 cents profits from the excess spending by naive consumers; the sophisticates, on the other hand, since they fully consider the changes in consumption while utilizing rewards strategically, can indeed benefit from the Platinum rewards so that the bank will lose 35 cents on them. This comparison illustrates that naifs, in fact, *cross-subsidizes* sophisticates through excess spending, in line with the findings in Gabaix and Laibson (2006); Agarwal et al. (2022).

[1]This number comes from a back-of-the-envelope calculation based on the balance sheets provided by the bank.

Figure A2: Counterfactual: Profits from Complementarity Ignorance



Profit To shed light on the managerial implications for the bank, I illustrate how the bank's decision on reward rates affects profitability, taking complementarity ignorance into consideration. The profit simulation in my counterfactual exercise is

$$\pi(\kappa) = D(\kappa)\,[0.0525(CR(\kappa) + CN(\kappa)) - \kappa CR(\kappa)]$$

where κ is the reward rate and $D(\kappa)$ is the demand for spending within the bank as a function of the reward rate.[2] A higher reward rate κ implies a higher probability of card usage and consumer acquisition probability. Meanwhile, inside of the tradeoff between excess spending and reward payout, the reward rate κ also changes consumption decisions. Notice that these analyses only consider rewards as a price discount but do not endogenize the hedonic values of Platinum goods and services. The literature, e.g., DellaVigna and Malmendier (2004); Han and Yin (2022); Agarwal et al. (2022), documents the possibility that naive consumers may take high-interest consumption debt due to behavioral bias such as self-control problems

[2] The demand function $D(\kappa)$ is calibrated and provided by the bank.

or insufficient understanding of the cost of borrowing, so these profit simulations are likely to be an underestimate.

Figure A2 plots the profit per consumer for both naifs and sophisticates. First of all, these profit functions are concave: an overly low reward rate will discourage consumers from spending, while an overly high reward rate will hurt the profit by an expensive reward payout, so it is reasonable to choose an optimal reward rate in the middle ground to balance the two levers. Zooming into the profit curves, a reward rate of around 15% maximized profit from both naifs and sophisticates. More importantly, the profit from a naif is larger than that from a sophisticate for a reward rate between 7% and 22% and smaller otherwise. By choosing an appropriate reward rate, complementarity ignorance by naifs can push the profit envelope outwards, while it can also backfire if the reward rate is poorly chosen.

The wedge between the profit curves for naifs and sophisticates is a signal of market decommoditization as in Bordalo et al. (2015): complementarity ignorance allows extra profitability through strategic reward design (quality of credit card products) so that it can soften the price competition between firms.

Appendix B

Appendix for “Interest Rate Misperception in the Credit Card Market”

B.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 a credit card 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 incur at the end of next month.
   a) You spend ¥5,000 this month and repay ¥3,000 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 this month and repay ¥1,000 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 this month and repay ¥0 at the end of this month

   i. 45
   ii. 55
   iii. 65
   iv. 75
   v. 85
   vi. 95
   vii. 105

3. Suppose your total savings are ¥10,000. How much interest 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 interest on credit cards 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 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 cards 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.[1]

1. *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?*[2]

    a) 15

    b) 25

    c) 35

    d) 45

    e) 55

    f) 65

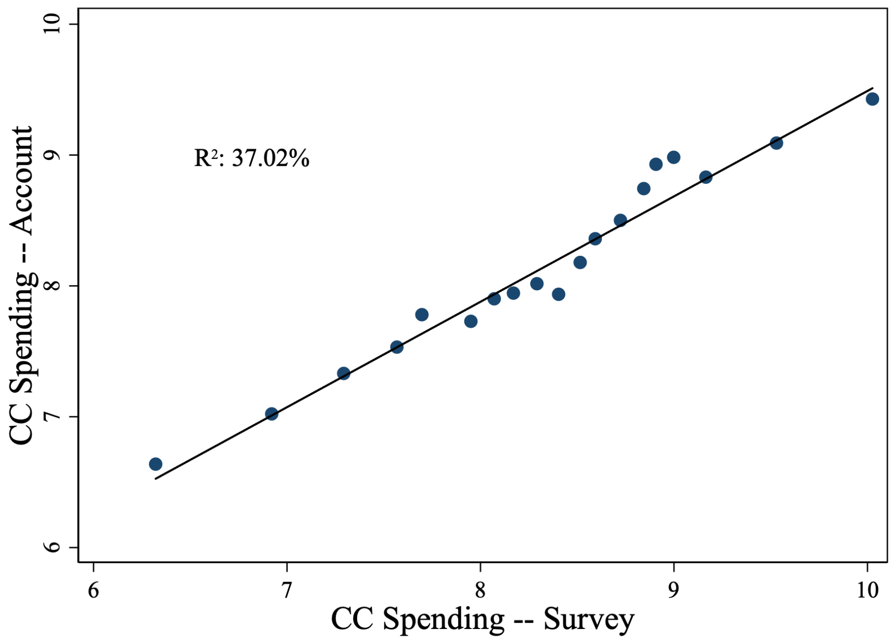
    g) 75

[1]Sent in a new page to a random 40% of those who paid interest costs on credit cards in 2020 before the experiment.

[2]All participants that paid interest in 2020 were revealed the information.

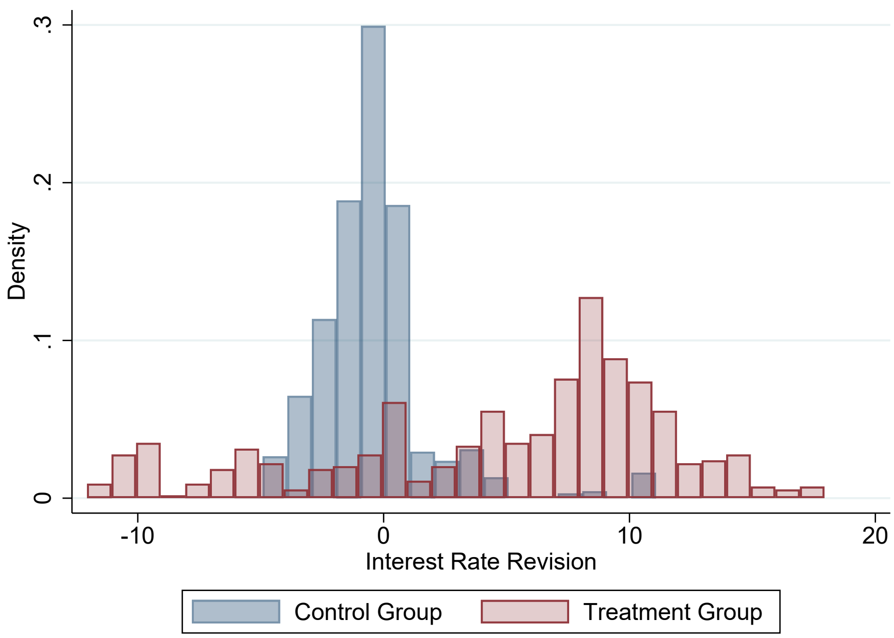
B.2 Additional Figures

Figure B1: 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 B2: 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.

B.3 Additional Tables

Table B1: Misperception of Debt Interest Rate

	(1) *Bias*	(2) *Bias*	(3) $\lvert Bias \rvert$	(4) $\lvert Bias \rvert$
Education	3.312***	3.097***	-0.571***	-0.601***
	(0.212)	(0.216)	(0.135)	(0.135)
Age	0.043**	0.034**	-0.068***	-0.048***
	(0.017)	(0.017)	(0.011)	(0.011)
Female	1.369***	1.413***	0.305	0.271
	(0.355)	(0.349)	(0.233)	(0.222)
Assets		0.000**		-0.000**
		(0.000)		(0.000)
Income		0.000		-0.000***
		(0.000)		(0.000)
Credit limit		-0.000***		0.000***
		(0.000)		(0.000)
Credit score		-0.069***		-0.064***
		(0.026)		(0.016)
Constant	6.841***	11.244***	10.555***	13.108***
	(0.759)	(1.526)	(0.530)	(0.942)
Observations	1219	1219	1219	1219
R^2	0.175	0.199	0.046	0.127

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

Table B2: Interest Rate Misperception and Debt

	(1) Debt	(2) Debt	(3) Debt	(4) Debt
Perceived r	-166.004***	-141.353***		
	(11.249)	(12.287)		
Downward=0 × Perceived r			31.122	54.465**
			(22.784)	(25.234)
Downward=1 × Perceived r			-284.859***	-249.870***
			(24.592)	(25.204)
Downward			6098.423***	5951.960***
			(637.769)	(674.610)
Female		311.695**		168.036
		(153.904)		(150.875)
Age		-15.955**		-12.711*
		(6.926)		(6.796)
Education		-232.316***		-294.542***
		(88.159)		(85.832)
Assets		0.011**		0.013***
		(0.005)		(0.005)
Income		-0.158*		-0.116
		(0.088)		(0.087)
Credit limit		0.102***		0.080***
		(0.014)		(0.015)
Credit score		4.542		15.857
		(11.296)		(11.378)
Constant	4844.877***	4103.940***	95.025	-1081.426
	(217.851)	(694.669)	(538.244)	(946.767)
Observations	1219	1219	1219	1219
R^2	0.153	0.215	0.191	0.246

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 consumers, 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 B3: Comparison between Control and Treatment Groups

	Control Mean	Treatment Mean
Age	38.389	37.967
Gender: female	0.585	0.549
Education	1.824	1.719
Spending	1538.5	1540.1
Income	2324.8	2371.2
Assets	25998.7	27213.4
Credit Limit	10075.9	10180.9
Credit Score	55.039	54.80

Note: This table shows the means of the demographic (age, gender, and education), financial behavior (spending, income, and assets), 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 for high school and below, 2 for some college, 3 for a bachelor's degree, and 4 for graduate school. The means are very close for all variables, suggesting that the treatment and control groups are comparable.

Table B4: IV First Stage – Bayesian Learning

	(1) Perceived r	(2) Perceived r
Perceived r^{prior}	1.098***	1.080***
	(0.012)	(0.013)
Treated	16.277***	16.250***
	(0.524)	(0.527)
Perceived r^{prior} × Treated	-0.731***	-0.728***
	(0.035)	(0.036)
Constant	-1.926***	-3.386***
	(0.160)	(0.865)
Observations	1219	1219
R^2	0.731	0.738
Controls	No	Yes

Note: This table presents the OLS fit of the first stage, following Equation (2.4). This framework, akin to Coibion et al. (2024), represents Bayesian learning. The sum of coefficients on *Perceived* r_i^{prior} and *Perceived* r_i^{prior} × *Treated* indicates the weight assigned to the prior relative to the signal provided in the information treatment, ranging from 0 to 1. 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 B5: 2SLS Estimates of Effect of Perceived Interest Rate on Debts: LATE

	(1) Debt	(2) Debt (Downward Bias)	(3) Debt (Upward Bias)
Perceived r	-126.411***	-131.417***	-135.646**
	(24.559)	(20.034)	(53.954)
Constant	3229.447***	3400.059***	3184.375***
	(688.610)	(766.404)	(1158.257)
Observations	1219	899	320
R^2	0.179	0.157	0.093
First-Stage F	208.193	701.166	31.083
Controls	Yes	Yes	Yes

Note: This table serves as a robustness check for the results in Table 2.4. It reports the 2SLS fit of debt on perceived interest rates, where the treatment status is an 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 consumers who underestimate and overestimate the interest rate, respectively. Since consumers are likely to adjust their perceived interest rates closer to the provided true information, results in columns (2) and (3) are likely to satisfy the monotonicity assumption (Angrist and Imbens, 1995) and can be deemed as LATE. White robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B6: Three-month ITT Effect of Information Treatment on Spending and Savings: Consumers Who Use Only One Bank

	(1) Spending	(2) Liquid assets	(3) Illiquid assets	(4) Necessities spending	(5) Luxuries spending	(6) Other spending
After × Treated	-194.627***	-1190.123	1551.363***	-47.843	-90.895	-55.889
	(61.297)	(877.030)	(402.186)	(54.067)	(59.570)	(53.025)
After	126.517***	633.555	-88.452	3.921	-7.521	130.116***
	(38.182)	(577.543)	(265.422)	(36.362)	(39.336)	(36.351)
Treated	-32.115	-436.576	575.482**	29.720	-52.909	-8.925
	(31.894)	(320.869)	(273.057)	(39.942)	(39.775)	(36.538)
Constant	-83.300	766.756	-1050.575	509.393***	-644.755***	52.063
	(132.654)	(2021.396)	(906.348)	(117.502)	(131.257)	(126.850)
Observations	1664	1664	1664	1664	1664	1664
R^2	0.683	0.794	0.715	0.085	0.491	0.084
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table serves as a robustness check for the results in Table 2.7, applying the same analyses but on the consumers 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.