When Biases Collide: The counterbalancing Effects of Overconfidence and Present Bias on Debt Behavior

Harshal Rajan Mulay (IIT Kanpur), Ayush Yadav (IIT Kanpur), Suman Saurabh (IIT Kanpur)

Abstract

Behavioral biases play a critical role in personal financial decision-making, often leading to suboptimal outcomes. Two biases of particular interest are overconfidence bias – the tendency to overestimate one's financial knowledge or abilities – and present bias – the preference for immediate gratification over future rewards. This paper examines how these biases affect debt behaviors among U.S. adults using data from the FINRA NFCS. This study finds that both overconfidence and present bias are independently associated with a higher likelihood of risky debt behaviors, reflected by overspending, receiving debt recovery calls, and credit card mismanagement. However, the joint presence of both biases consistently correlates with less risky debt outcomes than either bias alone, suggesting a mitigating effect when both biases co-exist. This counterintuitive pattern reflects cognitive dissonance, where the self-image of financial savviness arising from overconfidence bias contradicts the irresponsible behavior caused by present bias. Thus, individuals self-correct or restrain from extreme risky behavior to preserve a positive self-image. These findings offer nuanced insight into how behavioral biases operate not only independently but also in interaction, providing significant implications for behavioral finance theory and financial education policy.

1. Introduction

Over the past two decades, U.S. households have become steadily more reliant on consumer credit. By the end of 2024, total household liabilities reached a record \$18.04 trillion, with credit-card balances alone topping \$1.21 trillion—both all-time highs. Mortgages alone account for roughly 70% of this total, at about \$12.8 trillion, with credit card, auto loan, and student loan balances each comprising around 6–10% of aggregate debt. Rising indebtedness has coincided with widening fragility: the New York Federal Reserve reports that delinquency rates on newly-issued credit-card accounts have climbed back to pre-Great Recession levels, while the typical revolving borrower now pays double-digit interest. Against this macro backdrop, understanding why many consumers overspend, under-save and mismanage debt is as urgent for policy makers as it is for households themselves. Historical experience and empirical research indicate that excessive household leverage can amplify economic booms in the short run (by enabling spending) but in the long run tends to drag on growth and precipitate crises when shocks occur. Credit booms associated with heavy household borrowing can also misallocate resources (e.g. into housing or consumption) and slow productivity growth.

Given the above, it is critical to understand why some households accumulate unsustainable debt or fail to save adequately. Traditional economic models emphasize factors such as income, interest rates, and demographics; however, these alone do not fully account for the observed patterns of over-borrowing and under-saving (Dynan, 2012). Behavioral finance offers valuable insights by highlighting cognitive biases and heuristics that drive suboptimal financial decisions. Rather than assuming perfectly rational, time-consistent agents, the literature highlights systematic psychological biases that can push decisions away from the classical optimum. To study investment behavior two such biases—overconfidence bias and present bias regularly surface in laboratory experiments, brokerage records and household surveys. For instance, present bias leads individuals to overweigh immediate consumption and undervalue future obligations, making them prone to impulse spending and procrastination on debt repayment (O'Donoghue and Rabin, 1999; Kuchler and Pagel, 2021). Similarly, overconfidence in one's financial knowledge or abilities can cause individuals to underestimate risks and over-leverage themselves (Allgood and Wal- stad, 2016; Kim et al., 2020). Despite abundant evidence that both overconfidence and present bias individually worsen debt outcomes, relatively little is known about their interactive effects on routine credit behavior. Do the two biases reinforce one another, producing multiplicative harm, or does one sometimes offset the other?

The present paper therefore exploits the 2021 NFCS data ($n \approx 26,000$) to quantify how overconfidence and present bias separately and jointly relate to six financial outcomes, namely ”overspending”, ”debt recovery calls”, ”late payment”, ”partial credit card payment”, ”over utilisation of credit card” and ”overall credit behavior”. By delivering nationally representative marginal-effect estimates, the study bridges the gap between small-scale experiments and aggregate credit-market statistics.

We find that both overconfidence bias and present bias increases the probability of overspending, debt recovery calls, late payment of credit card bills, partial payment of credit card bills, over utilisation of credit card and overall bad credit card behavior. This is in line with the findings in existing literature. Overconfident people overestimate their financial management skills but ultimately end up in a sub optimal financial situation – overspending and bad credit card management. Similarly people with present bias value instant gratification over long term financial well being which results in poor financial management. But interestingly we find that the presence of both present bias and overconfidence bias reduces the adverse effect of individual biases. In other words these biases do not amplify each other but rather mitigate each other's effect. This can be explained as follows-

The joint presence of present bias and overconfidence bias can create cognitive dissonance, where individuals experience psychological discomfort due to conflicting beliefs about their financial competence and their actual impulsive behavior. Overconfidence makes them believe they are financially savvy, while present bias pushes them toward short-sighted spending, creating a tension between these self-views. Empirically, this tension manifests as a tendency for such individuals to moderate their spending before reaching severe financial distress, leading to less severe overspending and bad debt behavior. Essentially, the conflict between immediate gratification and self-perception as a responsible decision-maker results in a cycle of indulgence followed by corrective behavior to resolve this dissonance.

The remainder of the paper is divided into seven sections. Section 2 presents a literature review that motivate our hypotheses. Section 3 on Data and Variable Construction describes the 2021 NFCS sample, details the operationalization overconfidence and present-bias indices, and explains the list of control-variables used in this study. Section 4 on methodology lays down the logistic-regression framework. We present the results in Section 5. Section 6 discusses the alternate explanations of the results shown in the previous section. Finally, Section 7 presents the conclusion and summarizes contributions, notes limitations and outlines avenues for experiments and longitudinal work.

2 Literature Review and Hypothesis Development

2.1 Overconfidence Bias

A growing body of empirical research has investigated how overconfidence bias affects fi- nancial decisions like borrowing, saving, and investment. Overconfidence (often measured as an excessive belief in one's financial savvy relative to actual skill) should be linked to riskier and costlier financial behaviors. Verma (2017) finds that self-assessed finan- cial competence that is inflated by biases leads to "imprudent financial decisions" and lower financial satisfaction. This suggests that individuals who overestimate their finan- cial savvy are more prone to mistakes regardless of actual knowledge. In the consumer credit context, overconfident borrowers may underestimate their debt burden or overesti- mate their ability to repay, potentially leading to heavier debt loads and higher default risk. Kim et al. (2020) find that U.S. households exhibiting overconfidence in financial literacy (high subjective but low objective knowledge) were much more likely to become delinquent on mortgages: those classified as overconfident had mortgage delinquency rates roughly three times higher than households with accurate self-assessments. In the context of non-bank credit, recent work by (Lim, 2024) and (Agarwal et al., 2024) shows that overconfident consumers are more likely to rely on high-cost alternative financial services (AFSs) such as payday loans and title loans. Chen and Chen (2023) find that U.S. individuals with higher subjective financial confidence (a proxy for overconfidence) had higher odds of using costly AFSs. They also note that underconfidence (underestimating one's knowledge) is associated with more cautious behavior. These findings align with the idea that overconfidence inflates perceived ability to manage debt and lowers sensitivity to interest costs (Disney and Gathergood, 2013; Hauff and Nilsson, 2020).

Coming to credit card market, Allgood and Walstad (2016) reports that overconfident individuals tend to manage credit cards poorly, engaging in riskier credit usage despite lacking adequate knowledge. (George and Leszczyszyn, 2021) and (Greene, 2022) study the "credit card debt puzzle" and show that behavioral biases like overconfidence help explain why some consumers carry debt despite having liquid assets. In sum, the overconfidence bias is generally thought to promote excessive borrowing and neglect of savings, though its precise effect may depend on interacting factors like income or self- awareness.

We expect that overconfident individuals will have overly optimistic expectations about their future income or financial control. As a result, they may feel justified in spending more freely than they otherwise should. Consequently, we hypothesize that this will lead them to consistently spend beyond their means.

Hypothesis 1 (H1): Overconfident individuals are more likely to spend more relative to their income.

Overconfidence can lead to excessive borrowing and complacency about repayment. Overconfident borrowers may overestimate their ability to repay on time, so they may take on high debt without adequate repayment plans, a pattern of "problematic borrowing" linked to overconfidence. We thus expect that such borrowers are more likely to fall behind on payments and face collection calls as a consequence.

Hypothesis 2 (H2): Overconfident individuals are more likely to be contacted by debt recovery agents.

Overconfident individuals are expected to show poorer payment discipline. This inefficient behavior implies they might only pay the minimum due, incurring interest costs when they could have paid off the balance. We hypothesize that overconfidence bias will go hand-in- hand with suboptimal credit card management. Thus, we expect that overconfidence bias will be associated with behaviors like late payment, partial payment and over utilisation of credit cards.

Hypothesis 3 (H3): Overconfident individuals are more likely to engage in bad credit card behavior.

2.2 Present Bias

Present bias broadly defined as valuing immediate rewards disproportionately more than future ones is associated with less saving and more spending. The present bias litera- ture highlights strong tendencies toward immediate gratification in financial behavior. In the domain of present bias, there is consistent evidence that myopic preferences lead to adverse financial outcomes. Laibson (1997); O'Donoghue and Rabin (1999) find that present-biased individuals, those who disproportionately favor immediate gratification over future benefits tend to overspend, undersave, and postpone debt repayment . Wang and John (2025) document that in the U.S. pandemic context, more strongly present-biased individuals were significantly more likely to take out payday loans, and to borrow more frequently. These effects remain even after controlling for financial literacy, suggesting an inherent cognitive distortion. Xiao and Porto (2019) using Chinese urban data, show that present bias correlates positively with impulsive spending and negatively with saving behavior. They further note that empirical research consistently finds present bias related to "undesirable spending, borrowing, and saving behaviors." Similarly, behavioral finance reviews emphasize that present-biased preferences often manifest in credit- and debt-related choices: for example, Meier and Sprenger (2010) document reliance on credit borrowing and related problems among present-biased individuals. Kuchler and Pagel (2021) find that many U.S. credit card users fail to stick to their own repayment plans, this shortfall is best explained by present bias. In their study, consumers designated as present-biased systematically underpay their debt each month compared to what they themselves had planned. Meier and Sprenger (2010) use incentivized experiments and credit report data to show that present-biased individuals are significantly more likely to carry credit card balances and borrow on cards, even after controlling for income and demographics. In other words, those prone to present bias have higher credit card debt and spend down their borrowing limits.

We expect present-biased individuals to overspend, favoring immediate consumption at the expense of future finances. Consequently, we hypothesize that this will lead them to consistently spend beyond their means.

Hypothesis 4 (H4): Present bias has a significant positive effect on an individual's propen- sity to overspend.

We expect individuals exhibiting present bias to have a higher likelihood of falling into delinquency and being contacted by debt collectors as compared to those without this bias. Hence, we hypothesize that this will lead them to fall behind on payments and face collection calls as a consequence

Hypothesis 5 (H5): Present biased individuals are more likely to be contacted by debt recovery agents.

We expect present-biased individuals to exhibit poor credit card behaviors, are more likely to carry balances, pay only the minimum and incur extra fees on late payments, relative to unbiased individuals. Hence, we hypothesize that overconfidence bias will go hand-in-hand with suboptimal credit card management.

Hypothesis 6 (H6): Present biased individuals are more likely to engage in bad credit card behavior.

2.3 Interaction of Overconfidence Bias and Present Bias

Overconfidence and present bias have been found to correlate with excessive consumption and debt. However, as per best of our knowledge, no study has explicitly examined the interaction of overconfidence and present bias together in shaping credit or savings behav- ior. There may be potential non-linear, exacerbating, or even offsetting effects of having both biases simultaneously. This paper contributes by empirically testing these individual and joint effects.
On one hand, the two biases might amplify each other's individual effect. When present bias, which involves giving greater weight to immediate rewards over future consequences, operates alongside overconfidence bias, where individuals overestimate their abilities or knowledge, the outcome can be particularly concerning. For example, the combination of these two biases might cause individuals to focus on short-term pleasures and downplay the risk or cost of their actions, leading to poor financial decisions. Specifically, this could result in excessive spending beyond their means and an accumulation of bad debt, as people feel confident in their ability to repay later while disregarding the actual financial strain it may cause. In this way, the interplay of present bias and overconfidence can create a cycle of irresponsible financial behavior that is difficult to break.

On the other hand, the joint presence of these two biases might trigger cognitive dissonance. Cognitive dissonance theory describes the mental discomfort people feel when they hold conflicting beliefs or attitudes, often leading them to adjust their beliefs or be- havior to restore consistency (Harmon-Jones, 2019; Borah et al., 2023). In this context, an overconfident, present-biased individual embodies a built-in conflict: overconfidence gives them the belief that they are financially savvy or in control, while present bias drives them to behave imprudently. These two predispositions clash—one's self-image as a com- petent financial decision-maker versus one's impulsive, short-sighted spending. According to cognitive dissonance theory, such a person will experience psychological tension from this inconsistency (Fatima, 2019). To reduce the dissonance, the individual is motivated to either adjust their beliefs or adjust their behaviors (Borah et al., 2023; Mainali and Weber, 2025).

Empirically, this phenomenon may manifest in individuals exhibiting both present bias and overconfidence bias as being less likely to experience severe financial distress. Although they may engage in financially risky behaviors, they often moderate their actions before encountering significant financial difficulties. This would result in less severe instances of overspending and bad debt behavior among the doubly-biased, despite their continued impulsiveness. In short, the internal tension between "I want it now" and "I'm capable and responsible" creates a self-regulating dynamic, where the individual oscillates between indulgence and corrective behavior to ease psychological discomfort.

So, ex-ante, we cannot predict whether the interaction of present and overconfidence bias will have exacerbating or offsetting impact on overspending and bad debt behavior. So, we present the hypothesis in null format.

Null Hypothesis 7 (H7): The combined effect of overconfidence bias and present bias has no significant effect on an individual's propensity to overspend.

Null Hypothesis 8 (H8): The combined effect of overconfidence bias and present bias has no effect on the chances of an individual being contacted by debt recovery agents.

Null Hypothesis 9 (H9): The combined effect of overconfidence bias and present bias has no effect on an individual's chances to engage in bad credit card behavior.

3 Data and Variable Construction

This study uses microdata from the 2021 National Financial Capability Study (NFCS), a large cross-sectional survey of U.S. households sponsored by the FINRA Investor Educa- tion Foundation. The NFCS 2021 includes a nationally representative sample of roughly 28,000 respondents with rich information on financial knowledge, attitudes, and behaviors (financial literacy quiz scores, borrowing habits, saving, payment behaviors, demograph- ics, etc.). We choose the 2021 wave because it is the latest available and captures financial conditions in the wake of the COVID-19 pandemic and rising debt levels. It also contains detailed questions on debt forms and a financial literacy quiz, which enable construction of our bias measures and outcome variables. After filtering all the rows with NA entries we get data of 26.468 people for our analysis.

Our dependent variables are eight binary indicators, each of them are drawn from questions present in the NFCS survey reflecting key financial behaviors and attitudes:

Spending beyond income: whether the respondent reports spending more than their income in the past 12 months. This is a polytomous indicator with 3 values, 0 indicating that the respondent does not spend more than the income, 1 telling that the respondent sometimes spends more than income and 2 indicating that the respondent always spends more than the income.

Contacted by debt collectors: whether the respondent or household member was contacted by a collection agency for unpaid debts in the past year. This is a binary indicator with 0 indicating that the respondent was contacted by debt collectors and 1 indicating that respondent was not contacted by debt collectors.

Credit card payment – minimum only: whether in some months the respondent paid only the minimum payment on their credit cards. This is a binary indicator with 0 indicating that the respondent paid full amount in all the months and 1 indicating that respondent paid only minimum amount in some months.

Credit card payment – carried balance: whether in some months the respondent carried a balance and was charged interest. This is a binary indicator with 0 indicating that the respondent did not carry any balance to next month and 1 indicating that respondent carried over balance in some months.

Credit card – charged late fee: whether in some months the respondent was charged a late payment fee. This is a binary indicator with 0 indicating that the respondent was never charged a late fee for late payment and 1 indicating that respondent was charged a late fee for late payment in some months.

Credit card – used cash advance: whether in some months the respondent used cards for a cash advance. This is a binary indicator with 0 indicating that the respondent never used credit card for a cash advance and 1 indicating that respondent did use the credit card for cash advance in some months.

Credit card – over-limit fee: whether in some months the respondent incurred an over- the-limit fee. This is a binary indicator with 0 indicating that the respondent never used credit card for a cash advance and 1 indicating that respondent did use the credit card for cash advance in some months.

Credit card – overall behavior: This is measure of an overall credit behavior shown by the respondent that was constructed in the following manner- a score was obtained by sum- ming the above 5 credit card behaviors i.e. minimum only payment, carried over balance, charged late fee, used cash advance and over-limit fee. Now each one of them have a value of 0 or 1. Now, after finding the sum for all the respondents the median was found. If a respondent was above the median then a score of 1 was assigned indicating the respondent has a poor credit card usage pattern and if the score of the respondent was below 1 then a score of 0 was assigned indicating that that the respondent has a good credit card behavior usage behavior.

The key independent variables are measures of overconfidence and present bias.

Overconfidence bias for each person was evaluated as follows- Firstly a subjective score (what the person thinks) of their financial literacy was calculated. The subjective score was calculated using a question in the survey which asked-"On a scale from 1 to 7, where 1 means very low and 7 means very high, how would you assess your overall financial knowledge?". Using the median score of all people, if a person scored below the median then a score of 0 was allotted and if a person scored above the median then a score of 1 was allotted. This way we could segregate the people who thought they were financially literate against the opposite. Then an objective score i.e. the financially knowledge a person actually has was calculated. This was done using 7 multiple choice questions asked in the survey that judged a person on his/her financially literacy.
The questions were as follows- "i) Suppose you had $100 in a savings account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the account if you left the money to grow? ii) Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, how much would you be able to buy with the money in this account? iii) If interest rates rise, what will typically happen to bond prices? iv) Suppose you owe $1,000 on a loan and the interest rate you are charged is 20% per year compounded annually. If you didn't pay anything off, at this interest rate, how many years would it take for the amount you owe to double? v) Which of the following indicates the highest probability of getting a par- ticular disease? vi) A 15-year mortgage typically requires higher monthly payments than a 30-year mortgage, but the total interest paid over the life of the loan will be less. vii) Buying a single company's stock usually provides a safer return than a stock mutual fund."

Now, the median objective score of all the people in the survey was calculated using the scores in the questions above and the people who scored more than the median were given a score of 1 and other were given a score of 0. After getting the subjective and objective score, overconfidence bias in an individual was checked as follows:-i) If a person thinks he is financially literate and scored more than the median objective score then he shows no overconfidence bias and is allotted a score of “0” in the overconfidence bias column.

ii) If a person thinks he is financially literate but scored less than the median objective score then he shows overconfidence bias and is allotted a score of “1” in the overconfidence bias column. iii) If a person thinks he is not financially literate but scored more than the median objective score then he is rather underconfident and is allotted a score of “-1” in the overconfidence bias column. iv) If a person thinks he is not financially literate and scored less than the median objective score then he shows no bias and is allotted a score of “0” in the overconfidence bias column.

Present bias in the respondents was evaluated as follows- people were asked that “whether they have set aside emergency or rainy day funds that would cover their expenses for 3 months”, in case of sickness, job loss, economic downturn, or other emergencies. If the respondent said “yes” then a score of 1 was allotted and 0 for “no”. Now, a new column was made that recorded the present bias in a person. So, if the income of a person was above the median income among all the respondents and he had answered “no” to the above question then the person showed present bias and we labelled it as “1”. If a person had an income which was below the median income yet he answered “yes” to the above question then we marked it as “-1” as he showed negative of a person who shows present bias. For the other 2 cases i.e. when a person having low income and answered “no” to the above question and when a person having high income and answered “yes” to the above question we labelled it as “0” since it was the ideal scenario and no bias is being shown in such cases.

We also include an interaction term (Overconfidence × PresentBias) to test whether the combined effect of both biases differs from the sum of individual effects. A range of con- trol variables is included in all models: age, gender, race, education, household income, marital status and number of dependents. These covariates account for socioeconomic and attitudinal factors known to influence financial behaviors. Table 3.1 provides a summary of the statistics of all the variables used in the regression models.

Table 3.1: Descriptive Statistics

Group	Variable	Category	Mean	Count
Dependent Variables	Credit Behavior Overall (Bad)	0	0.57	15511
Dependent Variables	Credit Behavior Overall (Good)	1	0.43	11607
Dependent Variables	Partial Payment	0	0.43	11729
Dependent Variables	Partial Payment	1	0.33	9079
Dependent Variables	Minimum Payment	0	0.49	13419
Dependent Variables	Minimum Payment	1	0.27	7419
Dependent Variables	Late fee	0	0.64	17320
Dependent Variables	Late fee	1	0.13	3554
Dependent Variables	Over limit fee	0	0.68	18531
Dependent Variables	Over limit fee	1	0.08	2230
Dependent Variables	Cash Advance	0	0.66	18026
Dependent Variables	Cash Advance	1	0.11	2890
Dependent Variables	Recovery Calls	0	0.79	21433
Dependent Variables	Recovery Calls	1	0.18	4851
Dependent Variables	High Debt Perception	1	0.34	9231
Dependent Variables	High Debt Perception	0	0.65	17511
Dependent Variables	Overspending Less than income	1	0.54	14768
Dependent Variables	Overspending equal to income	2	0.33	8897
Dependent Variables	Overspending more than income	3	0.1	2817
Independent Variables	overconfidence bias underconfident	-1	0.09	2420
Independent Variables	overconfidence bias absent	0	0.57	15381
Independent Variables	overconfidence bias present	1	0.32	8667
Independent Variables	Future Oriented	-1	0.17	4707
Independent Variables	Present Bias Absent	0	0.64	17386
Independent Variables	Present Bias Present	1	0.14	3836
Control Variables	Age 18-24	1	0.11	3009
Control Variables	Age 25-34	2	0.17	4696
Control Variables	Age 35-44	3	0.17	4564
Control Variables	Age 45-54	4	0.17	4617
Control Variables	Age 55-64	5	0.17	4731
Control Variables	Age 65+	6	0.2	5501
Control Variables	Dependent Children-1	1	0.15	3996
Control Variables	Dependent Children-2	2	0.12	3269
Control Variables	Dependent Children-3	3	0.05	1300
Control Variables	Dependent Children-4	4	0.03	763
Control Variables	Dependent Children-5	5	0.29	7887
Control Variables	Dependent Children-6	6	0.37	9903
Control Variables	Education-No High School	1	0.03	737
Control Variables	Education-High School	2	0.18	4825
Control Variables	Education-Diploma	3	0.07	1897
Control Variables	Education-College	4	0.26	7065
Control Variables	Education-Associate's Degree	5	0.11	2943
Control Variables	Education-Bachelor's Degree	6	0.25	6682
Control Variables	Education-Post Graduate Degree	7	0.11	2969
Control Variables	Employment-Self employed	1	0.08	2141
Control Variables	Employment-Full Time	2	0.39	10454
Control Variables	Employment-Part Time	3	0.09	2360
Control Variables	Employment- Homemaker	4	0.07	1820
Control Variables	Employment-Student	5	0.03	760
Control Variables	Employment-Unable to work	6	0.06	1532
Control Variables	Employment-Unemployed	7	0.08	2196
Control Variables	Employment-Retired	8	0.22	5855
Control Variables	Income less than 15000	1	0.12	3327
Control Variables	Income 15000-25000	2	0.11	2942
Control Variables	Income 25000-35000	3	0.11	2918
Control Variables	Income 35000-50000	4	0.14	3847
Control Variables	Income 50000-75000	5	0.18	5007
Control Variables	Income 75000-100000	6	0.13	3570
Control Variables	Income 100000-150000	7	0.13	3470
Control Variables	Income 150000-200000	8	0.04	1212
Control Variables	Income 200000-300000	8	0.02	560
Control Variables	Income more than 300000	10	0.01	265
Control Variables	Marital Status-Married	1	0.49	13280
Control Variables	Marital Status- Single	2	0.33	9053
Control Variables	Marital Status- Separated	3	0.02	478
Control Variables	Marital Status- Divorced	4	0.11	3077
Control Variables	Marital Status- Widowed	5	0.05	1230

4 Methodology

We aim to examine the individual and combined effects of two cognitive biases—overconfidence bias and present bias on the eight dependent variables outlined in the previous section. For each dependent variable, we estimate a logistic regression with heteroskedasticity robust standard errors. Models are labelled 1-8 (for eight regressions) for each dependent variable
in our analysis which are: -

Spending beyond income: whether the respondent reports spending more than their income in the past 12 months. This is a polytomous indicator with 3 values, 0 indicating that the respondent does not spends more than the income, 1 indicating that the respondent sometimes spends more than income and 2 telling that the respondent always spends more than the income.
Contacted by debt collectors: whether the respondent or household member was contacted by a collection agency for unpaid debts in the past year. This is a binary indicator with 0 indicating that the respondent was contacted by debt collectors and 1 indicating that respondent was not contacted by debt collectors.

Credit card payment – minimum only: whether in some months the respondent paid only the minimum payment on their credit cards. This is a binary indicator with 0 indicating that the respondent paid full amount in all the months and 1 indicating that respondent paid only minimum amount in some months.

Credit card payment – carried balance: whether in some months the respondent carried a balance and was charged interest. This is a binary indicator with 0 indicating that the respondent did not carry any balance to next month and 1 indicating that respondent carried over balance in some months.

Credit card – charged late fee: whether in some months the respondent was charged a late payment fee. This is a binary indicator with 0 indicating that the respondent was never charged a late fee for late payment and 1 indicating that respondent was charged a late fee for late payment in some months.

Credit card – used cash advance: whether in some months the respondent used cards for a cash advance. This is a binary indicator with 0 indicating that the respondent never used credit card for a cash advance and 1 telling that respondent did use the credit card for cash advance in some months.

Credit card – over-limit fee: whether in some months the respondent incurred an over- the-limit fee. This is a binary indicator with 0 indicating that the respondent never used credit card for a cash advance and 1 indicating that respondent did use the credit card for cash advance in some months.

Credit card – overall behavior: This is measure of an overall credit behavior shown by the respondent that was constructed in the following manner- a score was obtained by sum- ming the above 5 credit card behaviors i.e. minimum only payment, carried over balance, charged late fee, used cash advance and over-limit fee. Now each one of them have a value of 0 or 1. Now, after finding the sum for all the respondents the median was found. If a respondent was above the median then a score of 1 was assigned indicating the respondent has a poor credit card usage pattern and if the score of the respondent was below 1 then a score of 0 was assigned indicating that that the respondent has a good credit card behavior usage behavior.

The independent variables are overconfidence bias and present bias each of them having a value of 0(if the respondent shows that bias) and 1(if the respondent does not shows the bias).

The equations for 8 regressions for each 8 dependent variables are as follows-

Model 1- With overconfidence bias as the independent variable

$$\text{Dependent Variable} = \beta_0 + \beta_1 \cdot \text{overconfidence bias} + \varepsilon \quad (4.1)$$

Model 2- With present bias as the independent variable

$$\text{Dependent Variable} = \beta_0 + \beta_1 \cdot \text{present bias} + \varepsilon \quad (4.2)$$

Model 3- With overconfidence and present bias as the independent variable

$$\text{Dependent Variable} = \beta_0 + \beta_1 \cdot \text{overconfidence bias} + \beta_2 \cdot \text{present bias} + \varepsilon \quad (4.3)$$

Model 4- With overconfidence, present bias and (overconfidence bias* present bias) as the independent variables

$$\text{Dependent Variable} = \beta_0 + \beta_1 \cdot \text{overconfidence bias} \pm \beta_2 \cdot \text{present bias}$$
$$+ \beta_3 \cdot \text{overconfidence full} \cdot \text{present bias} + \varepsilon \quad (4.4)$$

Model 5- With overconfidence bias and control variables as the independent variables Dependent

$$\text{Variable} = \beta_0 + \beta_1 \cdot \text{overconfidence bias} + \beta_2 \cdot \text{factor(age)} + \beta_3 \cdot \text{factor(race)}$$
$$+ \beta_4 \cdot \text{factor(education)} + \beta_5 \cdot \text{factor(marital status)} + \beta_6 \cdot \text{factor(income)}$$
$$+ \beta_7 \cdot \text{factor(employment)} + \beta_8 \cdot \text{factor(children)} + \varepsilon \quad (4.5)$$

Model 6- With present bias and control variables as the independent variables Dependent Variable

$$= \beta_0 + \beta_1 \cdot \text{present bias} + \beta_2 \cdot \text{factor(age)} + \beta_3 \cdot \text{factor(race)}$$
$$+ \beta_4 \cdot \text{factor(education)} + \beta_5 \cdot \text{factor(marital status)} + \beta_6 \cdot \text{factor(income)}$$
$$+ \beta_7 \cdot \text{factor(employment)} + \beta_8 \cdot \text{factor(children)} + \varepsilon \quad (4.6)$$

Model 7- With overconfidence bias, present bias and control variables as the independent variables

$$\text{Dependent Variable} = \beta_0 + \beta_1 \cdot \text{overconfidence bias} + \beta_2 \cdot \text{present bias} + \beta_3 \cdot \text{factor(age)} + \beta_4 \cdot \text{factor(race)}$$
$$+ \beta_5 \cdot \text{factor(education)} + \beta_6 \cdot \text{factor(marital status)} + \beta_7 \cdot \text{factor(income)}$$
$$+ \beta_8 \cdot \text{factor(employment)} + \beta_9 \cdot \text{factor(children)} + \varepsilon \quad (4.7)$$

Model 8- With overconfidence, present bias, (overconfidence bias* present bias) and control variables as the independent variables.

$$\text{Dependent Variable} = \beta_0 + \beta_1 \cdot \text{overconfidence bias} + \beta_2 \cdot \text{present bias} + \beta_4 \cdot \text{overconfidence full} \cdot \text{present bias}$$
$$+ \beta_5 \cdot \text{factor(age)} + \beta_6 \cdot \text{factor(race)} + \beta_7 \cdot \text{factor(education)}$$
$$+ \beta_8 \cdot \text{factor(marital status)} + \beta_7 \cdot \text{factor(income)}$$
$$+ \beta_9 \cdot \text{factor(employment)} + \beta_1 0 \cdot \text{factor(children)} + \varepsilon \quad (4.8)$$

The rationale for using logistic regression is twofold. First, the binary coding of outcomes makes logit a natural choice that respects the 0/1 nature (avoiding predicted probabilities outside [0,1]). Second, we are primarily interested in the sign and significance of biases, not in the exact magnitudes of change in raw terms. Logistic models, though nonlinear, allow straightforward hypothesis testing (via odds ratios or marginal effects) and can handle multiple interaction terms. Logistic Regression is a widely used statistical method for modeling the probability of a binary outcome based on one or more predictor variables. Unlike linear regression, which predicts continuous values, logistic regression estimates the probability that a given input belongs to a particular category (typically coded as 0 or 1). The model achieves this by applying the logistic (sigmoid) function to a linear combination of the input variables, thereby constraining the output to the interval (0, 1). The relationship between the predictors and the probability of the outcome is given by the following equation:

$$\pi(\mathbf{X}) = \frac{\exp(\beta_0 + \beta_1 X_1 + \cdots + \beta_k X_k)}{1 + \exp(\beta_0 + \beta_1 X_1 + \cdots + \beta_k X_k)} \quad (4.9)$$

where $\pi(\mathbf{X})$ denotes the probability of the outcome being 1, β_0 is the intercept, $\beta_1, \ldots, \beta_k$ are the coefficients associated with the predictor variables $X_1, \ldots, X_k$. The parameters of the model are typically estimated using maximum likelihood estimation (MLE), which finds the set of coefficients that maximize the likelihood of observing the given data. The logistic specifications allow us to interpret coefficients in terms of changes in the probability of each outcome. We present results in the next section as marginal effects (percentage-point changes in likelihood) for overconfidence, present bias, and their inter- action, controlling for all covariates.

5 Results

In this section, we present the analysis of the results from each of the regressions. Our expanded analysis yields several key findings. We have also analysed the marginal effects of all the independent variables on the dependent variable in each regression and have expressed it in percentage point change. The results of the 8 dependent variables and the 8 regressions for each dependent variable are as follows-

5.1 Impact of overconfidence and present bias in overspending

In Table 5.1 we use overspending as our dependent variable. The variable takes value 1 if spending is less than the income, 2 if spending is almost equal to income and 3 if spending is greater than income. We thus run a mutinomial logistic regression. This regression gives two outputs comparing classes 1 vs 2 and 1 vs 3. For sake of brevity we only report 1 vs 3 reasons.
We run the following specifications of the models- in first specifications we carry out a univariate regression with overconfidence bias alone. In second specification, we run a univariate regression with present bias alone. In this specification a bivariate regression with overconfidence and present bias. In fourth specification, we run the regression with overconfidence bias, present bias and their interaction term. In specification 5,6,7 and 8 we run the first 4 specifications with including other control variables.

We can see that in all specifications the coefficients of present bias and overconfidence bias are positive and significant. It means that both the biases increase the probability of overspending vis-à-vis normal spending. Further in columns 4 and 8 we see that the coefficient of the interaction term between overconfidence and present bias is negative and significant. This implies that when both the biases are present together, cognitive dissonance is triggered leading to correction in behaviour which results in marginally less overspending.

The coefficients of the regression represent the change in log odds ratio with respect to unit change in x. We are interested in quantifying the change in probabilities rather than the log odds ratio. Thus, we present the logistic transformations of the coefficients in Table 5.1 while discussing the results. Based on column 4 (where we do not include any control variables) we can see that the presence of overconfidence bias results in 3.79 pp increase in probability of overspending. Presence of present bias results in 9.56 pp increase in probability of overspending while the presence of both biases reduces the probability of overspending by 4.61 pp. Based on column 8 (where we include control variables) we can see that the presence of overconfidence bias results in 2.80 pp increase in probability of overspending. Presence of present bias results in 23.63 pp increase in probability of overspending while the presence of both biases reduces the probability of overspending by 3.52 pp.

Table 5.1: Regression Results for Overspending

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
overconfidence bias	0.106*** (0.035)		0.138*** (0.035)	0.135*** (0.036)	-0.055 (0.038)		0.048 (0.040)	0.049 (0.040)
present bias		0.361*** (0.037)	0.363*** (0.037)	0.422*** (0.041)		2.015*** (0.058)	2.017*** (0.058)	2.101*** (0.063)
overconfidence bias:present bias				-0.214*** (0.060)				-0.267*** (0.068)
Age 25-34					0.333*** (0.086)	0.256*** (0.090)	0.246*** (0.091)	0.248*** (0.091)
Age 35-44					0.210** (0.091)	0.086 (0.096)	0.065 (0.097)	0.066 (0.097)
Age 45-54					-0.036 (0.094)	-0.184* (0.099)	-0.186* (0.100)	-0.189* (0.100)
Age 55-64					-0.674*** (0.105)	-0.629*** (0.110)	-0.653*** (0.111)	-0.654*** (0.111)
Age 65+					-1.343*** (0.144)	-1.227*** (0.150)	-1.240*** (0.151)	-1.241*** (0.151)
Education-High School					-0.312** (0.127)	-0.088 (0.132)	-0.098 (0.136)	-0.101 (0.136)
Education-Diploma					-0.200 (0.140)	-0.019 (0.145)	-0.018 (0.149)	-0.024 (0.149)
Education-College					-0.156 (0.126)	0.070 (0.130)	0.063 (0.134)	0.064 (0.134)
Education-Associate's Degree					-0.291** (0.139)	-0.015 (0.144)	-0.023 (0.148)	-0.018 (0.148)
Education-Bachelor's Degree					-0.638*** (0.134)	-0.178 (0.140)	-0.189 (0.143)	-0.182 (0.143)
Education-Post Graduate Degree					-0.035 (0.149)	0.525*** (0.156)	0.534*** (0.159)	0.546*** (0.159)
Marital Status- Single					-0.031 (0.066)	-0.136** (0.068)	-0.147** (0.069)	-0.144** (0.069)
Marital Status- Separated					0.688*** (0.152)	0.345** (0.162)	0.340** (0.163)	0.344** (0.163)
Marital Status- Divorced					0.307*** (0.079)	0.115 (0.082)	0.095 (0.083)	0.094 (0.083)
Marital Status- Widowed					0.261** (0.130)	0.150 (0.134)	0.134 (0.136)	0.132 (0.136)
Income 15000-25000					-0.303*** (0.079)	-0.251*** (0.083)	-0.282*** (0.084)	-0.285*** (0.084)
Income 25000-35000					-0.697*** (0.083)	-0.581*** (0.088)	-0.598*** (0.089)	-0.601*** (0.089)
Income 35000-50000					-1.405*** (0.086)	-1.283*** (0.091)	-1.306*** (0.092)	-1.303*** (0.092)
Income 50000-75000					-2.227*** (0.095)	-4.012*** (0.114)	-4.048*** (0.116)	-4.070*** (0.116)
Income 75000-100000					-2.554*** (0.114)	-4.224*** (0.129)	-4.264*** (0.130)	-4.289*** (0.131)
Income 100000-150000					-2.893*** (0.125)	-4.484*** (0.139)	-4.528*** (0.141)	-4.542*** (0.141)
Income 150000-200000					-3.095*** (0.187)	-4.617*** (0.197)	-4.689*** (0.200)	-4.695*** (0.200)
Income 200000-300000					-2.900*** (0.238)	-4.428*** (0.263)	-4.467*** (0.263)	-4.472*** (0.264)
Income more than 300000					-2.604*** (0.286)	-4.007*** (0.294)	-4.108*** (0.302)	-4.096*** (0.302)
Employment-Full Time					-0.382*** (0.085)	-0.477*** (0.090)	-0.495*** (0.091)	-0.502*** (0.091)
Employment-Part Time					-0.566*** (0.109)	-0.605*** (0.115)	-0.630*** (0.116)	-0.634*** (0.116)
Employment- Homemaker					-0.488*** (0.113)	-0.696*** (0.119)	-0.722*** (0.121)	-0.724*** (0.121)
Employment-Student					-0.748*** (0.164)	-0.791*** (0.174)	-0.807*** (0.175)	-0.808*** (0.175)
Employment-Unable to work					0.396*** (0.110)	0.076 (0.115)	0.055 (0.117)	0.056 (0.117)
Employment-Unemployed					0.498*** (0.100)	0.284*** (0.106)	0.249** (0.107)	0.246** (0.107)
Employment-Retired					-0.827*** (0.125)	-0.810*** (0.130)	-0.821*** (0.131)	-0.819*** (0.131)
Dependent Children-2					-0.004 (0.083)	-0.006 (0.087)	0.009 (0.087)	0.011 (0.087)
Dependent Children-3					-0.065 (0.116)	-0.022 (0.120)	-0.036 (0.122)	-0.036 (0.122)
Dependent Children-4					0.246* (0.129)	0.207 (0.135)	0.207 (0.136)	0.208 (0.137)
Dependent Children-5					-0.633*** (0.081)	-0.692*** (0.084)	-0.699*** (0.085)	-0.696*** (0.085)
Dependent Children-6					-0.758*** (0.071)	-0.769*** (0.074)	-0.770*** (0.075)	-0.766*** (0.075)
Constant	-1.695*** (0.023)	-1.633*** (0.021)	-1.680*** (0.023)	-1.686*** (0.023)	1.028*** (0.174)	1.699*** (0.181)	1.769*** (0.186)	1.763*** (0.186)
Akaike Inf. Crit.	48,263.72	47,186.36	46,318.85	46,301.38	41,413.03	37,788.02	37,056.54	37,043.84

*$p < 0.1$;
**$p < 0.05$;
***$p < 0.01$.
Coefficients are reported with standard errors in parentheses.

5.2 Impact of overconfidence and present bias on debt recovery calls

In Table 5.2 we use debt recovery calls as our dependent variable. The variable takes value 0 if they didn't receive any debt recovery call and 1 if they had received a debt recovery call at least once. We thus run a logistic regression. This regression gives one output comparing classes 0 vs 1. We run the following specifications of the models- in first specifications we carry out a univariate regression with overconfidence bias alone. In second specification, we run a univariate regression with present bias alone. In this specification a bivariate regression with overconfidence and present bias. In fourth specification, we run the regression with overconfidence bias, present bias and their interaction term. In specification 5,6,7 and 8 we run the first 4 specifications with including other control variables.

We can see that in all specifications the coefficients of present bias and overconfidence bias are positive and significant. It means that both the biases increase the probability of getting a debt recovery call vis-à - vis not getting a debt recovery call. Further in columns 4 and 8 we see that the coefficient of the interaction term between overconfidence and present bias is negative and significant. This implies that when both the biases are present together, cognitive dissonance is trigerred leading to correction in behaviour which results in marginally less chances of getting a debt recovery call.

The coefficients of the regression represent the change in log odds ratio with respect to unit change in x. We are interested in quantifying the change in probabilities rather than the log odds ratio. Thus we present the logistic transformations of the coefficients in Table 5.2 while discussing the results. Based on column 4 (where we do not include any control variables) we can see that the presence of overconfidence bias results in 3.89 pp increase in probability of getting debt recovery calls. Presence of present bias results in 11.82 pp increase in probability of getting debt recovery calls while the presence of both biases reduces the probability of getting debt recovery calls by 4.64 p. Based on column 8 (where we include control variables) we can see that the presence of overconfidence bias results in 1.72 pp increase in probability of getting debt recovery calls. Presence of present bias results in 24.89 pp increase in probability of getting debt recovery calls while the presence of both biases reduces the probability of getting debt recovery calls by 4.02 pp.

Table 5.2: Regression Results for Recovery Calls

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Overconfidence Bias	0.112*** (0.027)		0.144*** (0.027)	0.156*** (0.028)	-0.003 (0.028)		0.059** (0.029)	0.069** (0.029)
Present Bias		0.423*** (0.029)	0.431*** (0.029)	0.482*** (0.031)		1.038*** (0.040)	1.046*** (0.040)	1.093*** (0.043)
Overconfidence × Present Bias				-0.186*** (0.046)				-0.161*** (0.048)
Age 18–24					0.503*** (0.065)	0.462*** (0.067)	0.450*** (0.067)	0.452*** (0.067)
Age 25–34					0.360*** (0.069)	0.310*** (0.071)	0.299*** (0.072)	0.300*** (0.072)
Age 35–44					0.059 (0.072)	-0.004 (0.074)	-0.013 (0.074)	-0.015 (0.074)
Age 45–54					-0.472*** (0.081)	-0.432*** (0.083)	-0.442*** (0.083)	-0.443*** (0.083)
Age 55–64					-1.229*** (0.109)	-1.083*** (0.112)	-1.112*** (0.112)	-1.113*** (0.112)
Age 65+					0.090** (0.039)	0.114*** (0.040)	0.120*** (0.040)	0.117*** (0.040)
Education-High School					-0.093 (0.099)	0.007 (0.100)	0.004 (0.102)	0.003 (0.102)
Education-Diploma					0.015 (0.109)	0.103 (0.110)	0.093 (0.112)	0.088 (0.112)
Education-College					0.134 (0.098)	0.229** (0.098)	0.223** (0.101)	0.223** (0.101)
Education-Associate's Degree					0.065 (0.106)	0.188* (0.107)	0.190* (0.109)	0.194* (0.109)
Education-Bachelor's Degree					-0.389*** (0.103)	-0.162 (0.104)	-0.167 (0.107)	-0.164 (0.107)
Education-Post Graduate Degree					-0.108 (0.114)	0.145 (0.116)	0.144 (0.118)	0.150 (0.118)
Marital Status- Single					-0.015 (0.049)	-0.065 (0.050)	-0.060 (0.050)	-0.058 (0.050)
Marital Status- Separated					0.569*** (0.109)	0.413*** (0.112)	0.411*** (0.113)	0.412*** (0.113)
Marital Status- Divorced					0.404*** (0.058)	0.282*** (0.059)	0.284*** (0.060)	0.283*** (0.060)
Marital Status- Widowed					0.591*** (0.095)	0.518*** (0.097)	0.544*** (0.098)	0.542*** (0.098)
Income 15000-25000					0.229*** (0.064)	0.286*** (0.065)	0.258*** (0.066)	0.257*** (0.066)
Income 25000-35000					0.142** (0.067)	0.223*** (0.068)	0.207*** (0.069)	0.205*** (0.069)
Income 35000-50000					-0.113* (0.066)	0.003 (0.068)	-0.023 (0.068)	-0.022 (0.068)
Income 50000-75000					-0.488*** (0.069)	-1.337*** (0.078)	-1.363*** (0.079)	-1.371*** (0.079)
Income 75000-100000					-0.748*** (0.079)	-1.520*** (0.087)	-1.554*** (0.088)	-1.564*** (0.088)
Income 100000-150000					-0.902*** (0.085)	-1.603*** (0.091)	-1.628*** (0.092)	-1.632*** (0.092)
Income 150000-200000					-0.926*** (0.117)	-1.583*** (0.122)	-1.609*** (0.123)	-1.609*** (0.123)
Income 200000-300000					-1.081*** (0.168)	-1.694*** (0.173)	-1.705*** (0.174)	-1.703*** (0.174)
Income more than 300000					-1.050*** (0.229)	-1.730*** (0.237)	-1.737*** (0.238)	-1.728*** (0.237)
Employment-Full Time					-0.180*** (0.062)	-0.190*** (0.064)	-0.203*** (0.065)	-0.206*** (0.065)
Employment-Part Time					-0.343*** (0.079)	-0.330*** (0.082)	-0.345*** (0.082)	-0.347*** (0.083)
Employment- Homemaker					-0.281*** (0.083)	-0.344*** (0.085)	-0.355*** (0.086)	-0.356*** (0.086)
Employment-Student					-0.742*** (0.129)	-0.750*** (0.133)	-0.787*** (0.135)	-0.787*** (0.135)
Employment-Unable to work					0.291*** (0.084)	0.158* (0.086)	0.161* (0.087)	0.162* (0.087)
Employment-Unemployed					-0.171** (0.078)	-0.292*** (0.081)	-0.303*** (0.081)	-0.303*** (0.081)
Employment-Retired					-0.615*** (0.093)	-0.567*** (0.096)	-0.562*** (0.096)	-0.560*** (0.096)
Dependent Children-2					0.093 (0.058)	0.094 (0.060)	0.096 (0.060)	0.098 (0.060)
Dependent Children-3					0.111 (0.078)	0.096 (0.080)	0.109 (0.080)	0.109 (0.080)
Dependent Children-4					0.341*** (0.092)	0.308*** (0.095)	0.318*** (0.095)	0.319*** (0.095)
Dependent Children-5					-0.247*** (0.059)	-0.253*** (0.060)	-0.259*** (0.061)	-0.257*** (0.061)
Dependent Children-6					-0.693*** (0.052)	-0.684*** (0.054)	-0.675*** (0.054)	-0.672*** (0.054)
Constant	-1.507*** (0.017)	-1.471*** (0.016)	-1.503*** (0.018)	-1.512*** (0.018)	-0.664*** (0.133)	-0.428*** (0.135)	-0.397*** (0.138)	-0.403*** (0.138)

*$p < 0.1$;
**$p < 0.05$;
***$p < 0.01$.
Coefficients are reported with standard errors in parentheses.

5.3 Impact of overconfidence and present bias on late payment

In Table 5.3 we use late credit card payment as our dependent variable. The variable takes value 0 if they had never carried over a balance and 1 if they had carried over a balance and were charged interest. We thus run a logistic regression. This regression gives one output comparing classes 0 vs 1.

We run the following specifications of the models- in first specifications we carry out a univariate regression with overconfidence bias alone. In second specification, we run a univariate regression with present bias alone. In this specification a bivariate regression with overconfidence and present bias. In fourth specification, we run the regression with overconfidence bias, present bias and their interaction term. In specification 5,6,7 and 8 we run the first 4 specifications with including other control variables.

We can see that in all specifications the coefficients of present bias and overconfidence bias are positive and significant. It means that both the biases increase the probability of carrying over a balance vis-à-vis not carrying over a balance. Further in columns 4 and 8 we see that the coefficient of the interaction term between overconfidence and present bias is negative and significant. This implies that when both the biases are present together, cognitive dissonance is triggered leading to correction in behaviour which results in marginally less chances of carrying over a balance.The coefficients of the regression represent the change in log odds ratio with respect to unit change in x. We are interested in quantifying the change in probabilities rather than the log odds ratio. Thus we present the logistic transformations of the coefficients in Table 5.3 while discussing the results. Based on column 4 (where we do not include any control variables) we can see that the presence of overconfidence bias results in 3.89 pp increase in probability of carrying over a balance. Presence of present bias results in 11.82 pp increase in probability of carrying over a balance while the presence of both biases reduces the probability of carrying over a balance by 4.64 p. Based on column 8 (where we include control variables) we can see that the presence of overconfidence bias results in 1.72 pp increase in probability of carrying over a balance. Presence of present bias results in 24.89 pp increase in probability of carrying over a balance while the presence of both biases reduces the probability of carrying over a balance by 4.02 pp.

Table 5.3: Regression Results for Late Payment

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
overconfidence bias	0.075*** (0.024)		0.125*** (0.025)	0.128*** (0.025)	-0.020 (0.025)		0.048* (0.027)	0.044* (0.027)
present bias		0.754*** (0.026)	0.762*** (0.026)	0.841*** (0.029)		1.400*** (0.035)	1.408*** (0.035)	1.461*** (0.037)
overconfidence bias:present bias				-0.299*** (0.043)				-0.208*** (0.044)
Age 25-34					0.466*** (0.065)	0.416*** (0.069)	0.427*** (0.070)	0.428*** (0.070)
Age 35-44					0.519*** (0.068)	0.485*** (0.073)	0.487*** (0.073)	0.486*** (0.073)
Age 45-54					0.517*** (0.068)	0.488*** (0.073)	0.498*** (0.073)	0.495*** (0.073)
Age 55-64					0.150** (0.071)	0.209*** (0.076)	0.229*** (0.077)	0.229*** (0.077)
Age 65+					-0.192** (0.083)	-0.090 (0.088)	-0.073 (0.088)	-0.074 (0.088)
Education-High School					0.068 (0.132)	0.210 (0.137)	0.221 (0.140)	0.217 (0.139)
Education-Diploma					0.031 (0.141)	0.160 (0.146)	0.180 (0.149)	0.172 (0.149)
Education-College					0.238* (0.130)	0.370*** (0.135)	0.394*** (0.138)	0.395*** (0.138)
Education-Associate's Degree					0.022 (0.134)	0.195 (0.140)	0.220 (0.142)	0.223 (0.142)
Education-Bachelor's Degree					-0.321** (0.131)	-0.068 (0.136)	-0.042 (0.139)	-0.038 (0.139)
Education-Post Graduate Degree					-0.465*** (0.136)	-0.198 (0.141)	-0.175 (0.144)	-0.171 (0.144)
Marital Status- Single					-0.037 (0.044)	-0.096** (0.047)	-0.090* (0.048)	-0.088* (0.048)
Marital Status- Separated					0.354*** (0.135)	0.247* (0.146)	0.239 (0.146)	0.238 (0.146)
Marital Status- Divorced					0.427*** (0.052)	0.320*** (0.055)	0.318*** (0.056)	0.318*** (0.056)
Marital Status- Widowed					0.323*** (0.075)	0.291*** (0.080)	0.286*** (0.081)	0.280*** (0.081)
Income 15000-25000					0.383*** (0.077)	0.450*** (0.082)	0.425*** (0.083)	0.423*** (0.083)
Income 25000-35000					0.291*** (0.076)	0.440*** (0.081)	0.418*** (0.082)	0.416*** (0.082)
Income 35000-50000					0.206*** (0.073)	0.378*** (0.078)	0.353*** (0.079)	0.355*** (0.079)
Income 50000-75000					0.067 (0.072)	-1.045*** (0.081)	-1.075*** (0.082)	-1.072*** (0.082)
Income 75000-100000					-0.074 (0.076)	-1.099*** (0.085)	-1.136*** (0.085)	-1.136*** (0.085)
Income 100000-150000					-0.300*** (0.079)	-1.260*** (0.087)	-1.292*** (0.088)	-1.289*** (0.088)
Income 150000-200000					-0.404*** (0.096)	-1.319*** (0.103)	-1.348*** (0.104)	-1.343*** (0.104)
Income 200000-300000					-0.627*** (0.123)	-1.498*** (0.129)	-1.519*** (0.130)	-1.511*** (0.130)
Income more than 300000					-0.680*** (0.164)	-1.523*** (0.170)	-1.555*** (0.171)	-1.543*** (0.171)
Employment-Full Time					0.094 (0.058)	0.028 (0.062)	0.020 (0.062)	0.014 (0.062)
Employment-Part Time					-0.085 (0.073)	-0.147* (0.078)	-0.157** (0.079)	-0.161** (0.079)
Employment- Homemaker					-0.145* (0.082)	-0.300*** (0.087)	-0.299*** (0.088)	-0.302*** (0.088)
Employment-Student					-0.370*** (0.121)	-0.475*** (0.129)	-0.476*** (0.130)	-0.478*** (0.130)
Employment-Unable to work					0.418*** (0.098)	0.105 (0.103)	0.100 (0.104)	0.101 (0.105)
Employment-Unemployed					0.008 (0.085)	-0.221** (0.091)	-0.217** (0.092)	-0.215** (0.092)
Employment-Retired					-0.417*** (0.071)	-0.363*** (0.075)	-0.380*** (0.075)	-0.380*** (0.075)
Dependent Children-2					0.086 (0.056)	0.082 (0.059)	0.092 (0.060)	0.093 (0.060)
Dependent Children-3					0.093 (0.076)	0.094 (0.080)	0.087 (0.081)	0.087 (0.081)
Dependent Children-4					0.084 (0.098)	0.078 (0.104)	0.071 (0.105)	0.072 (0.105)
Dependent Children-5					-0.137*** (0.052)	-0.135** (0.055)	-0.132** (0.055)	-0.132** (0.055)
Dependent Children-6					-0.359*** (0.048)	-0.345*** (0.051)	-0.341*** (0.051)	-0.341*** (0.051)
Constant	-0.272*** (0.015)	-0.253*** (0.015)	-0.282*** (0.016)	-0.291*** (0.016)	-0.278* (0.159)	0.195 (0.167)	0.184 (0.170)	0.180 (0.169)
Observations	20,564	20,176	19,977	19,977	20,564	20,176	19,977	19,977
Log Likelihood	-14,083.08	-13,366.20	-13,222.70	-13,198.27	-13,151.15	-12,015.04	-11,886.67	-11,875.23
Akaike Inf. Crit.	28,170.16	26,736.40	26,451.40	26,404.55	26,380.30	24,108.09	23,853.33	23,832.45

$^{*}p < 0.1$;
$^{**}p < 0.05$;
$^{***}p < 0.01$.
Coefficients are reported with standard errors in parentheses.

In Table 5.4 we use second measure of late credit card payment as our dependent variable. The variable takes value 0 if a late fee had not been charged and 1 if a late fee had been charged for late payment. We thus run a logistic regression. This regression gives one output comparing classes 0 vs 1.

We run the following specifications of the models- in first specifications we carry out a univariate regression with overconfidence bias alone. In second specification, we run a univariate regression with present bias alone. In this specification a bivariate regression with overconfidence and present bias. In fourth specification, we run the regression with overconfidence bias, present bias and their interaction term. In specification 5,6,7 and 8 we run the first 4 specifications with including other control variables.

We can see that in all specifications the coefficients of present bias and overconfidence bias are positive and significant. It means that both the biases increase the probability of being charged a late fee for late payment. Further in columns 4 and 8 we see that the coefficient of the interaction term between overconfidence and present bias is negative and significant. This implies that when both the biases are present together, cognitive dissonance is triggered leading to correction in behaviour which results in marginally less chances of being charged a late fee for late payment.

The coefficients of the regression represent the change in log odds ratio with respect to unit change in x. We are interested in quantifying the change in probabilities rather than the log odds ratio. Thus we present the logistic transformations of the coefficients in Table 5.4 while discussing the results. Based on column 4 (where we do not include any control variables) we can see that the presence of overconfidence bias results in 9.84 pp increase in probability of late payment fee. Presence of present bias results in 14.95 pp increase in probability of late payment fee while the presence of both biases reduces the probability of late payment fee by 10.73 pp Based on column 8 (where we include control variables) we can see that the presence of overconfidence bias results in 6.27 pp increase in probability of late payment fee. Presence of present bias results in 24.93 pp increase in probability of late payment fee while the presence of both biases reduces the probability of late payment fee by 8.44 pp.

Table 5.4: Regression Results for Late Payment

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
overconfidence bias	0.328*** (0.032)		0.356*** (0.033)	0.399*** (0.033)	0.167*** (0.032)		0.221*** (0.034)	0.252*** (0.034)
present bias		0.443*** (0.033)	0.473*** (0.033)	0.617*** (0.038)		0.949*** (0.043)	0.983*** (0.044)	1.095*** (0.048)
overconfidence bias:present bias				-0.436*** (0.054)				-0.341*** (0.053)
Age 25-34					0.031 (0.071)	0.011 (0.074)	0.017 (0.075)	0.022 (0.075)
Age 35-44					-0.131* (0.077)	-0.173** (0.079)	-0.168** (0.080)	-0.167** (0.080)
Age 45-54					-0.590*** (0.080)	-0.667*** (0.083)	-0.644*** (0.084)	-0.645*** (0.084)
Age 55-64					-1.019*** (0.091)	-0.997*** (0.094)	-0.965*** (0.095)	-0.962*** (0.095)
Age 65+					-1.619*** (0.123)	-1.532*** (0.126)	-1.512*** (0.127)	-1.509*** (0.128)
Education-High School					-0.028 (0.148)	0.038 (0.149)	0.038 (0.153)	0.026 (0.153)
Education-Diploma					0.162 (0.158)	0.228 (0.160)	0.238 (0.164)	0.222 (0.164)
Education-College					0.030 (0.146)	0.069 (0.147)	0.088 (0.151)	0.087 (0.151)
Education-Associate's Degree					-0.143 (0.154)	-0.073 (0.155)	-0.050 (0.158)	-0.050 (0.158)
Education-Bachelor's Degree					-0.358** (0.149)	-0.220 (0.150)	-0.176 (0.154)	-0.172 (0.154)
Education-Post Graduate Degree					-0.151 (0.157)	0.004 (0.159)	0.049 (0.162)	0.056 (0.162)
Marital Status- Single					0.193*** (0.056)	0.151*** (0.057)	0.168*** (0.058)	0.173*** (0.058)
Marital Status- Separated					0.598*** (0.146)	0.467*** (0.152)	0.462*** (0.152)	0.460*** (0.152)
Marital Status- Divorced					0.252*** (0.073)	0.145** (0.074)	0.143* (0.075)	0.138* (0.075)
Marital Status- Widowed					0.227* (0.125)	0.174 (0.127)	0.161 (0.129)	0.153 (0.129)
Income 15000-25000					0.138 (0.090)	0.160* (0.092)	0.130 (0.093)	0.130 (0.093)
Income 25000-35000					0.031 (0.090)	0.093 (0.092)	0.079 (0.093)	0.079 (0.093)
Income 35000-50000					-0.095 (0.086)	-0.048 (0.089)	-0.053 (0.090)	-0.046 (0.090)
Income 50000-75000					-0.355*** (0.087)	-1.201*** (0.097)	-1.236*** (0.098)	-1.241*** (0.098)
Income 75000-100000					-0.540*** (0.095)	-1.304*** (0.104)	-1.357*** (0.105)	-1.367*** (0.105)
Income 100000-150000					-0.558*** (0.099)	-1.248*** (0.106)	-1.295*** (0.108)	-1.296*** (0.108)
Income 150000-200000					-0.606*** (0.126)	-1.268*** (0.133)	-1.325*** (0.134)	-1.320*** (0.134)
Income 200000-300000					-0.485*** (0.160)	-1.158*** (0.168)	-1.183*** (0.169)	-1.168*** (0.169)
Income more than 300000					-0.399* (0.206)	-1.036*** (0.214)	-1.082*** (0.215)	-1.057*** (0.215)
Employment-Full Time					-0.170** (0.071)	-0.222*** (0.073)	-0.218*** (0.074)	-0.228*** (0.074)
Employment-Part Time					-0.214** (0.091)	-0.245*** (0.094)	-0.249*** (0.095)	-0.257*** (0.095)
Employment- Homemaker					-0.442*** (0.102)	-0.575*** (0.106)	-0.554*** (0.106)	-0.558*** (0.107)
Employment-Student					-0.564*** (0.141)	-0.654*** (0.146)	-0.623*** (0.147)	-0.621*** (0.147)
Employment-Unable to work					-0.065 (0.117)	-0.266** (0.119)	-0.270** (0.121)	-0.265** (0.121)
Employment-Unemployed					0.120 (0.098)	-0.046 (0.101)	-0.028 (0.103)	-0.026 (0.103)
Employment-Retired					-0.570*** (0.109)	-0.504*** (0.112)	-0.516*** (0.113)	-0.512*** (0.113)
Dependent Children-2					0.172*** (0.066)	0.151** (0.067)	0.162** (0.068)	0.164** (0.068)
Dependent Children-3					0.077 (0.088)	0.034 (0.090)	0.039 (0.091)	0.040 (0.091)
Dependent Children-4					0.377*** (0.106)	0.362*** (0.108)	0.344*** (0.109)	0.343*** (0.109)
Dependent Children-5					-0.386*** (0.071)	-0.445*** (0.072)	-0.433*** (0.073)	-0.430*** (0.073)
Dependent Children-6					-0.628*** (0.060)	-0.675*** (0.062)	-0.651*** (0.062)	-0.646*** (0.062)
Constant	-1.675*** (0.021)	-1.598*** (0.019)	-1.697*** (0.022)	-1.729*** (0.022)	-0.386** (0.181)	0.069 (0.184)	-0.015 (0.188)	-0.037 (0.188)
Observations	20,616	20,230	20,018	20,018	20,616	20,230	20,018	20,018
Log Likelihood	-9,339.78	-9,117.33	-8,942.99	-8,910.06	-8,293.67	-7,891.55	-7,765.13	-7,744.77
Akaike Inf. Crit.	18,683.56	18,238.66	17,891.97	17,828.13	16,665.33	15,861.11	15,610.26	15,571.54

*$p < 0.1$;
**$p < 0.05$;
***$p < 0.01$.
Coefficients are reported with standard errors in parentheses.

5.4 Impact of overconfidence and present bias on partial payment

In Table 5.5 we use partial credit card payment as our dependent variable. The variable takes value 0 if they had paid the credit card balance in full. and 1 if they had sometime paid only minimum payments. We thus run a logistic regression. This regression gives one output comparing classes 0 vs 1.

We run the following specifications of the models- in first specifications we carry out a univariate regression with overconfidence bias alone. In second specification, we run a univariate regression with present bias alone. In this specification a bivariate regression with overconfidence and present bias. In fourth specification, we run the regression with overconfidence bias, present bias and their interaction term. In specification 5,6,7 and 8 we run the first 4 specifications with including other control variables.

We can see that in all specifications the coefficients of present bias and overconfidence bias are positive and significant. It means that both the biases increase the probability of paying only the minimum balance vis-à - vis paying in full. Further in columns 4 and 8 we see that the coefficient of the interaction term between overconfidence and present bias is negative and significant. This implies that when both the biases are present together, cognitive dissonance is triggered leading to correction in behaviour which results in marginally less chances of just paying the minimum balance.

The coefficients of the regression represent the change in log odds ratio with respect to unit change in x. We are interested in quantifying the change in probabilities rather than the log odds ratio. Thus we present the logistic transformations of the coefficients in Table 5.5 while discussing the results. Based on column 4 (where we do not include any control variables) we can see that the presence of overconfidence bias results in 9.29 pp increase in probability of paying only the minimum balance. Presence of present bias results in 18.46 pp increase in probability of paying only the minimum balance while the presence of both biases reduces the probability of paying only the minimum balance by 9.84 p. Based on column 8 (where we include control variables) we can see that the presence of overconfidence bias results in 6.32pp increase in probability of paying only the minimum balance. Presence of present bias results in 31.31 pp increase in probability of paying only the minimum balance while the presence of both biases reduces the probability of paying only the minimum balance by 6.71 pp.

Table 5.5: Regression Results for Partial Payment

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
overconfidence bias	0.299*** (0.025)		0.355*** (0.026)	0.376*** (0.026)	0.151*** (0.027)		0.246*** (0.028)	0.254*** (0.028)
present bias		0.629*** (0.026)	0.660*** (0.027)	0.775*** (0.030)		1.367*** (0.036)	1.398*** (0.036)	1.470*** (0.038)
overconfidence bias:present bias				-0.399*** (0.044)				-0.270*** (0.045)
Age 25-34					0.259*** (0.066)	0.188*** (0.070)	0.210*** (0.071)	0.215*** (0.071)
Age 35-44					0.056 (0.070)	-0.046 (0.074)	-0.027 (0.074)	-0.025 (0.075)
Age 45-54					-0.249*** (0.070)	-0.388*** (0.074)	-0.344*** (0.075)	-0.344*** (0.075)
Age 55-64					-0.754*** (0.075)	-0.797*** (0.079)	-0.741*** (0.080)	-0.739*** (0.080)
Age 65+					-1.214*** (0.091)	-1.194*** (0.096)	-1.148*** (0.097)	-1.146*** (0.097)
Education-High School					0.142 (0.135)	0.227 (0.140)	0.251* (0.143)	0.242* (0.142)
Education-Diploma					0.256* (0.145)	0.355** (0.150)	0.399*** (0.153)	0.387** (0.153)
Education-College					0.164 (0.134)	0.210 (0.138)	0.264* (0.141)	0.264* (0.141)
Education-Associate's Degree					-0.039 (0.138)	0.050 (0.143)	0.104 (0.146)	0.106 (0.146)
Education-Bachelor's Degree					-0.415*** (0.135)	-0.258* (0.139)	-0.184 (0.142)	-0.180 (0.142)
Education-Post Graduate Degree					-0.424*** (0.141)	-0.238 (0.146)	-0.169 (0.149)	-0.164 (0.148)
Marital Status- Single					-0.021 (0.047)	-0.086* (0.050)	-0.075 (0.050)	-0.071 (0.050)
Marital Status- Separated					0.340** (0.138)	0.170 (0.148)	0.163 (0.148)	0.160 (0.148)
Marital Status- Divorced					0.196*** (0.056)	0.050 (0.060)	0.046 (0.060)	0.044 (0.060)
Marital Status- Widowed					0.032 (0.088)	-0.026 (0.093)	-0.046 (0.094)	-0.054 (0.094)
Income 15000-25000					0.309*** (0.080)	0.357*** (0.083)	0.342*** (0.085)	0.340*** (0.085)
Income 25000-35000					0.093 (0.079)	0.176** (0.083)	0.167** (0.084)	0.164* (0.084)
Income 35000-50000					-0.047 (0.075)	0.066 (0.079)	0.081 (0.080)	0.084 (0.081)
Income 50000-75000					-0.347*** (0.074)	-1.506*** (0.084)	-1.529*** (0.085)	-1.526*** (0.085)
Income 75000-100000					-0.471*** (0.080)	-1.540*** (0.088)	-1.570*** (0.089)	-1.570*** (0.089)
Income 100000-150000					-0.769*** (0.084)	-1.759*** (0.092)	-1.791*** (0.093)	-1.787*** (0.093)
Income 150000-200000					-0.859*** (0.104)	-1.796*** (0.111)	-1.826*** (0.112)	-1.818*** (0.112)
Income 200000-300000					-1.359*** (0.145)	-2.252*** (0.153)	-2.264*** (0.154)	-2.250*** (0.154)
Income more than 300000					-1.263*** (0.191)	-2.140*** (0.198)	-2.173*** (0.200)	-2.151*** (0.199)
Employment-Full Time					-0.089 (0.061)	-0.183*** (0.065)	-0.186*** (0.065)	-0.194*** (0.065)
Employment-Part Time					-0.205*** (0.078)	-0.306*** (0.083)	-0.300*** (0.083)	-0.306*** (0.083)
Employment- Homemaker					-0.312*** (0.086)	-0.520*** (0.091)	-0.513*** (0.092)	-0.517*** (0.092)
Employment-Student					-0.413*** (0.120)	-0.527*** (0.127)	-0.475*** (0.128)	-0.474*** (0.129)
Employment-Unable to work					0.301*** (0.098)	-0.010 (0.104)	-0.015 (0.105)	-0.012 (0.105)
Employment-Unemployed					-0.044 (0.088)	-0.270*** (0.094)	-0.259*** (0.095)	-0.257*** (0.095)
Employment-Retired					-0.568*** (0.079)	-0.537*** (0.084)	-0.560*** (0.085)	-0.558*** (0.085)
Dependent Children-2					0.149** (0.058)	0.168*** (0.061)	0.181*** (0.062)	0.183*** (0.062)
Dependent Children-3					0.177** (0.078)	0.200** (0.083)	0.193** (0.083)	0.194** (0.083)
Dependent Children-4					0.419*** (0.102)	0.420*** (0.108)	0.417*** (0.109)	0.416*** (0.109)
Dependent Children-5					-0.314*** (0.056)	-0.336*** (0.059)	-0.320*** (0.059)	-0.318*** (0.059)
Dependent Children-6					-0.466*** (0.051)	-0.470*** (0.053)	-0.447*** (0.054)	-0.444*** (0.054)
Constant	-0.670*** (0.016)	-0.599*** (0.015)	-0.691*** (0.017)	-0.712*** (0.017)	0.474*** (0.164)	1.182*** (0.171)	1.038*** (0.174)	1.025*** (0.174)
Observations	20,587	20,196	19,989	19,989	20,587	20,196	19,989	19,989
Log Likelihood	-13,319.30	-12,840.48	-12,598.51	-12,556.91	-11,613.86	-10,619.20	-10,456.57	-10,438.22
Akaike Inf. Crit.	26,642.60	25,684.96	25,203.02	25,121.82	23,305.73	21,316.40	20,993.13	20,958.45

*$p < 0.1$;
**$p < 0.05$;
***$p < 0.01$.
Coefficients are reported with standard errors in parentheses.

5.5 Impact of overconfidence and present bias on over utilisation

In Table 5.6 we use over utilisation as our dependent variable. The variable takes value 0 if an over limit fee had never been charged for exceeding the credit line and 1 if a over limit fee had been charged for exceeding the credit line. We thus run a logistic regression. This regression gives one output comparing classes 0 vs 1.

We run the following specifications of the models- in first specifications we carry out a univariate regression with overconfidence bias alone. In second specification, we run a univariate regression with present bias alone. In this specification a bivariate regression with overconfidence and present bias. In fourth specification, we run the regression with overconfidence bias, present bias and their interaction term. In specification 5,6,7 and 8 we run the first 4 specifications with including other control variables.

We can see that in all specifications the coefficients of present bias and overconfidence bias are positive and significant. It means that both the biases increase the probability of being charged an over limit fee for exceeding the credit line.. Further in columns 4 and 8 we see that the coefficient of the interaction term between overconfidence and present bias is negative and significant. This implies that when both the biases are present together, cognitive dissonance is triggered leading to correction in behaviour which results in marginally less chances of being charged an over limit fee for exceeding the credit line. The coefficients of the regression represent the change in log odds ratio with respect to unit change in x. We are interested in quantifying the change in probabilities rather than the log odds ratio. Thus we present the logistic transformations of the coefficients in Table 5.6 while discussing the results. Based on column 4 (where we do not include any control variables) we can see that the presence of overconfidence bias results in 17.55 pp increase in probability of being charged an over limit fee for exceeding the credit line. Presence of present bias results in 13.02 pp increase in probability of being charged an over limit fee for exceeding the credit line while the presence of both biases reduces the probability of being charged an over limit fee for exceeding the credit line by 9.72 p. Based on column 8 (where we include control variables) we can see that the presence of overconfidence bias results in 13.27 pp increase in probability of being charged an over limit fee for exceeding the credit line. Presence of present bias results in 20.06 pp increase in probability of being charged an over limit fee for exceeding the credit line while the presence of both biases reduces the probability of being charged an over limit fee for exceeding the credit line by 6.86 pp.

Table 5.6: Regression Results for Over Utilisation

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Overconfidence bias	0.673*** (0.040)		0.698*** (0.041)	0.733*** (0.042)	0.470*** (0.040)		0.519*** (0.042)	0.544*** (0.042)
Present bias		0.314*** (0.039)	0.361*** (0.040)	0.533*** (0.050)		0.665*** (0.052)	0.734*** (0.053)	0.850*** (0.061)
Overconfidence bias:present bias				-0.394*** (0.067)				-0.276*** (0.067)
Age 25-34					-0.150* (0.080)	-0.213*** (0.082)	-0.195** (0.083)	-0.194** (0.083)
Age 35-44					-0.498*** (0.088)	-0.581*** (0.090)	-0.558*** (0.091)	-0.559*** (0.091)
Age 45-54					-1.042*** (0.096)	-1.182*** (0.098)	-1.106*** (0.099)	-1.108*** (0.099)
Age 55-64					-1.645*** (0.117)	-1.697*** (0.119)	-1.625*** (0.120)	-1.624*** (0.120)
Age 65+					-2.307*** (0.174)	-2.352*** (0.177)	-2.265*** (0.178)	-2.266*** (0.179)
Education-High School					-0.004 (0.172)	0.063 (0.173)	0.019 (0.176)	0.006 (0.176)
Education-Diploma					0.292 (0.183)	0.356* (0.185)	0.332* (0.187)	0.317* (0.187)
Education-College					-0.131 (0.171)	-0.121 (0.172)	-0.104 (0.174)	-0.107 (0.174)
Education-Associate's Degree					-0.161 (0.180)	-0.120 (0.182)	-0.132 (0.184)	-0.135 (0.184)
Education-Bachelor's Degree					-0.319* (0.174)	-0.214 (0.175)	-0.169 (0.178)	-0.168 (0.178)
Education-Post Graduate Degree					0.095 (0.182)	0.215 (0.184)	0.250 (0.186)	0.253 (0.186)
Marital Status- Single					-0.002 (0.068)	-0.081 (0.069)	-0.058 (0.069)	-0.055 (0.069)
Marital Status- Separated					0.659*** (0.165)	0.567*** (0.169)	0.553*** (0.171)	0.554*** (0.171)
Marital Status- Divorced					0.306*** (0.092)	0.193** (0.093)	0.212** (0.094)	0.205** (0.094)
Marital Status- Widowed					0.291* (0.170)	0.269 (0.173)	0.249 (0.174)	0.243 (0.174)
Income 15000-25000					0.142 (0.107)	0.175 (0.108)	0.138 (0.110)	0.139 (0.110)
Income 25000-35000					0.011 (0.107)	0.016 (0.109)	-0.020 (0.110)	-0.018 (0.111)
Income 35000-50000					-0.254** (0.105)	-0.234** (0.107)	-0.256** (0.108)	-0.250** (0.108)
Income 50000-75000					-0.538*** (0.106)	-1.169*** (0.119)	-1.249*** (0.120)	-1.250*** (0.120)
Income 75000-100000					-0.448*** (0.114)	-1.026*** (0.124)	-1.112*** (0.125)	-1.119*** (0.126)
Income 100000-150000					-0.455*** (0.118)	-0.966*** (0.126)	-1.062*** (0.128)	-1.062*** (0.128)
Income 150000-200000					-0.445*** (0.147)	-0.919*** (0.153)	-1.028*** (0.155)	-1.023*** (0.155)
Income 200000-300000					-0.485** (0.192)	-0.986*** (0.197)	-1.040*** (0.199)	-1.028*** (0.199)
Income more than 300000					-0.235 (0.236)	-0.722*** (0.242)	-0.809*** (0.245)	-0.793*** (0.245)
Employment-Full Time					-0.224*** (0.084)	-0.268*** (0.085)	-0.271*** (0.086)	-0.280*** (0.086)
Employment-Part Time					-0.325*** (0.109)	-0.384*** (0.111)	-0.394*** (0.112)	-0.402*** (0.112)
Employment- Homemaker					-0.837*** (0.129)	-0.953*** (0.131)	-0.951*** (0.133)	-0.953*** (0.133)
Employment-Student					-0.513*** (0.160)	-0.664*** (0.166)	-0.611*** (0.167)	-0.610*** (0.167)
Employment-Unable to work					0.049 (0.141)	-0.108 (0.142)	-0.118 (0.144)	-0.113 (0.144)
Employment-Unemployed					-0.161 (0.119)	-0.339*** (0.121)	-0.315** (0.123)	-0.314** (0.123)
Employment-Retired					-0.711*** (0.154)	-0.660*** (0.156)	-0.707*** (0.157)	-0.704*** (0.158)
Dependent Children-2					0.092 (0.075)	0.055 (0.076)	0.085 (0.077)	0.087 (0.077)
Dependent Children-3					0.042 (0.100)	0.043 (0.101)	0.053 (0.102)	0.052 (0.102)
Dependent Children-4					0.412*** (0.117)	0.393*** (0.118)	0.372*** (0.120)	0.372*** (0.120)
Dependent Children-5					-0.620*** (0.093)	-0.678*** (0.093)	-0.636*** (0.094)	-0.633*** (0.094)
Dependent Children-6					-0.708*** (0.071)	-0.778*** (0.072)	-0.725*** (0.073)	-0.720*** (0.073)
Constant	-2.332*** (0.028)	-2.129*** (0.023)	-2.352*** (0.029)	-2.383*** (0.030)	-0.494** (0.210)	0.066 (0.212)	-0.115 (0.216)	-0.130 (0.216)
Observations	20,518	20,121	19,922	19,922	20,518	20,121	19,922	19,922
Log Likelihood	-6,855.09	-6,800.63	-6,580.70	-6,563.66	-5,950.60	-5,789.33	-5,650.71	-5,642.27
Akaike Inf. Crit.	13,714.17	13,605.25	13,167.41	13,135.31	11,979.20	11,656.66	11,381.41	11,366.54

*$p < 0.1$;
**$p < 0.05$;
***$p < 0.01$.
Coefficients are reported with standard errors in parentheses.

In Table 5.7 we use second measure of over utilisation of credit card as our dependent variable. The variable takes value 0 if in some months the respondent did not use credit card for a cash advance and 1 if in some months the respondent used credit card for a cash advance. We thus run a logistic regression. This regression gives one output comparing classes 0 vs 1.

We run the following specifications of the models- in first specifications we carry out a univariate regression with overconfidence bias alone. In second specification, we run a univariate regression with present bias alone. In this specification a bivariate regression with overconfidence and present bias. In fourth specification, we run the regression with overconfidence bias, present bias and their interaction term. In specification 5,6,7 and 8 we run the first 4 specifications with including other control variables.

We can see that in all specifications the coefficients of present bias and overconfidence bias are positive and significant. It means that both the biases increase the probability of using credit card for a cash advance. Further in columns 4 and 8 we see that the coefficient of the interaction term between overconfidence and present bias is negative and significant. This implies that when both the biases are present together, cognitive dissonance is triggered leading to correction in behaviour which results in marginally less chances of using credit card for a cash advance.

The coefficients of the regression represent the change in log odds ratio with respect to unit change in x. We are interested in quantifying the change in probabilities rather than the log odds ratio. Thus we present the logistic transformations of the coefficients in Table 5.7 while discussing the results. Based on column 4 (where we do not include any control variables) we can see that the presence of overconfidence bias results in 17.92 pp increase in probability of using credit card for a cash advance. Presence of present bias results in 6.29 pp increase in probability of using credit card for a cash advance while the presence of both biases reduces the probability of using credit card for a cash advance by 6.32 pp. Based on column 8 (where we include control variables) we can see that the presence of overconfidence bias results in 14.15 pp increase in probability of using credit card for a cash advance. Presence of present bias results in 12.71 pp increase in probability of using credit card for a cash advance while the presence of both biases reduces the probability of using credit card for a cash advance by 4.29 pp.

Table 5.7: Regression Results for Over Utilisation

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
overconfidence bias	0.732*** (0.036)		0.745*** (0.037)	0.750*** (0.037)	0.551*** (0.037)		0.578*** (0.037)	0.582*** (0.038)
present bias		0.089** (0.035)	0.143*** (0.035)	0.253*** (0.044)		0.379*** (0.047)	0.449*** (0.047)	0.520*** (0.054)
overconfidence bias:present bias				-0.254*** (0.061)				-0.172*** (0.060)
Age 25-34					-0.216*** (0.075)	-0.252*** (0.076)	-0.228*** (0.077)	-0.228*** (0.077)
Age 35-44					-0.391*** (0.081)	-0.425*** (0.082)	-0.410*** (0.083)	-0.412*** (0.083)
Age 45-54					-0.980*** (0.088)	-1.083*** (0.089)	-1.009*** (0.090)	-1.011*** (0.090)
Age 55-64					-1.237*** (0.099)	-1.285*** (0.100)	-1.202*** (0.101)	-1.203*** (0.101)
Age 65+					-1.645*** (0.132)	-1.697*** (0.134)	-1.612*** (0.135)	-1.613*** (0.135)
Education-High School					-0.104 (0.154)	-0.001 (0.155)	-0.050 (0.158)	-0.055 (0.158)
Education-Diploma					-0.044 (0.166)	0.061 (0.167)	-0.002 (0.170)	-0.008 (0.170)
Education-College					-0.280* (0.153)	-0.252 (0.154)	-0.251 (0.156)	-0.251 (0.157)
Education-Associate's Degree					-0.393** (0.161)	-0.324** (0.163)	-0.341** (0.165)	-0.340** (0.165)
Education-Bachelor's Degree					-0.496*** (0.156)	-0.422*** (0.157)	-0.387** (0.160)	-0.383** (0.160)
Education-Post Graduate Degree					-0.127 (0.163)	-0.037 (0.164)	-0.003 (0.167)	0.002 (0.167)
Marital Status- Single					0.090 (0.061)	0.036 (0.061)	0.067 (0.062)	0.069 (0.062)
Marital Status- Separated					0.522*** (0.155)	0.444*** (0.158)	0.434*** (0.160)	0.434*** (0.160)
Marital Status- Divorced					0.079 (0.083)	0.009 (0.084)	0.024 (0.085)	0.021 (0.085)
Marital Status- Widowed					0.129 (0.136)	0.146 (0.138)	0.102 (0.140)	0.096 (0.140)
Income 15000-25000					0.152 (0.096)	0.203** (0.096)	0.177* (0.098)	0.177* (0.098)
Income 25000-35000					0.058 (0.096)	0.097 (0.097)	0.070 (0.098)	0.070 (0.099)
Income 35000-50000					-0.239** (0.094)	-0.218** (0.095)	-0.220** (0.097)	-0.218** (0.097)
Income 50000-75000					-0.466*** (0.094)	-0.837*** (0.104)	-0.903*** (0.106)	-0.903*** (0.106)
Income 75000-100000					-0.476*** (0.102)	-0.802*** (0.110)	-0.871*** (0.112)	-0.873*** (0.112)
Income 100000-150000					-0.356*** (0.105)	-0.623*** (0.111)	-0.693*** (0.113)	-0.692*** (0.113)
Income 150000-200000					-0.358*** (0.131)	-0.637*** (0.135)	-0.704*** (0.137)	-0.702*** (0.137)
Income 200000-300000					-0.594*** (0.177)	-0.924*** (0.182)	-0.944*** (0.184)	-0.938*** (0.184)
Income more than 300000					-0.477** (0.227)	-0.736*** (0.228)	-0.804*** (0.231)	-0.795*** (0.231)
Employment-Full Time					-0.321*** (0.076)	-0.356*** (0.076)	-0.355*** (0.077)	-0.360*** (0.077)
Employment-Part Time					-0.296*** (0.097)	-0.321*** (0.097)	-0.323*** (0.099)	-0.327*** (0.099)
Employment- Homemaker					-1.057*** (0.122)	-1.146*** (0.123)	-1.124*** (0.124)	-1.126*** (0.124)
Employment-Student					-0.311** (0.141)	-0.414*** (0.143)	-0.344** (0.145)	-0.342** (0.145)
Employment-Unable to work					0.045 (0.125)	-0.081 (0.125)	-0.060 (0.127)	-0.058 (0.127)
Employment-Unemployed					-0.244** (0.109)	-0.374*** (0.110)	-0.336*** (0.112)	-0.336*** (0.112)
Employment-Retired					-0.523*** (0.118)	-0.515*** (0.119)	-0.537*** (0.121)	-0.537*** (0.121)
Dependent Children-2					0.127* (0.070)	0.108 (0.070)	0.125* (0.071)	0.126* (0.071)
Dependent Children-3					0.065 (0.093)	0.046 (0.094)	0.054 (0.095)	0.054 (0.095)
Dependent Children-4					0.093 (0.117)	0.084 (0.116)	0.041 (0.119)	0.042 (0.119)
Dependent Children-5					-0.617*** (0.080)	-0.654*** (0.080)	-0.617*** (0.081)	-0.615*** (0.081)
Dependent Children-6					-0.635*** (0.065)	-0.692*** (0.065)	-0.646*** (0.066)	-0.644*** (0.066)
Constant	-2.068*** (0.025)	-1.832*** (0.020)	-2.072*** (0.026)	-2.083*** (0.026)	-0.199 (0.190)	0.204 (0.192)	-0.008 (0.196)	-0.013 (0.196)
Observations	20,661	20,272	20,063	20,063	20,661	20,272	20,063	20,063
Log Likelihood	-8,075.31	-8,123.90	-7,814.43	-7,805.71	-7,226.99	-7,152.00	-6,945.25	-6,941.17
Akaike Inf. Crit.	16,154.62	16,251.81	15,634.85	15,619.43	14,531.97	14,382.00	13,970.49	13,964.34

*$p < 0.1$;
**$p < 0.05$;
***$p < 0.01$.
Coefficients are reported with standard errors in parentheses.

5.6 Impact of overconfidence and present bias in credit card behavior

In Table 5.8 we use credit card usage pattern as our dependent variable. The variable takes value 0 if a the respondent has a good credit card usage pattern and 1 the respondent has a bad credit card usage pattern. We thus run a logistic regression. This regression gives one output comparing classes 0 vs 1.

We run the following specifications of the models- in first specifications we carry out a univariate regression with overconfidence bias alone. In second specification, we run a univariate regression with present bias alone. In this specification a bivariate regression with overconfidence and present bias. In fourth specification, we run the regression with overconfidence bias, present bias and their interaction term. In specification 5,6,7 and 8 we run the first 4 specifications with including other control variables.

We can see that in all specifications the coefficients of present bias and overconfidence bias are positive and significant. It means that both the biases increase the probability of having a bad credit card usage pattern Further in columns 4 and 8 we see that the coefficient of the interaction term between overconfidence and present bias is negative and significant. This implies that when both the biases are present together, cognitive dissonance is triggered leading to correction in behaviour which results in marginally less chances of having a bad credit card usage pattern.

The coefficients of the regression represent the change in log odds ratio with respect to unit change in x. We are interested in quantifying the change in probabilities rather than the log odds ratio. Thus we present the logistic transformations of the coefficients in Table 5.8 while discussing the results. Based on column 4 (where we do not include any control variables) we can see that the presence of overconfidence bias results in 7.40 pp increase in probability of having a bad credit card usage pattern. Presence of present bias results in 16.26 pp increase in probability of having a bad credit card usage pattern while the presence of both biases reduces the probability of having a bad credit card usage pattern by 5.65 p. Based on column 8 (where we include control variables) we can see that the presence of overconfidence bias results in 5.85 pp increase in probability of having a bad credit card usage pattern. Presence of present bias results in 20.01 pp increase in probability of having a bad credit card usage pattern while the presence of both biases reduces the probability of having a bad credit card usage pattern by 4.59 pp.

Table 5.8: Regression Results for Credit Behavior

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
overconfidence bias	0.243*** (0.021)		0.298*** (0.022)	0.298*** (0.022)	0.185*** (0.022)		0.236*** (0.023)	0.235*** (0.023)
present bias		0.581*** (0.023)	0.614*** (0.023)	0.675*** (0.025)		0.761*** (0.030)	0.800*** (0.031)	0.848*** (0.032)
overconfidence bias:present bias				-0.227*** (0.037)				-0.184*** (0.038)
Age 25-34					0.047 (0.052)	-0.012 (0.054)	0.011 (0.055)	0.012 (0.055)
Age 35-44					-0.096* (0.056)	-0.160*** (0.057)	-0.146** (0.058)	-0.146** (0.058)
Age 45-54					-0.206*** (0.056)	-0.284*** (0.058)	-0.248*** (0.059)	-0.251*** (0.059)
Age 55-64					-0.353*** (0.060)	-0.355*** (0.061)	-0.318*** (0.062)	-0.319*** (0.062)
Age 65+					-0.661*** (0.071)	-0.621*** (0.073)	-0.590*** (0.074)	-0.590*** (0.074)
Education-High School					0.445*** (0.093)	0.504*** (0.093)	0.503*** (0.095)	0.500*** (0.095)
Education-Diploma					0.403*** (0.100)	0.442*** (0.101)	0.437*** (0.103)	0.431*** (0.103)
Education-College					0.622*** (0.091)	0.664*** (0.092)	0.674*** (0.094)	0.673*** (0.094)
Education-Associate's Degree					0.548*** (0.097)	0.623*** (0.097)	0.636*** (0.100)	0.638*** (0.100)
Education-Bachelor's Degree					0.334*** (0.093)	0.445*** (0.094)	0.472*** (0.096)	0.475*** (0.096)
Education-Post Graduate Degree					0.270*** (0.099)	0.401*** (0.100)	0.427*** (0.102)	0.431*** (0.102)
Marital Status- Single					-0.156*** (0.038)	-0.225*** (0.039)	-0.210*** (0.040)	-0.209*** (0.040)
Marital Status- Separated					-0.125 (0.101)	-0.295*** (0.104)	-0.300*** (0.105)	-0.298*** (0.105)
Marital Status- Divorced					0.129*** (0.045)	0.043 (0.046)	0.041 (0.047)	0.041 (0.047)
Marital Status- Widowed					0.179*** (0.067)	0.137** (0.069)	0.126* (0.070)	0.124* (0.070)
Income 15000-25000					0.618*** (0.057)	0.664*** (0.058)	0.656*** (0.059)	0.654*** (0.059)
Income 25000-35000					0.688*** (0.058)	0.757*** (0.060)	0.761*** (0.061)	0.759*** (0.061)
Income 35000-50000					0.774*** (0.056)	0.887*** (0.058)	0.890*** (0.059)	0.892*** (0.059)
Income 50000-75000					0.729*** (0.056)	0.143** (0.061)	0.120* (0.062)	0.118* (0.062)
Income 75000-100000					0.614*** (0.061)	0.074 (0.065)	0.052 (0.066)	0.049 (0.066)
Income 100000-150000					0.506*** (0.064)	0.009 (0.068)	-0.015 (0.069)	-0.014 (0.069)
Income 150000-200000					0.341*** (0.082)	-0.129 (0.085)	-0.152* (0.086)	-0.149* (0.086)
Income 200000-300000					0.106 (0.108)	-0.371*** (0.111)	-0.369*** (0.111)	-0.364*** (0.111)
Income more than 300000					0.169 (0.144)	-0.323** (0.146)	-0.320** (0.148)	-0.311** (0.148)
Employment-Full Time					0.150*** (0.050)	0.134*** (0.051)	0.130** (0.052)	0.126** (0.052)
Employment-Part Time					-0.038 (0.063)	-0.048 (0.064)	-0.057 (0.065)	-0.059 (0.065)
Employment- Homemaker					-0.462*** (0.069)	-0.568*** (0.071)	-0.556*** (0.072)	-0.557*** (0.072)
Employment-Student					-0.329*** (0.095)	-0.341*** (0.098)	-0.314*** (0.099)	-0.317*** (0.099)
Employment-Unable to work					-0.109 (0.074)	-0.282*** (0.075)	-0.255*** (0.077)	-0.255*** (0.077)
Employment-Unemployed					-0.408*** (0.067)	-0.536*** (0.069)	-0.536*** (0.070)	-0.537*** (0.070)
Employment-Retired					-0.330*** (0.063)	-0.283*** (0.064)	-0.294*** (0.065)	-0.293*** (0.065)
Dependent Children-2					0.109** (0.049)	0.113** (0.050)	0.113** (0.051)	0.114** (0.051)
Dependent Children-3					0.184*** (0.067)	0.182*** (0.069)	0.174** (0.069)	0.174** (0.069)
Dependent Children-4					0.159* (0.083)	0.156* (0.085)	0.146* (0.086)	0.146* (0.086)
Dependent Children-5					-0.257*** (0.045)	-0.285*** (0.046)	-0.267*** (0.047)	-0.265*** (0.047)
Dependent Children-6					-0.391*** (0.042)	-0.397*** (0.043)	-0.373*** (0.043)	-0.372*** (0.043)
Constant	-0.329*** (0.013)	-0.265*** (0.013)	-0.324*** (0.014)	-0.332*** (0.014)	-0.832*** (0.118)	-0.504*** (0.119)	-0.587*** (0.122)	-0.591*** (0.122)
Observations	26,468	25,929	25,468	25,468	26,468	25,929	25,468	25,468
Log Likelihood	-18,038.35	-17,387.44	-16,993.04	-16,974.52	-17,107.15	-16,436.44	-16,096.01	-16,084.38
Akaike Inf. Crit.	36,080.71	34,778.87	33,992.09	33,957.04	34,292.29	32,950.89	32,272.03	32,250.75

*$p < 0.1$;
**$p < 0.05$;
***$p < 0.01$.
Coefficients are reported with standard errors in parentheses.

The observed negative interaction effects in all the models above where individuals with both biases exhibit less severe financial mismanagement than expected are consistent with behavioral theories such as cognitive dissonance, risk compensation, and self-regulation through mental accounting. These mechanisms may instigate internal checks, leading biased individuals to engage in partial corrections or avoid extreme outcomes, thereby moderating their overall financial behavior.

To summarise our results across all models, the coefficients for overconfidence and present bias are statistically significant (mostly at $p < 0.01$) and in the expected direction. Key dependent variables include: spending beyond income, being contacted by debt collectors, and poor credit card behaviors (such as only making minimum payments, carrying unpaid balances, incurring late fees or over-limit fees, taking cash advances, etc.), as well as an overall composite index of credit card mismanagement.

The interaction terms present a unique results which shows that the interaction terms are negative and significant in almost all cases. This means an individual who is both overconfident and present-biased tends to exhibit fewer problematic financial behaviors (or less severe ones) than expected by simply adding the two biases' effects.

6 Alternate Explanations

In addition to the predictive power of overconfidence and present bias, the interaction of these biases introduces nuanced behavioral dynamics that are best understood through cognitive dissonance theory as discussed earlier. In this section we provide 2 alternate explanations through risk compensation and behavioral trade-offs, and self-regulation via mental accounting. These mechanisms also provide explanatory support for the observed outcomes, particularly the non-linear or dampened effects of holding both biases simultaneously.

Risk compensation theory suggests that individuals subconsciously regulate their behavior to maintain a comfortable level of perceived risk. When two biases—present bias (which leads to impulsive spending) and overconfidence (which leads to underestimating risk) coexist, they might push a person toward risky financial behaviors more rapidly. How- ever, this heightened risk exposure can trigger an internal alarm, prompting self-corrective actions like reducing spending or avoiding particularly dangerous decisions. As a result, individuals may engage in behavioral trade-offs or alternating periods of risk and caution, leading to less extreme outcomes than either bias alone might predict. This internal bal- ancing act can explain why the combined impact of both biases may appear weaker than expected, as one bias tempers the other.

Self-regulation and mental accounting help explain how individuals with both present bias and overconfidence may avoid extreme financial behavior. Present bias drives short- term indulgence, but overconfidence fosters a belief in one's ability to manage finances, leading to the creation of informal mental budgets or self-imposed spending rules. While present bias may cause rule-breaking, overconfidence sustains belief in future correction, prompting compensatory behaviors like cutting back elsewhere or planning to do so. This dynamic—fueled by goal conflict, justifications, and self-correction creates a pattern of oscillation between indulgence and restraint. As a result, financial behavior stays within a moderate range, with mental accounting serving as a reference point that limits damage even when plans aren't perfectly followed.

Collectively, these behavioral theories suggest that while each bias independently contributes to the financial behaviors, their joint presence does not simply add up. Instead, the interplay can sometimes trigger internal psychological mechanisms that lead to re- straint, justifications, or corrective action. These theoretical models therefore support the negative interaction effects observed in empirical results particularly the finding that in- dividuals with both biases are, in some cases are less likely to engage in extreme financial behavior than those with only one.

7 Conclusion

This paper investigates the influence of two prominent behavioral biases—overconfidence and present bias—on a wide spectrum of personal financial behaviors using data from the National Financial Capability Study (NFCS). Drawing from a nationally representative sample of over 26,000 U.S. adults, the study provides robust empirical evidence of how these cognitive distortions shape financial decision-making.

The findings reveal that both overconfidence and present bias independently correlate with a higher propensity for financially risky behaviors, including overspending, credit card mis- management, and greater perceived debt burden. These outcomes are consistent with prior literature that has linked behavioral biases to suboptimal financial choices. However, the study's most striking and counterintuitive result is that the joint presence of both biases is associated with significantly lower financial risk than when either bias is present alone. This unexpected moderating interaction suggests the presence of psychological compen- satory mechanisms, such as cognitive dissonance, mental accounting, and self-regulation. Individuals who simultaneously exhibit both biases may engage in corrective behaviors to preserve internal consistency or maintain a positive self-image. These dynamics underscore the importance of considering not just the independent effects of behavioral traits, but also how they interact in complex and sometimes paradoxical ways.

The implications of these findings are twofold. First, they contribute to the growing field of behavioral finance by demonstrating the non-linear and interactive nature of cognitive biases in financial behavior. Second, they suggest a need to redesign financial education and intervention strategies to account for these interactions. Tailored programs that rec- ognize the diversity and interplay of behavioral traits may be more effective in promoting sound financial decision-making than one-size-fits-all approaches.

Future research could extend this work by exploring other combinations of biases and by incorporating experimental designs to uncover the causal mechanisms behind the observed patterns. In sum, this paper highlights the nuanced ways in which behavioral biases influence financial outcomes and advocates for a more holistic and psychologically informed approach to financial policy, education, and research.

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