THE UNIVERSITY OF CHICAGO

ESSAYS ON CONSUMER FINANCIAL DECISION MAKING

A DISSERTATION SUBMITTED TO

THE FACULTY OF THE UNIVERSITY OF CHICAGO

BOOTH SCHOOL OF BUSINESS

IN CANDIDACY FOR THE DEGREE OF

DOCTOR OF PHILOSOPHY

BY

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CHICAGO, ILLINOIS

JUNE 2025

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Acknowledgements

This dissertation would not have been possible without the invaluable guidance of my advisors and the support of my friends and family. I am deeply indebted to my committee chair, Daniel Bartels, whose mentorship has been pivotal from the very beginning. From my first project to the final stages of this dissertation, he has been a constant source of support. I am extremely grateful to Abigail Sussman for inspiring my interest in consumer financial decision making, and to all my committee members—Daniel Bartels, Abigail Sussman, Berkeley Dietvorst, and Stephanie Smith—for their guidance throughout this process. I would also like to thank my collaborators, Emma Levine, Justin Landy, Elizabeth Huppert, Sam Borislow, Alex Moore, and Neil Stewart. I have learned so much from each of you, and I am truly fortunate to have you as co-authors. Finally, I could not have reached this point without the support of my fellow students, friends, and family. Your encouragement over the years has meant so much to me.

Overview

A primary goal of consumer financial decision making research is to better understand how consumers manage their spending, savings and debts (Sussman, Hershfield, and Netzer 2023). In this dissertation, I build on this research by studying how consumers manage their credit cards.

Many consumers have credit cards and have to make frequent decisions about how to spend, repay, and monitor their use. In 2023, it was estimated that 32% of transactions in the US were made using credit cards, and that the share of credit card use is rising, particularly among younger consumers (Bayeh, Cubides, and O'Brien 2024). With this increase in spending on credit cards comes an increase in credit card debt, which has now exceeded $1.21 trillion (Federal Reserve Bank of New York 2025). Although many US cardholders repay their balances in full and avoid interest charges, the majority choose to revolve their balances (Grodzicki and Koulayev 2019), with nearly a third choosing to pay near the minimum—typically a small fraction of their total balances (Keys and Wang 2019).

Although credit cards are an important source of liquidity and a mechanism for smoothing consumption, mismanagement can be costly. In February 2025, the average interest rate on US credit cards was 21.37%, and this average has stayed above 20% since 2023 (Federal Reserve Bank of St. Louis 2025). Further, missing payments can result in late fees, negatively impact credit scores, and increase interest rates.

Fortunately, online tools to help consumers manage their credit cards are becoming more prevalent (Federal Reserve Board 2016). For instance, many banks offer mobile banking apps that make it easier to monitor spending and make payments. In general, better access to financial account information may improve spending and savings decisions (Carlin, Olaffson, and Pagel

2019; Levi and Benartzi 2021). However, credit cards are complex financial products. The impact of spending and repayment on one's future debt can be difficult for consumers to comprehend, even with considerable help (Soll, Keeney, and Larrick 2013).

In two essays, I uncover new effects of constrained memory and attention, heuristics, and goal pursuit on consumer credit card management. Moreover, I differentiate between competing theories in the literature and offer alternative explanations for well-known findings. Essay 1 focuses on difficulties with keeping track of credit card debt, and how these difficulties can influence downstream spending decisions. Essay 2 focuses on the repayment side by examining how consumers determine exactly how much to repay each month.

More specifically, in Essay 1, co-authored with Daniel Bartels, I examine how well consumers recall and estimate their credit card balances. Being aware of one's credit card debt is an important first step toward managing it effectively. I find that consumers are significantly more likely to remember the leftmost digit of their balances compared to right digits (i.e., a left-digit bias). These systematic recall errors cause biased debt estimates when previously observed balances are near round numbers. Specifically, observing balances just under round numbers (e.g., $2,987.45) leads to underestimation of future debt, whereas observing balances just over round numbers (e.g., $3,019.43) leads to overestimation of future debt. As a result, two cardholders with the same amount of debt may be differentially likely to spend—and sometimes overspend—depending on whether the most recent balance they observed was under or over a round number.

Although these patterns appear consistent with some theories of left-digit bias studied in the domain of price perception (e.g., Thomas and Morwitz 2005), I find that a more basic memory constraint—difficulty recalling right digits of complex numbers—can explain these

patterns. This distinction is important because these theories make different predictions about when left-digit effects arise. For example, perception-based theories of left-digit bias predict that the bias can affect consumer choices even when full information is available (i.e., memorizing numbers is not required) (Sokolova et al. 2020). In this essay, I find that changes in the left digit disproportionately influence spending decisions in this context only when balances have to be recalled.

I also shed light on a moderator of misestimation. With lab experiments and data from a large commercial bank, I find that close reference points (e.g., credit limits) can increase attention to, and recall accuracy of, credit card balances. This research offers insights into how bank and budgeting apps can structure their interfaces to assist with credit card management, including when to notify consumers of their balances (e.g., after they exceed round numbers) and how to present balances to improve recall accuracy and reduce bias (e.g., alongside close reference points).

In Essay 2, co-authored with Daniel Bartels and Abigail Sussman, I consider the repayment side of credit card management. Prior research suggests that focal payment options on credit card statements capture attention and can influence payment decisions through an anchoring process (Stewart 2009). More specifically, consumers appear to use the minimum or three-year amount as a starting point for determining their final payments. Because adjustments from anchors tend to be minimal (Epley and Gilovich 2006), final payments may end up near these focal payment options and are therefore influenced by the size of these amounts.

In line with prior research, I find that these focal payment options do capture attention and affect payments. However, in contrast to prior research, I find that they are better characterized as targets or reference points. Unlike anchors, which are neutral starting points

(Tversky and Kahneman 1974), targets separate outcomes that meet or fall short of them as satisfying or disappointing, respectively (e.g., Heath, Larrick, and Wu 1999). Across five studies, I find that payments bunch at and just above some focal payment options as theories of targets (but not anchors) would predict, and that consumers report feeling disproportionately more satisfied with payments that meet (vs. fall short of) these amounts. This research suggests that these values can motivate consumers who otherwise would have paid slightly less than the focal payment option to increase their payments.

Focal payment options on credit card statements, including the minimum, three-year amount and suggested payments, may often be treated more like targets than anchors. However, I also uncover a focal payment framing—placeholder text example payments—that appears to influence payments through an anchoring process. This finding provides a point of reference for how anchors can affect decisions in a credit card repayment context, and further highlights how anchoring effects differ from other focal payment option effects that are often assumed to be generated from anchoring (e.g., McHugh and Ranyard 2016; Stewart 2009).

Together, these two essays provide new insights into consumer financial decision making in the context of credit card management.

Essay 1: Misestimating Credit Card Balances: The Effect of Right-Digit Recall Errors on Spending Decisions

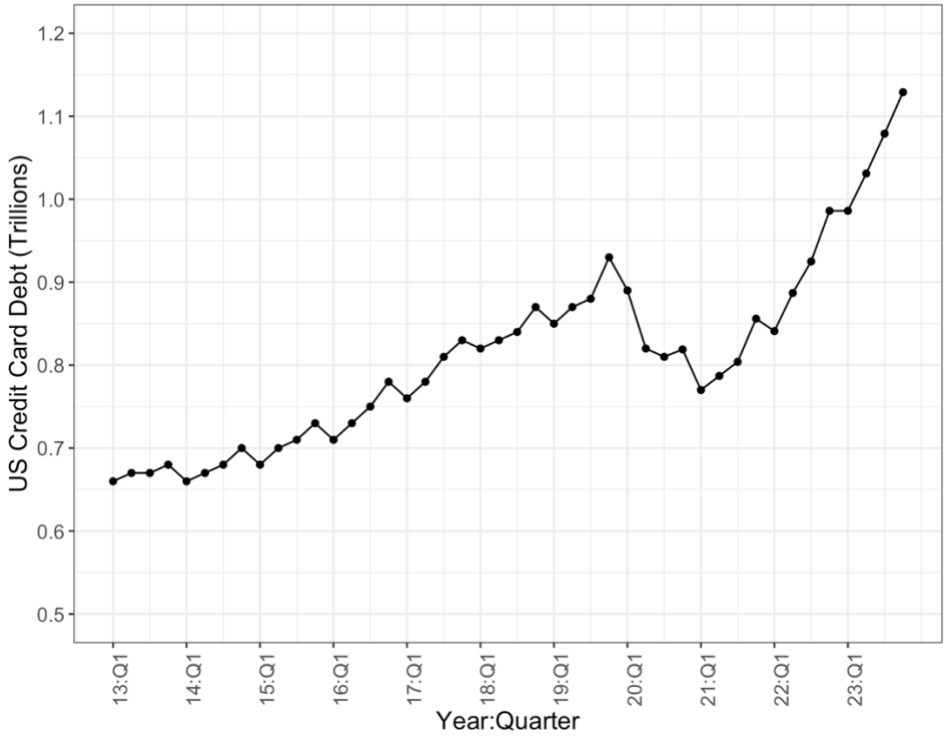
Abstract

Many consumers use online apps to periodically monitor their credit card balances. The authors examine how previously observed balances influence consumers' estimates of their debts, available resources, and their spending decisions. Consumers are more likely to underestimate their credit card debt and continue spending if they last observed a balance just under (vs. over) the closest multiple of $1,000. Accurate recall of the leftmost digit and inaccurate recall of right digits can account for this effect (e.g., a left-digit bias). Further, the authors distinguish this memory-based mechanism from other prominent perception-based theories of left-digit bias. Although right digits are more likely to be misremembered than left digits in general, consumers have a better memory for right digits when they observe their balances alongside nearby reference points, like close credit limits. Together, these findings offer insights into how aware consumers are of their finances, when consumers are more at risk of underestimating their debts and overspending, and the influence of right-digit recall errors on consumer decision making.

Total US credit card debt has now surpassed a trillion dollars (see Figure 1.1). This sharp rise in credit card debt over the last few years underscores the importance of understanding how consumers manage their credit cards—including how aware they are of their debts and available resources.

Consider your own credit card balance. Do you know your exact balance? Do you know the leftmost digit of your balance? The second or third? When was the last time you monitored your balances? Many consumers have easy access to their past spending behavior via online banking and budgeting tools (Federal Reserve Board 2016). However, most consumers check this information only a few times per month, relying instead on memory to assess their debts and available resources as they spend. For instance, Brazilian credit card users logged into a personal finance management app 5.11 times per month on average (median of 2) (Medina 2021). Bank customers from Iceland, who were active users of an online banking platform, logged in to this platform in 6.1% of observed days (Olafsson and Pagel 2017). Although inattention to personal finances can be intentional when the costs of monitoring outweigh the benefits, in many cases, inattention can lead consumers to accidentally overspend and incur financial penalties (Caflisch et al. 2018; PEW 2012).

Figure 1.1: US Credit Card Debt



Notes: Ten years of quarterly-level US credit card data publicly available through the Federal Reserve Bank of New York Reports and Data (2013 to 2023). https://www.newyorkfed.org/microeconomics/hhdc/background.html

Prior research has examined when consumers are more susceptible to forgetting past expenses, and therefore, to overestimating their available resources. For example, consumers forget more expenses when using payment methods that demand less attention to and rehearsal of their expenses, such as a credit card versus a check that requires consumers to write down their expenses (Soman 2001). Studies in this area typically focus on isolated spending events where consumers start with a zero balance and estimate total spending up to a certain point (e.g., end of a month, end of a shopping trip). However, because consumers periodically check their balances using online banking and budgeting tools, estimating one's available resources may

often involve recalling the last observed balance in addition to recent expenses. The current project builds on prior research by examining how previously observed balances influence estimates of current debts and available resources, and downstream spending decisions.

To illustrate, consider a cardholder with a current credit card balance of $2,621.32. They last checked their balance a week ago using an online banking app. Since then, they have made additional purchases with this credit card. Are they equally like to underestimate their current balance (i.e., $2,621.32) if their last observed balance was $2,023.49 versus $2,073.49 or $1,973.49?

In incentive compatible shopping simulations, we observed a left-digit bias. Specifically, observing credit card balances just under (versus over) multiples of $1,000 made consumers more likely to underestimate their debts and overspend. For example, participants who had exceeded a $3,300 budget were more likely to continue overspending when their last observed balance was just under (versus over) $3,000. We find that accurate recall of leftmost digits and inaccurate recall of right digits affects these spending decisions. A common pattern of inaccurate recall in our studies would be recalling a balance of $2,073.49 as “two thousand something” and incorrectly guessing the right digits.

Although prior research on left-digit bias has found similar recall errors in prices (e.g., Schindler and Wiman 1989) and other numeric product attributes (e.g., Lacetera, Pope, and Sydnor 2012), few studies have examined and uncovered direct effects of right-digit recall errors on consumer choices. In many cases, left-digit bias may arise when values, like prices, are observable as consumers make choices (e.g., Manning and Sprott 2009), and therefore, recall may not be necessary to observe a bias. We build on this work by manipulating whether consumers must recall or can observe their balances as they make spending decisions. Because

consumers do not often directly observe balances while spending (Morewedge, Holtzman, and Epley 2007)—unlike prices or other numeric product attributes—recall errors themselves may be particularly relevant in this context.

In addition, we found that observing balances with nearby reference points in mind (e.g., a credit limit) can moderate the effect of previously observed balances on current debt estimates and spending decisions. Processing balances relative to nearby spending limits necessitates deeper encoding of right digits to avoid crossing over those limits. For example, having a credit card balance of $2,981.34 and a credit limit of $3,000 (vs. $5,000) increases the likelihood of incurring over-limit fees due to minor right-digit changes. Knowing these digits becomes even more important when limits are close. In line with this idea, we found improvements in right-digit recall accuracy when balances were close to credit limits, and that cardholders from a large retail bank are more likely to log in to their online bank accounts when their balances are just below credit limits (controlling for repayment days). We discuss these findings in light of research on numeric goal-monitoring (e.g., Allen et al. 2017) and studies showing a stronger left-digit bias in perceived magnitude when focal values are presented alongside reference values (Kim, Malkoc, and Goodman 2019; Thomas and Morwitz 2005; Sokolova, Seenivasan, and Thomas 2020).

In sum, we highlight an important consumer context where right-digit recall errors can predictably impact downstream debt estimation and spending decisions. This project sheds light on how aware consumers are of their finances, the impact of common numerical biases on financial monitoring and spending behaviors, and the challenges consumers face in managing their finances.

Estimating Expenses and Available Resources

Research on how consumers budget and track their available resources often adopts a mental accounting framework (e.g., Heath and Soll 1996; Thaler 1999; Zhang, Sussman, Wang-Ly, and Lyu 2022). This approach suggests that consumers "book and post" expenses to different mental accounts to monitor spending. Setting budgets for these accounts allows consumers to compare their spending to their budgets to decide whether to continue spending. In this framework, misestimation of available resources may occur when small or unusual expenses are not booked or are posted to different accounts (Cheema and Soman 2006; Sussman and Alter 2012).

Instead of actively updating accounts as they spend, Soman (2001) suggests that consumers retrospectively assess their prior spending to determine whether they have enough resources to continue spending. This assessment often requires recalling and summing past expenses. A failure to recall past expenses can leave consumers with the impression that they have more slack in their budgets than they have, therefore increasing the likelihood of additional spending. Soman suggests that payment methods that require less rehearsal of expenses, like credit cards (vs. checks), make it easier to forget past expenses and increase future spending. Subsequent research has similarly found that expenses that are more accessible in memory are more likely to be used to estimate future expenses (Srivastava and Raghubir 2002) and including cumulative spending on receipts curbs additional spending by reminding consumers of their past expenses (Poddar, Ellis, and Ozcan 2014).

Even when all expenses are salient and recall is not required, estimates of cumulative spending may be predictably underestimated. Consumers appear to underestimate sums of

expenses on average, such as the total value of their grocery baskets (Goswami, Greenberg, and Schley 2021).

Across this stream of research, available resources may be misestimated because consumers fail to book or post expenses to mental accounts, recall expenses, or sum up expenses. In other words, misestimation occurs due to difficulties with managing and remembering expenses. Online banking and budgeting tools serve to mitigate these challenges by clearly presenting current checking and credit card balances to consumers. However, because balances are only periodically observed (Medina 2021), estimating one's available resources at any given time may involve recalling both the last observed balance and recent expenses. Therefore, difficulties with recalling previously observed balances—in addition to remembering individual expenses—may affect downstream debt estimates and spending decisions.

In this project, we build on prior research by examining how previously observed balances influence estimates of available resources and spending decisions. More specifically, we draw on literature concerning how people process and recall multi-digit values to make predictions about which kinds of the balances lead to overestimating available resources (or underestimating debts).

Processing and Recalling Multi-Digit Values

For US consumers, credit card balances are often complex multi-digit values, typically in the thousands (Keys and Wang 2019; Stango and Zinman 2009). Research across marketing, economics and psychology has explored how people process multi-digit values and how well they can recall them.

In general, leftmost digits of prices and other numerical product attributes are recalled more accurately than right digits (Coulter 2001; Lacetera et al. 2012; Schindler and Chandrashekaren 2004; Schindler and Wiman 1989). For example, Lacetera, Pope, and Sydnor (2012) found that people recalled the leftmost digit of a car's mileage with over 90% accuracy (5-digit number like 62,847), but accuracy dropped to just over 50% for the second digit. This pattern extends beyond consumer domains, characterizing recall for multi-digit numbers and lists of numbers (Eriksson and Lindskog 2017; Hinrichs and Novick 1982).

The probability of accurate recall seems to depend on a value's complexity, defined by the number of syllables, unique digits or how round it is (Cowan and Hardman 2021; Nguyen, Hofman, and Goldstein 2022; Vanhuele, Laurent, and Drèze 2006). For example, a complex price like $3.78 is less accurately recalled than a simpler price like $3.00 (Laurent and Vanhuele 2023).

Building on this research, we predict that recall for financial balances will express a similar pattern of errors—left digits will be recalled with higher accuracy than right digits.

H1: Recall accuracy for digits in a balance will decrease from left to right.

Although consumers may struggle to recall the exact digits of complex balances, they may deal with this complexity by rounding (Laurent and Vanhuele 2023; Sokolova et al. 2020). For example, consumers may recall $2,983.15 and $3,016.85 as roughly $3,000. Therefore, the underlying magnitude may be preserved in memory despite forgetting specific digits.

Alternatively, left digits may be well preserved in memory, while right digits are more easily forgotten. For example, a consumer who observed a balance of $2,983.15 may only

remember seeing “two thousand something”. In this case, the direction of recall errors is predictable, and these errors may be large. Any incorrect guesses for the hundreds place and most incorrect guesses for the tens place will produce underestimation for balances just below round numbers (Schindler and Chandrashekaren 2004). Conversely, balances just over a round number, like $3,016.85 may be recalled as “three thousand something”, leading to overestimation through the same process.

These recall errors may impact downstream spending decisions. Consider a consumer who uses a credit card for daily expenses and has a current balance of $2,628.25. As the end of the month approaches, they determine that they should stop spending once the balance reaches $3,000, given their expected income and savings goals. Suppose they last observed the balance when it was at $1,993.25 (first case), or alternatively, after the next small purchase when it was at $2,003.25 (second case). Assuming accurate recall of recent expenses, confidently recalling the leftmost digit but not the right digits would result in estimating the current balance as an amount between $1,635.00 and $2,634.99 in the first case (i.e., the recalled balance plus $635 of recent expenses) or between $2,625.00 and $3,624.99 in the second case (i.e., the recalled balance plus $625 of recent expenses). From this consumer’s perspective, the risk of overspending appears greater in the second case—if the last observed balance was $2,003.25—because the possible current balance range includes their $3,000 spending limit. In contrast, if the last observed balance was $1,993.25, they may assume they have more slack in their budget and spend more freely. We test if observing balances just under (versus over) round numbers (e.g., multiples of $1,000) will increase the likelihood of downstream spending on credit cards.

H2: Holding the current balance constant, previously observing balances just under versus over round numbers will increase the likelihood of spending on credit cards.

The above example illustrates how a change in the leftmost digit can have a disproportionate effect on spending decisions—a *left-digit bias*. A large body of research has documented the effects of left-digit changes on consumer behavior, often in the domain of prices (Bhattacharya, Holden, and Jacobsen 2012; Carver and Padgett 2012; Choi, Li, and Samper 2019; Coulter 2001; Kim et al. 2022; Lacetera et al. 2012; Manning and Sprott 2009; Thomas and Morwitz 2005; Sokolova et al. 2020; Strulov-Shlain 2023). In this literature, left-digit bias is commonly attributed to distortions in perceived magnitude when consumers are observing multi-digit values (e.g., Thomas and Morwitz 2005). Therefore, recalling values may not be necessary to observe a left-digit bias, and in some cases, a left-digit bias may be weaker in memory-based judgments due to rounding (Sokolova et al. 2020).

There are several perception-based theories of left-digit bias that do not depend on recall errors. One explanation for left-digit bias is that consumers disproportionately attend to the leftmost digit and truncate or partially ignore the right digits (Bizer and Schindler 2005; Lacetera et al. 2012; Schindler 1984; Schindler and Chandrashekaren 2004; Schindler and Wiman 1989). For example, consider pricing an item at either $2.99 or $3.00. Truncating the right digits of $2.99 would result in perceiving $2.99 as $2—a much smaller amount—while truncating the right digits of $3.00 would not change magnitude perceptions of the price (still $3). Another explanation is that consumers anchor onto the leftmost digit when perceiving underlying magnitude (Thomas and Morwitz 2005). As a result, the perceived magnitude is biased toward the left digit. Lastly, part of why prices with different left digits appear so dissimilar is that round

numbers are treated like thresholds. Kim, Malkoc, and Goodman (2022) found that the difference between a base price of $2.99 and an upgrade price of $3.45, for example, seems larger than the difference between a base price of $3.00 and an upgrade price of $3.46. Although the true difference is identical, prices on either side of the round number threshold seem less similar.

Each of these explanations relates to how consumers process and perceive the magnitude of multi-digit numbers when they are making judgments or choices. Although inaccurate recall of the right digits can be a consequence of biased perception, prior research in this area rarely isolates the direct effects of right-digit recall errors on consumer judgments and choices. Further, recalling values is often unnecessary to produce left-digit effects. For example, left-digit changes in prices appear to affect upgrade choices when consumers can directly observe those prices while making choices (e.g., Kim et al. 2022).

In this project, we test if recall errors or biased perceptions drive an effect of observing balances just above or below round numbers on spending decisions. To test this distinction, we manipulate whether participants must recall balances or can observe them when they are deciding whether to continue spending. This distinction is important because it affects intervention decisions to reduce bias. If the bias is perception-based (e.g., consumers anchor on left digits), then providing consumers with the exact balance at the point of spending may not reduce bias. In contrast, if the bias is memory-based (e.g., consumers forget right digits), then providing the exact balance should reduce bias.

H3: Holding the current balance constant, previously observing balances just under (vs. over) round numbers will increase willingness to spend on credit cards only when those balances must be recalled.

Prior research has often documented a left-digit bias in perception when focal values are presented alongside reference values with different left digits (Kim et al. 2022; Manning and Sprott 2009; Thomas and Morwitz 2005; Sokolova et al. 2020). We test whether the presence of reference values moderates the impact of observed balances on spending decisions. Specifically, we focus on spending limits that consumers can compare their balances against. In this context, as consumers approach credit limits, they may better recall the right digits of their balances to avoid incurring over-limit fees. Recall may improve in situations where changes in right digits have added consequences. For example, the difference between $3,900 and $3,999 is more important if one's credit limit is $4,000 instead of $6,000. Previous research finds that people can adjust their behavior to avoid crossing round number reference points (Pope and Simonsohn 2011). For example, marathon runners tend to finish just before versus after the four-hour mark (Allen et al. 2017), suggesting that runners may know the right digits of their race times to strive to finish just before the four-hour mark.

We predict that comparing balances to nearby reference values in the form of spending limits will attenuate the effect of observing balances just under versus over round numbers on downstream spending.

H4: The presence of a close spending limit will attenuate the effect of previously observing balances just under versus over round numbers on downstream spending decisions.

Overview

We test these hypotheses across six studies. We find that observing credit card balances just under (vs. over) round numbers can increase the likelihood of downstream spending due to difficulties with recalling right digits. In Studies 1 and 2, participants completed a shopping simulation with consequential spending decisions. Study 3 moves out of the hypothetical lab context to investigate how well consumers know their own balances. Study 4 introduces salient, nearby spending limits to test for moderation. Study 5 is an analysis of data from a large retail bank where we observe an increase in the probability of logging in when balances are just below credit limits (controlling for repayment days). Complementing this analysis, Study 6 finds improved right-digit recall accuracy when participants encode balances with nearby spending limits in mind. With the exception of Study 5 (bank analysis), all studies reported in this essay were pre-registered through AsPredicted.

Study 1: Credit Card Spending Simulation

Using an incentive-compatible spending simulation, we examined the impact of observing balances just under versus over round numbers on downstream spending decisions.

Method

Participants

We aimed to recruit 800 participants through Prolific before exclusions (US-based). Participants were excluded from analyses if they failed an attention check (n = 5), indicated that they wrote down their balance or any prices (n = 71), or if their recall errors were greater than $1,000 in absolute value (n = 47). Exclusions were pre-registered

(https://aspredicted.org/PG9_YLY). The final sample included 677 participants (56.1% women, M_{age} = 42.74, $M_{hhincome}$ is between 45k – 65k (bucketed income question)).

Design

Participants were randomly assigned to a credit card with an initial observed balance just under ($2,983.15) or just over ($3,016.85) $3,000.

Materials and Procedure

Participants were informed that they would be making a few spending decisions using a hypothetical credit card. Information about the credit card, including the balance, was displayed on an image of a mobile banking app. This image was selected to simulate the experience of opening a mobile banking app to check the balance. The balance was manipulated to be just under ($2,983.15) or just over ($3,016.85) $3,000. These specific balances were selected to be similarly complex (six unique digits) and the same distance from the closest multiple of $1,000.

After observing their balances, participants moved to the next page to learn more about the shopping simulation. The shopping simulation was adapted from prior research (Goswami, Greenberg, and Schley 2021; Soman 2001). Participants indicated their preferences for one of two options and imagined purchasing these options during the remainder of the month on their hypothetical credit cards. Further, they were told that each additional purchase would increase the balance that they observed at the beginning of the survey. They were instructed to observe the prices, read the product descriptions, and decide which product they would prefer. In each choice, the price and product category were held constant between the two options. The product categories and prices varied across choices (see Table 1.1).

Table 1.1: Spending Simulation Product Categories and Prices

Order	Product Category	Price
1	Candles	$31.00
2	Appetizers	$17.00
3	Shoes	$75.00
4	Detergents	$12.99
5	Snacks	$5.99
6	Sunglasses	$95.00
7	Pizzas	$18.49
8	Books	$14.50
9	Wines	$22.99
10	Hats	$35.00

Notes: All participants observed the same choice sets in the same order except for the hats category. Only participants who had an initial credit card balance under $3,000 made an additional purchase in this category to equate final balances.

Participants in both conditions were presented with the same nine choices. However, to ensure that the final balance was similar in both conditions, participants who initially observed a balance just under $3,000 made one additional purchase ($35 hat). After the spending simulation, all participants ended up with a credit card balance within a few dollars of $3,010. The exact balances were $3,311.11 for participants who initially observed a balance of $2,983.15 and $3,309.81 for participants who initially observed a balance of $3,016.85. Importantly, both conditions ended with a balance greater than $3,300, and the small difference between these final balances did not work in favor of H2. Participants who last observed a balance just under $3,000 made more purchases and ended up with a slightly larger balance.

After completing the spending simulation, participants were asked to consider the current balance on their credit cards, defined as the initial balance they observed at the start (on the

mobile app) plus any subsequent expenses. To assess their willingness to continue spending, they were asked to imagine that they would now like to buy $40 worth of clothes using their credit card as long as the current balance is less than or equal to $3,300. We offered a $0.20 bonus (equivalent to a 25% increase in their total compensation) under two conditions: If the current balance on the credit card was less than $3,300 and participants decided to buy the clothes, they would receive the bonus. Alternatively, if the current balance exceeded $3,300 and they decided not to buy the clothes, they would receive the bonus. This design rewards participants either for spending within their means or for prudently avoiding expenditures they cannot afford. In either case, choosing incorrectly (i.e., spending beyond $3,300 or not spending below $3,300) resulted in no bonus. In both conditions, the true current balance was over $3,300, meaning the incentivized correct decision was to refrain from buying the clothes.

After making their spending decisions, participants were asked to freely recall the last observed credit card balance that was presented to them in the mobile app image. Lastly, participants completed a brief demographic survey, indicated if they wrote down their balances or any expenses, and were notified of whether they earned the bonus. Bonuses were paid within one week of completing the study.

Results

We pre-registered a series of regressions to assess the impact of the last observed balance on the decision to make an additional purchase. Table 1.2 presents the results. In line with H2, the last observed balance had a significant impact on spending decisions (see Table 1.2, Model 1). Participants who last observed a balance just under $3,000 were more likely to make an additional purchase and therefore less likely to receive a bonus payment (Under $3,000 = 35.12%, Over $3,000 = 19.65%).

In addition, the last observed balance had a significant impact on recall errors (see Table 1.2, Model 3). Recall errors were calculated as the recalled balance minus the actual balance. On average, participants *underestimated* the last observed balance by $185.42 (Median = $79.65) when it was $2,983.15. In contrast, participants *overestimated* the last observed balance by $108.53, on average, (Median = $83.15) when it was $3,016.85. Regressing the decision to spend on both condition and recall errors suggests that the last observed balance manipulation was primarily responsible for the effect on spending (see Table 1.2, Model 2).

Table 1.2: Study 1 Regression Results for Overspending

	Purchase Clothes		Recall Error
	Model 1	**Model 2**	**Model 3**
Intercept	-1.408***	-1.352***	108.530***
	(0.136)	(0.140)	(13.88)
Under $3,000	0.795***	0.635**	-293.950***
	(0.178)	(0.203)	(19.70)
Recall Errors		-0.001†	
		(0.000)	
R-Squared			0.248
Num. Obs	677	677	677

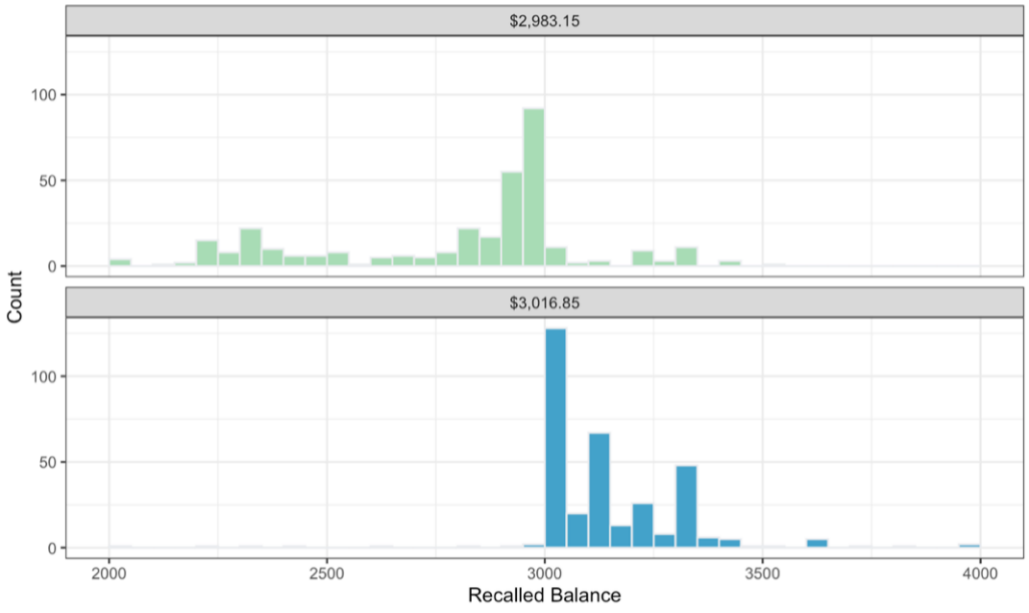
Notes: ***$p < .001$, **$p < .01$, *$p < .05$, †$p < .10$. Standard errors are in parentheses. The decision to purchase the clothes was regressed on condition and recall errors using logistic regression models. Recall errors were regressed on condition using a linear regression model.

The marginally significant negative effect of recall errors suggests that the likelihood of additional spending increased when the extent of underestimation was greater. However, this

weaker effect suggests that participants may not be confident in their point estimates. For example, if two participants who last observed a balance of $2,983.15 confidently (but incorrectly) remember the hundreds place as '2' and '8', then the participant who remembers a much smaller balance should be much more likely to continue spending, all else equal. Instead, participants may be incorrectly guessing the right digits because they are not confident about those digit values. In other words, both participants may only confidently recall the last observed balance as an amount greater than $2,000 but less than $3,000.

For a fairer test of recall accuracy by digit position, we did not exclude observations with recall errors greater than $1,000 (a pre-registered exclusion). Results are similar regardless of this exclusion. A large majority of participants (86.50%) could recall the leftmost digit (i.e., thousands place), but a minority of participants were correct about the right digits (hundreds place = 40.75%, tens place = 17.82%, ones place = 11.05%). To better understand the extent of recall errors for the last observed balance, we plotted histograms of recalled balances by condition (see Figure 1.2).

Figure 1.2: Study 1 Recalled Balances



Notes: Distributions of recalled balances. Bins are $50 and include the lower bound.

Discussion

Results from Study 1 suggest that observing credit card balances just under (over) round numbers is more likely to lead consumers to underestimate (overestimate) their current credit card debt. As a result, consumers may be more likely to end up with larger balances (i.e., spend more) when the last observed credit card balance is just under versus over a round number.

In relation to prior research (Sokolova et al. 2020), participants did not appear to round observed balances to recall the magnitude as about $3,000 in both conditions, on average. If this were true, we would not expect to observe this difference in willingness to make an additional purchase between conditions. Moreover, by eliciting estimates of the observed initial balances, we found that left digits were much more likely to be recalled accurately than right digits. This finding is in line with H1 and prior research on recalling complex numbers (Lacetera et al. 2012; Schindler and Chandrashekaren 2004; Schindler and Wiman 1989). Regarding left-digit biased magnitude perceptions, overestimation of $3,016.85 suggests that many participants did not simply truncate the right digits and perceive $3,016.85 as about $3,000. Despite a true difference of $33.70 between the two observed balances, due to both under- and overestimation, the average difference between recalled balances was $293.95.

One limitation of this design is that the size of the last observed balance is confounded with whether it falls just under or over a round number (i.e., $2,983.15 is smaller than $3,016.85). An alternative explanation could be that previously observing smaller balances increases the probability of underestimating debts and additional spending, regardless of whether the left digit is the same or different. We ran a replication with observed credit card balances that

differed by a similar amount but had the same left digit ($3,016.85 vs. $3,051.24). We did not find a significant difference in the probability of overspending between conditions, which suggests that a change in the left digit is necessary to produce the effect on spending (see Appendix A for results).

A second limitation is that participants learned about their budgets only after observing their balances in the app. In many cases, consumers may be tracking a balance against a budget throughout the month. We replicated the effect when consumers were aware of their budgets before they observed their balances and completing the shopping trip (see Appendix B for results). However, this effect may be attenuated when balances are just below salient budgets. We further explore how monitoring balances alongside budgets moderates the bias in Studies 4 and 6.

We observed a weak correlation between recall errors and spending in Study 1. Therefore, it is still unclear if recall mediates the effect of observing balances just under or over round numbers on current debt estimates and subsequent spending. Like prior research demonstrating both right-digit recall errors and biased decisions (e.g., Lacetera et al. 2012), it is unclear if recall is necessary to produce a bias in spending. In Study 2, we directly manipulated the necessity for recall to test this mechanism.

Study 2: Recalling Versus Perceiving Balances While Making Choices

Study 2 examined if recall is necessary to observe an effect of observing balances just under versus over round numbers on downstream spending. In Study 1, all participants had to rely on their memories of previously observed balances and expenses to estimate their current

debts and decide whether to continue spending. Yet, it is possible that a similar effect would have emerged even if participants could directly observe their balances while making their spending decisions. For example, due to left-digit anchoring (Thomas and Morwitz 2005) or threshold crossing (Kim et al. 2022), the difference between $2,983.15 and $3,300 may feel disproportionately larger than the difference between $3,016.85 and $3,300—even when these values are directly observed (i.e., recall is unnecessary).

If the spending effect in Study 1 is replicated under both conditions (i.e., balances are recalled or directly observed while making choices), then recall is not necessary to observe the effect. Alternatively, if the effect is only observed when balances must be recalled, then biased recall errors may mediate the relationship between left-digit changes and spending decisions in this choice context. From a theoretical perspective, this distinction matters because prior theorizing on left-digit bias (largely in the domain of price evaluations) suggests that left-digit effects may be *more* likely when consumers are directly observing values versus recalling values (Sokolova et al. 2020). From a practical perspective, the interventions required to attenuate left-digit effects depend on the mechanism. If the mechanism is biased recall errors (vs. a bias in perception), then simply displaying balances while consumers are making choices should reduce bias.

Method

Participants

We aimed to recruit 1,600 participants through Prolific before exclusions (US-based). Participants were excluded from analyses if they failed an attention check (n = 9) or indicated that they wrote down their balances or any prices (n = 96). Exclusions were pre-registered

(https://aspredicted.org/VDW_Q3K). The final sample included 1,497 participants (51.2% women, M_{age} = 40.25, $M_{hhincome}$ is between 55k – 65k (bucketed income question)).

Design

The experiment had a 2 (last observed balance: $2,983.15 vs. $3,016.85) x 2 (recalling last observed balance: necessary vs. not necessary) between-subjects design.

Materials and Procedure

If participants were randomly assigned to a condition where they had to recall the last observed credit card balance, the materials and procedure were identical to Study 1. They either observed a balance just under or over $3,000 and decided whether to make an additional purchase after learning about the $3,300 spending constraint. The other half of participants also observed an initial balance either just under or over $3,000 and completed the spending simulation; however, they were reminded of this balance on the credit card before deciding whether to make an additional purchase. The last observed balance (either $2,983.15 or $3,016.85) and the $3,300 spending constraint were both salient when participants were deciding whether to continue spending. In other words, participants had access to information about the last observed balance at the point of making a spending decision.

Results

We regressed the decision to continue spending on the last observed balance and recall conditions. We pre-registered a logistic regression to assess if directly observing the last observed balance and spending constraint while deciding whether to spend attenuated the main effect found in Study 1. There was a significant interaction (see Table 1.3). We replicated the effect from Study 1 when participants had to recall the last balance they observed to estimate their current available resources. Participants were more likely to overspend and miss out on the

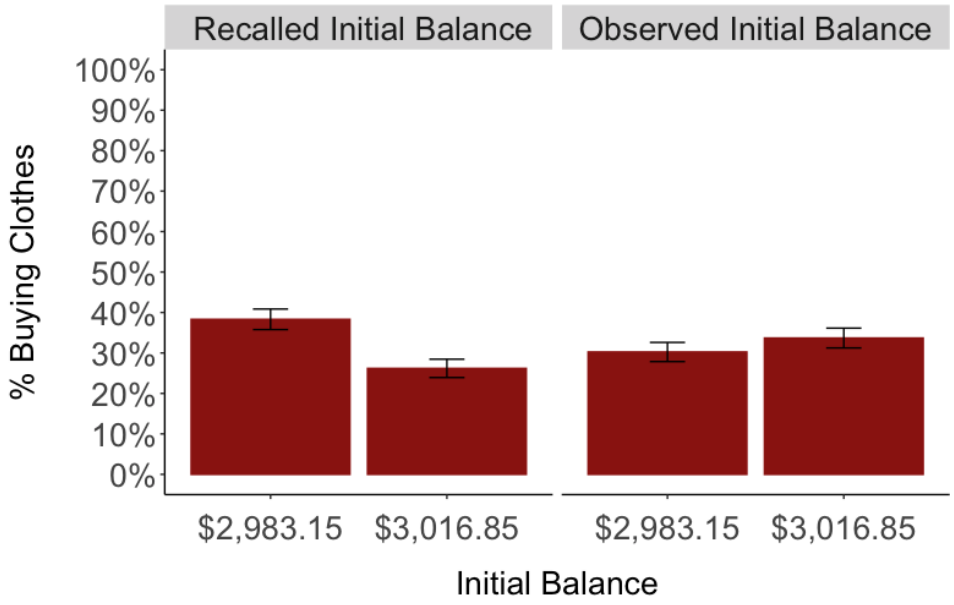
bonus when the last balance they observed was $2,983.15 (38.32%) versus $3,016.85 (26.19%) (see Figure 1.3). In contrast, when the last observed balance was available as consumers were making decisions, the effect was eliminated. Participants were similarly likely to overspend when the last observed balance was $2,983.15 (30.24%) versus $3,016.85 (33.69%).

Table 1.3: Study 2 Regression Results for Overspending

	Model
Intercept	-0.836***
	(0.112)
Over $3,000	0.159
	(0.157)
Recall Required	0.360*
	(0.155)
Interaction	-0.719**
	(0.223)
Num. Obs	1,497

Notes: ***$p < .001$, **$p < .01$, *$p < .05$, †$p < .10$. The dependent variable is the decision to make an additional purchase (buy = 1; not buy = 0). Standard errors are in parentheses.

Figure 1.3: Fraction of Participants Who Overspent



Notes: Error bars are standard errors.

Discussion

When participants were not required to recall the last observed balance, the effect of observing balances just under versus over round numbers on downstream spending was eliminated. This finding suggests that recall errors for the last observed balance mediates this relationship. Unlike prior research on left-digit bias that focuses on the impact of biased perceptions on spending decisions (e.g., Kim et al. 2022; Manning and Sprott 2009), we shed light on a context where right-digit recall errors themselves affect one's ability to make prudent spending decisions.

One limitation of Studies 1 and 2 is that we used two specific balances to represent balances that are just under versus over round numbers ($2,983.15 and $3,016.85). Our goal was to balance digit complexity and distance from the closest multiple of $1,000. However, to speak more generally about how the kinds of balances consumers observe affect future estimates of

their cumulative spending and available resources, we would ideally sample from a variety of different balance amounts. We addressed this limitation in Studies 3 and 6.

Further, despite simulating shopping experiences in Studies 1 and 2, the hypothetical nature of these experiments could account for the steep drop in recall accuracy for right digits. In Study 3, we asked participants to recall and report their own credit card balances to test if consumers struggle to keep track of the right digits of their own balances.

Study 3: Recalling and Reporting Balances

Method

Participants

A total of 800 participants were recruited from Prolific to participate in a survey about their personal finances (US-based and even male/female recruitment features selected). Participants were informed upfront that they would be asked to report information about their financial situation, and they were asked to return the job to Prolific if they were unwilling to provide such information. Participants were excluded from analyses if they 1) failed an attention check (n = 6), 2) indicated that they did not actually check and report their exact balances when instructed[1] (n = 111), and 3) if they did not enter their balances or reported a zero balance (n = 51). Exclusions were pre-registered (https://aspredicted.org/2YT_LYS).

[1] To encourage honest reporting, participants were informed that they would not receive any penalty or payment reduction if they indicated that they did not actually look up their exact account balances.

There were 632 participants who recalled and reported checking account balances and met the exclusion criteria. Within this sample, 50.2% were women, and they ranged in age from 19 to 76 years old (M = 39.3) with a median annual income of $45,000[2]. Fewer participants recalled and reported credit card balances (n = 480), but the sample was largely overlapping (98.3% of these participants also reported checking balances) and therefore demographics were similar, including 50.9% women with an age range from 19 to 75 (M = 39.7) and a median annual household income of $50,000.

Materials and Procedure

Participants were asked to estimate their exact balances in their main checking account and on their main credit card (randomized order). Then, they were asked to check and report their actual balances using their online banking apps. If they did not have a bank account or credit card, or they decided against reporting their balances, they were asked to enter NA.

After estimating and reporting their balances, participants indicated the number of days it had been since they last checked their balances, how frequently they check their balances each month (on average), and the fraction of their monthly expenses from cash/debit versus credit. They then provided information about their age, gender, annual income and wealth, and completed an attention check. Lastly, they indicated if they actually checked and reported their exact balances.

Results

[2] Unlike Studies 1 and 2 that used a bucketed income question, participants in this study freely reported their income using an open text box.

Account Management

To draw comparisons between how consumers manage their credit cards versus their checking accounts, we created a subsample of participants who passed the exclusion criteria for both credit card and checking balances (n = 472).

We first observed how recently participants checked their balances. A paired samples *t*-test revealed that fewer days had passed on average since participants last observed their checking balances versus credit card balances ($M_{checking} = 3.67$, $M_{credit} = 7.56$, $t(468) = -3.43$, $p < .001$). The median number of days that had passed since participants last checked their balances was one day for checking and three days for credit cards.

A similar pattern emerges for the number of times participants checked their balances in a typical month. A paired samples *t*-test revealed that participants observed their checking account balances more frequently, on average, than their credit card balances ($M_{checking} = 14.07$, $M_{credit} = 8.74$, $t(471) = -12.45$, $p < .001$). The median number of times participants observed their checking balances in a typical month (10 times) was higher than their credit card balances (4 times). These results are in line with the prior research suggesting that balances are only periodically observed (Medina 2021).

Lastly, participants' typical monthly transactions were split evenly between cash or debit (48.5%) and credit (49.2%).

Recall Errors

We focused on a subset of data with balances in the thousands throughout the project since these balances are representative of average US consumers (checking n = 256; credit n = 222). However, recall accuracy by digit position is similar when including all balances greater than or equal to $100 (pre-registered inclusion criterion for this analysis).

For both checking and credit card balances, recall was most accurate for the thousands place (checking = 79.3%; credit = 80.6%), followed by a large drop in accuracy for the hundreds place (checking = 39.1%; credit = 40.5%) and tens place (checking = 24.6%; credit = 25.7%). Logistic regressions (separate models for checking and credit) were used to predict digit recall accuracy based on the first three digit positions (thousands place = 1, hundreds place = 2, tens place = 3). In line with our experiments and in support of H1, these models confirm that participants were significantly less likely to accurately recall digits that were further to the right ($ps < .001$).

We compared balances that were under the closest multiple of $1,000 (i.e., hundreds place digit between 5 and 9) versus over the closest multiple of $1,000 (i.e., hundreds place digit between 0 and 4). For both checking and credit card balances, participants were more likely to underestimate balances by at least one dollar[3] when they were under the closest multiple of $1,000 (checking = 56.7%; credit = 65.9%) versus over (checking = 45.4%; credit = 48.9%). We pre-registered four logistic regression models to formally test these differences. We regressed an underestimation indicator (1 = underestimated by at least $1, 0 = else) on an indicator for the balance being under the closest multiple of $1,000. We ran separate models for credit card and checking balances, and separate models controlling for balance, recency of last log in (log transformed), log income, and log wealth. Without controls, these models revealed a significant effect of having a balance under versus over the closest multiple of $1,000 for credit card

[3] Less than 4% of participants estimate digits right of the decimal place. Including errors at this level would significantly increase average underestimation rates across conditions.

balances (β = 0.71, p = .012), but only a marginally significant effect for checking balances (β = 0.46, p = .076). With controls, these models revealed a significant effect for both credit card balances (β = 1.10, p = .005) and checking balances (β = 0.80, p = .024).

To better understand the extent of recall errors, we compared average recall errors for balances under versus over the closest multiple of $1,000. Like Study 1, recall errors were calculated as the recalled balance minus the true balance (i.e., negative errors represent underestimation). Means were heavily influenced by outliers (e.g., an error of $10,255.67). We again pre-registered an exclusion rule of errors greater than $1,000 in either direction. This rule roughly aligns with removing errors greater than the 95th percentile and less than the 5th percentile, and so it is not unusually restrictive (excluded 19 participants from the credit card analysis and 23 participants from the checking analysis).

Participants underestimated their balances to a greater degree when they were under versus over the closest multiple of $1,000 (checking: -$78.68 vs. -$33.48; credit card: -$101.09 vs. -$2.49). We estimated separate regressions for checking and credit card balances, as well as separate models that controlled for balance, recency of last log in (log transformed), log income, and log wealth. These regressions revealed that average recall error for balances just under versus over the closest multiple of $1,000 is lower but only significantly lower for credit card balances (checking without controls: β = -45.20, p = .212, checking with controls: β = -66.8, p = .186; credit card without controls: β = -98.59, p = .010; credit card with controls: β = -109.25, p = .033).

Discussion

Consumers were much more aware of the leftmost digit of their own credit card and checking account balances than the right digits. Consumers may struggle to recall and track the right digits of their balances, leading to predictable estimation biases.

As expected, we found that consumers were more likely to underestimate their balances when they were under (versus over) the closest multiple of $1,000. Unexpectedly, average recall errors were slightly negative for balances over the closest multiple of $1,000, meaning balances were slightly underestimated, not overestimated, on average. There are two key differences between this study and Study 1 that may account for this difference. First, our conditions included balances that were closer to the midpoint between multiples of $1,000 (e.g., $2,500). Conditions were simply split by whether balances were under or over the closest multiple of $1,000. For balances further from multiples of $1,000, it is harder to make predictions about the direction of recall errors. Second, it is unclear if these consumers had previously observed the balances they reported or observed different balances when they last checked their accounts. For example, if someone's current exact balance is $3,131.57, but their previously observed balance was $2,973.12, we would expect them to underestimate the current balance.

Although recall errors were more extreme for credit card balances, we observed a similar pattern of misestimation for checking account balances. Given that checking and credit card balances move in opposite directions with additional spending, this study suggests that the same mechanism may cause consumers to overestimate resources after observing credit card balances just under round numbers, but underestimate resources after observing checking accounts just under round numbers. We revisit this idea in the General Discussion.

In the next studies, we consider moderators that may improve recall accuracy and therefore reduce bias. One possible moderator is whether consumers encode and rehearse their

balances in the context of close reference points. When typical daily expenses could cause consumers to overspend because their balances are close to spending limits, they may pay more attention to the right digits and rehearse them more to avoid overspending. We test these possibilities in Studies 4 – 6.

Study 4: Encoding Balances Alongside Spending Limits

Method

Participants

We aimed to recruit 800 participants through Prolific before exclusions (US-based). Participants were excluded from analyses if they failed an attention check (n = 11), indicated that they wrote down the balance or any prices (n = 77), or if their recall errors were greater than $1,000 in absolute value (n = 19). Exclusions were pre-registered (https://aspredicted.org/VM5_ZWL). The final sample included 694 participants (60.5% women, M_{age} = 38.51, $M_{hhincome}$ is between 55k – 65k (bucketed income question)).

Design

Following Studies 1 and 2, participants were randomly assigned to observe an initial credit card balance just under ($2,983.15) or just over ($3,016.85) $3,000.

Materials and Procedure

The materials and procedure were nearly identical to Study 1. The only difference was that all participants were told that they can afford to have a total credit card balance of $3,300 right before they observed their initial credit card balances and started the spending simulation.

Results

When participants learned about the $3,300 spending limit just before observing their initial balances, the effect of previously observing a balance just under versus over a round number on spending decisions was attenuated. Participants who last observed a balance just under $3,000 decided to make an additional purchase 31.56% of the time. A slightly smaller fraction of participants, 27.04%, decided to make an additional purchase when they observed a balance just over $3,000. This difference was in the same direction as the effect from Study 1 but no longer statistically significant at the $p < .05$ level ($\beta = 0.219$, $p = .191$).

Recall errors were less extreme in this study relative to Study 1. When the last observed balance was just under $3,000, participants *underestimated* it by $63.68 on average (Median = - $33.15). When the last observed balance was just over $3,000, participants *overestimated* it by $62.82 on average (Median = $14.15). For comparison, Study 1 recall errors were more extreme in both directions (average underestimation = - $185.42 (Median = - $79.65); average overestimation = $108.53 (Median = $83.15)).

Discussion

Study 4 results suggest that being aware of close spending limits attenuates the effect of observing balances just under versus over round numbers on downstream spending. Further, less extreme recall errors suggest that consumers may focus more on right digits to avoid accidentally overspending. This study highlights the importance of setting clear spending limits and monitoring balances relative to those limits. However, for credit card balances just over round numbers, lower recall accuracy for right digits may lead to more conservative spending. In a context where overspending is much more costly than underspending, these errors may be helpful.

From a theoretical perspective, we highlight a context in which comparisons to reference points can weaken choice effects due to left-digit changes. In contrast, prior research in the pricing domain has often found a left-digit bias when focal prices are observed alongside reference prices (e.g., Manning and Sprott 2009). We posit that the movement of balances toward reference values (e.g., budgets) with additional spending may be one theoretically important distinction, given that prices in prior studies are often fixed and not moving toward or away from reference prices. However, more work is needed to understand these differences.

In Studies 5 and 6, we further examine this spending limit moderator by testing if the difference between balances and spending limits affects 1) how aware consumers are of their balances and 2) how well consumers can recall right digits. In Study 5, we analyzed bank account login data from a large retail bank to test if cardholders are more likely to log in when balances are near credit limits. Logins served as a proxy for motivation to know one's balance. In Study 6, we followed up this bank data analysis with a lab experiment to directly manipulate the difference between balances and credit limits and measure recall errors.

Study 5: Analysis of Bank Account Logins

We obtained a sample of end-of-day credit card balances from a large retail bank. The sample includes five months of data (February to June 2022) comprising 2.74 million balances from 19,579 accounts and 17,331 customers. Using online account logins as a proxy for motivation to know one's credit card balance, the goal of this analysis was to test if the probability of logging in increases as balances get close to credit limits, controlling for repayment days.

We focused on a subsample of observations in which customers had positive balances below their credit limits and had active accounts. Active accounts were defined as having at least one change in the balance, login event, and repayment. This subset includes 1.76 million balances from 14,510 accounts and 13,103 customers.

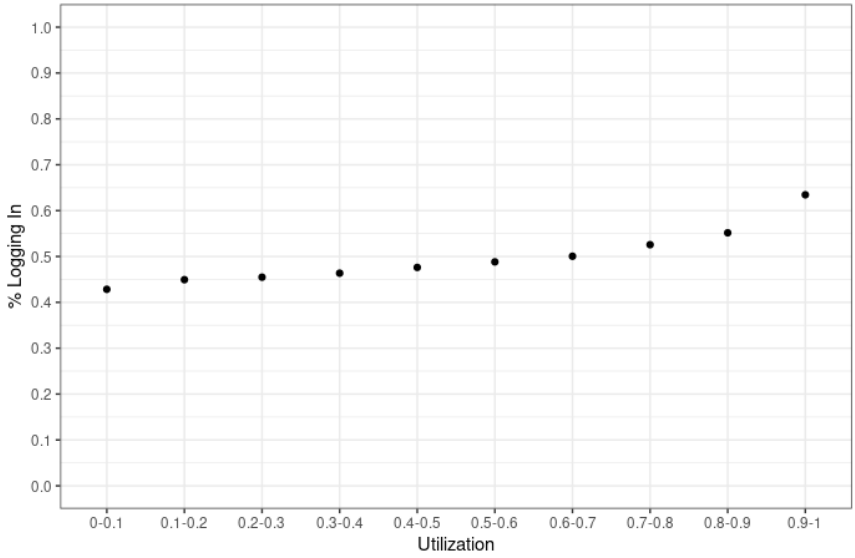
Utilization served as our measure of balance proximity to the credit limit. Utilization was calculated by dividing the end-of-day balance by the credit limit. We ran linear probability models[4] regressing a daily login indicator (1 = logged in at least once; 0 = did not log in) on utilization, an indicator for repayment, and credit limit (see Table 1.4). We estimated aggregate models (Models 1 and 3) and models that included account, day-of-the-week, day-of-the-month, and month fixed effects (Models 2 and 4).

Results

Both across and within accounts, we found that the probability of logging in increases as utilization increases, controlling for repayment days. In other words, as balances increased toward the credit limit, customers were more likely to log in to their online accounts. However, Figure 1.4 depicts a positive, non-linear relationship between utilization and the probability of logging in. Customers were only slightly more likely to log in when their balances were not just below their credit limits (i.e., lower utilization). When balances were very close to credit limits (i.e., high utilization), customers were much more likely to log in.

[4] Linear probability models were used for ease of interpretability. Results are similar using logistic regression.

Figure 1.4: Probability of Logging in as a Function of Utilization



Notes: Bins include the lower bound.

Table 1.4: Regression Results for the Probability of Logging In

	Model 1	Model 2	Model 3	Model 4
Intercept	0.444***		0.480***	
	(0.001)		(0.001)	
Utilization	0.166***	0.009***	-0.096***	-0.026***
	(0.001)	(0.002)	(0.004)	(0.006)
Utilization^2			0.261***	0.036***
			(0.004)	(0.006)
Repayment	0.266***	0.184***	0.265***	0.184***
	(0.001)	(0.001)	(0.001)	(0.001)
Credit Limit	-0.000***	-0.000	-0.000***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Account FE		X		X
Month FE		X		X
Weekday FE		X		X
Day-of-Month FE		X		X
R-Squared	0.047	0.022	0.049	0.022
Obs.	1,763,038	1,763,038	1,763,038	1,763,038

Notes: ***$p < .001$, **$p < .01$, *$p < .05$, †$p < .10$. Linear probability models regressing logins on utilization, repayment events, and credit card limits. Models 2 and 4 included

account, month, day-of-week and day-of-month fixed effects. Standard errors are in parentheses.

Discussion

Customers from a large retail bank were slightly more likely to log in to their online bank accounts as credit utilization increased, but much more likely when their balances were very close to their credit limits. Treating logins as a proxy for motivation to know one's balance, these findings suggests that cardholders are more concerned with knowing their balances as they near their credit limits. In Study 6, we conducted an experiment to directly assess how recall accuracy changes as balances approach credit limits.

Study 6: Balance Proximity to Credit Limits

Method

Participants

A total of 721 Prolific participants participated (US-based and even male/female recruitment features selected). After excluding participants who failed an attention check (n = 10) or reported that they wrote down their balances (n = 39), the final sample included 672 participants (50% women, M_{age} = 35.76, $M_{hhincome}$ is between 45k – 65k (bucketed income question)). Exclusions were pre-registered (https://aspredicted.org/77Q_X7P).

Design

Participants were randomly assigned to a condition in a 2 (balance: $1,800.00-$1,999.00 vs. $2,800.00-$2,999.00) x 3 (credit limit: none, $3,000, $5,000) between-subjects design. Exact

balances were randomly generated for each participant within these two ranges. Importantly, our prior studies suggest that balances in both ranges tend to be underestimated. Therefore, introducing a credit limit factor allows for a test of whether consumers underestimate their balances to lesser extent when 1) credit limits are introduced and 2) those credit limits are closer to balances.

Materials and Procedure

Participants who were randomly assigned to observe a credit limit first learned that their hypothetical credit card had a limit of either $3,000 or $5,000. Participants who did not observe a credit limit (i.e., none condition) skipped this page. After, all participants were asked to imagine that it is nearing the end of the month, and they observed their exact credit card balance. Further, they imagined that this credit card was used to make most of their monthly purchases.

Participants then completed six filler tasks. The fillers included 1) a demographics survey asking about age, gender and household income, 2) a discounting task that asked participants to indicate their preference between a smaller-soon and larger-later reward, 3) the short-term Propensity to Plan for Money scale (Lynch et al. 2010), 4) the Tightwad-Spendthrift scale (Rick, Cryder, and Loewenstein 2008), 5) two questions about forecasted slack in time and money (Zauberman and Lynch 2005), and 6) if they mostly spend with a debit card or a credit card in a typical month. We selected tasks related to financial decision making to reduce skepticism that these tasks primarily operated as filler tasks between observing and recalling balances.

After the filler tasks, participants attempted to recall their exact credit card balances. On the next page, they also attempted to recall their exact monthly credit limits. Lastly, they indicated if they wrote down their balances.

Results

Collapsing across conditions, recall accuracy decreased as the digit position moved to the right. Participants correctly recalled the leftmost digit in 82.0% of cases, with recall accuracy dropping to 57.4% for the hundreds place. Accuracy continued to drop to 30.7% for the tens place. A logistic regression that treats digit position as numeric (e.g., thousands place = 1, hundreds place = 2, tens place = 3) revealed a significant decrease in accuracy for digits farther to the right ($\beta = -1.46$, $p < .001$).

We regressed recall errors on credit limits (dummy variables for 3k and 5k), balance (dummy variable for > $2,000), and their interaction terms. Recall errors were defined as the recalled balance minus the true balance. This regression tests how introducing credit limits that are closer to or further from balances affects recall errors.

No significant differences in average recall error between conditions were found, but these null results are heavily influenced by extreme outliers (e.g., an error of $26,899.27). We pre-registered exclusions of outliers defined as errors greater than $1,000 (n = 95) or using Tukey's rule (n = 209). For 64 of these 95 errors greater than $1,000, it appears participants incorrectly reported the credit limit as the balance (e.g., recalling a balance of $5,000 when they had a $5,000 credit limit and a true balance below $2,000). This confusion likely stemmed from our asking participants to recall the credit limit and the credit balance on different pages. To highlight that these recalled values are different and to test the robustness of these results, we ran a replication with different balances and credit limits where participants recalled the credit limit and balance on the same page. The key results of this replication do not meaningfully differ from the key results reported here (see Appendix C).

Using either exclusion criterion, we found an interaction. Introducing a $3,000 credit limit (relative to no limit) had a larger effect on reducing underestimation (i.e., increasing

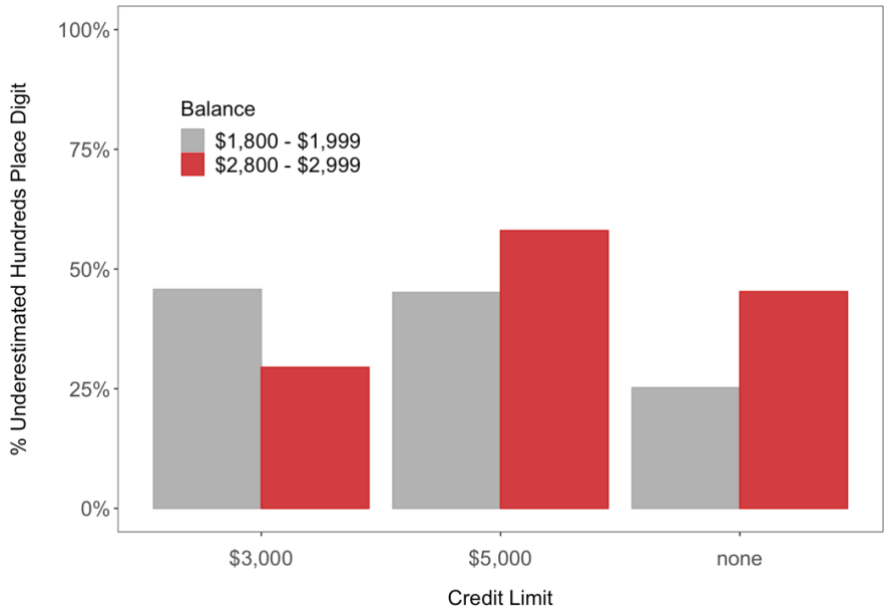
accuracy) when balances were just under $3,000 ($2,800.00 - $2,999.00) versus further from $3,000 ($1,800.00 - $1,999.99) ($1,000 exclusion: $\beta = 142.98$, $p = .005$; Tukey's exclusion: $\beta = 56.56$, $p < .001$). There was no significant interaction when a $5,000 credit limit was introduced. In both cases, having a balance between $1,800.00 and $1,999.99 or $2,800.00 and $2,999.99 is still relatively far from the $5,000 credit limit. Introducing this $5,000 credit limit did not impact recall accuracy differentially across conditions.

We then focused in on errors at the hundreds place. Errors at the hundreds place are what produce predictable recall errors for balances in the thousands. Using a logistic regression, we regressed a dummy for underestimating the hundreds place on credit limits (dummy variables for 3k and 5k), balance (dummy variable for > $2,000), and their interaction terms. Consistent with average recall errors, we found a significant interaction. Introducing a $3,000 credit limit (relative to no limit) reduced the probability of underestimating the hundreds place digit when balances were just below $3,000 ($2,800.00 - $2,999.00) while it slightly increased the probability of underestimating the hundreds place digit when balances were just below $2,000 and further away ($1,800.00 - $1,999.99) ($\beta = -1.60$, $p < .001$; see Figure 1.5)[5]. This interaction holds for a subset of participants who correctly recalled the leftmost digit. Under this restriction, recalling a smaller hundreds place value must be underestimation and not the result of rounding up (e.g., recalling $2,938.12 as $3,000) ($\beta = -1.67$, $p = .002$). Like average recall errors, this interaction is not significant when the credit limit is $5,000 ($\beta = -0.38$, $p = .332$).

[5] This interaction holds when participants who appeared to incorrectly report the credit limit instead of estimating the balance (i.e., enter exactly $3,000 or $5,000) are excluded. See Appendix C.

Interestingly, we observed a lower probability of underestimating the hundreds place digit when balances were just below $2,000 versus $3,000. Future research could investigate how the leftmost digit affects recall accuracy of the right digits.

Figure 1.5: Fraction of Participants Who Underestimated the Hundreds Place



Notes: Balances estimates that are equal to the credit limits (i.e., $3,000 or $5,000) are included. See Appendix C for alternate figure excluding these observations.

Discussion

These findings suggest that consumers are better able to recall the right digits of their balances (specifically the hundreds place) when close reference points are introduced, such as credit limits. When a change in the hundreds place digit could result in spending over a credit limit, consumers, reasonably, are less likely to forget it.

These results also suggest that even if consumers observe their balances alongside spending limits, they still may be at risk of overestimating their available resources and spending more if salient spending limits are further out (see Appendix B).

General Discussion

Building on theories of left-digit bias and goal monitoring, Essay 1 offers new insights into how well consumers know their credit card balances and when they are at risk of misestimating their debts and available resources. Although paying more attention to one's balances may protect against financial mistakes in general (Caflisch et al. 2018), observing some kinds of balances may be more beneficial than others. Our findings suggest that consumers are more likely to underestimate their credit card debt (and therefore overestimate their available resources) when the last balance they observed was under versus over a multiple of $1,000. As a result, they are at a higher risk of overspending. This pattern arises from challenges in recalling the right digits of complex numbers. However, encoding balances alongside salient and close reference points (e.g., credit limits) improves recall and moderates these risks.

Contribution

This project contributes to the marketing literature by expanding on when and how consumers misestimate their finances. Previous research finds that unusual or exceptional expenses are more difficult to track and to anticipate than typical expenses (Heath and Soll 1996; Sussman and Alter 2012). Moreover, some payment methods, like credit cards, can make it easier to forget specific expenses (Gafeeva, Hoelzl, and Roschk 2018; Soman 2001). Generally, consumers may underestimate their spending when summing up past expenses (Goswami,

Greenberg, and Schley 2021). In addition to investigating how well consumers recall and manage their expenses, our research emphasizes the significance of balance recall errors for consumer spending and savings decisions. With widespread access to online banking and budgeting apps, consumers can easily observe their financial information. However, they check this information infrequently, and it is unlikely to be salient during many transactions (the median participant logs in 4x per month; Medina (2021) finds similar results). To estimate their available resources, consumers must often rely on their memory of their last observed balances and their recent transactions. Even when they only incur a few new, easy to remember transactions, they still risk misestimating their cumulative spending and resources because complex balances are difficult to remember.

In addition, this project enhances our understanding of how prominent numbers affect consumer judgments and decisions (Santana, Thomas, and Morwitz 2020). We focused on how consumers process and recall multi-digit numbers. Prior research on left-digit bias for prices and other multi-digit numeric attributes is primarily concerned with studying distortions in perceived magnitude of values just under round numbers (e.g., Thomas and Morwitz 2005). Although inaccurate recall of right digits can be a byproduct of left-digit biased processing, there is little evidence that right-digit recall errors themselves influence consumer behavior. In this context, we find that recall is necessary to detect an effect of left-digit changes on downstream spending decisions.

We also found that right digit recall improves when balances are encoded alongside close spending limits. This finding aligns with prior research on round number reference points and goal monitoring. For example, many marathon runners finish just under rather than over three hours (Allen et al. 2017; Markle et al. 2016). Achieving this feat likely requires closely

monitoring the right digits of their running times (e.g., 2 hours and 51 minutes with one mile left, or 2 hours and 59 minutes with one mile left). Although we identified significantly larger right-digit errors when balances were evaluated in isolation or further from relevant reference points, Studies 4 and 6 suggest that consumers better remember right digits to avoid spending over limits.

Although introducing close comparison points may mitigate bias by improving right-digit recall errors in this context, prior research on price perception finds that introducing close comparison points can strengthen a left-digit bias in perception (Troll et al. 2024). This difference highlights the importance of studying the effects of left-digit changes in a variety of consumer contexts. The choice of whether to introduce or remove a close comparison point to debias consumers depends on the choice context.

From a managerial perspective, this research provides retail banks and budgeting platforms with a better understanding of how aware their customers are of their own resources and when they may be more likely to underestimate their debts and overspend. Recent research finds that, in general, increasing attention to mobile banking information can decrease discretionary spending and fees (Carlin et al. 2019; Levi and Benartzi 2022). Our research suggests that the specific balances consumers observe in their accounts may moderate downstream debt estimates and spending decisions.

To improve consumers' recall of the balances they have observed and reduce left-digit effects, online banking and budgeting apps could encourage consumers to set close spending limits and display those limits clearly alongside balances. In lieu of getting consumers to explicitly set spending limits, apps could encourage comparisons by clearly displaying how much consumers spent in the last month or the nearest round number. As an added benefit, prior

research finds that consumers are more likely to repay debts when they round them (Isaac, Wang, and Schindler 2021).

Many of these platforms allow consumers to set balance push notifications once balances exceed some amount. Given that people often choose and adopt round number cutoffs (e.g., Pope and Simonsohn 2011), these push notifications would increase the probability that consumers observe credit card balances that are just over versus under round numbers, which may protect against underestimating their debts.

Future Directions

Across our studies, we focused on how consumers manage a single balance. However, many consumers attempt to keep track of several accounts simultaneously, such as the balance in their checking account and on their credit card(s). Future research could explore how managing multiple accounts influences estimates of available resources. One prediction from this research is that consumers with otherwise similar credit card and checking account balances may be differentially likely to overestimate their available resources. For example, a consumer who last observed a $4,001.34 credit card balance and $4,993.12 in their checking account may feel significantly more constrained than a consumer who last observed a $3,993.12 credit card balance and $5,001.34 in their checking account—despite less than a $20 difference in net assets between these consumers. However, if consumers treat their checking account balances like spending limits, left-digit changes may have weaker effects due to improved right-digit recall.

In addition to spending, another key variable of interest is the amount of money consumers save or allocate to paying down their debt. One prediction from this research is that consumers may save less or allocate less to their payments if they underestimate their debts. This could result in taking on more interest than anticipated for cardholders who regularly make

partial payments. On the other hand, if consumers overestimate their debts and set aside more for repayments, do they choose to pay more than planned or reallocate those additional funds? A better understanding of how consumers recall and estimate multiple debts and savings accounts would offer a more complete picture of how biased memory errors affect credit card management.

Conclusion

In sum, Essay 1 offers new insights into how aware consumers are of their debts and available resources, and how predictable memory errors can influence spending decisions. Moreover, it highlights an important interplay between left-digit bias in perception, right-digit recall errors, and goal-driven monitoring. Beyond an academic audience, our findings may be particularly useful for retail banks that aim to better understand their customers' abilities to manage their credit cards and how to help them make better spending decisions.

Essay 2 focuses on the repayment side of credit card management. In addition to monitoring balances and spending within budgets, consumers must decide how much to repay each month. Both aspects are crucial for successful credit card management.

A growing body of research has aimed to study how consumers choose their monthly payments (Agarwal et al. 2015; Guttman-Kenney et al. 2025; Hendy, Slonim, and Atalay 2021; Keys and Wang 2019; McHugh and Ranyard 2016; Medina and Negrin 2022; Navarro-Martinez et al. 2011; Sakaguchi et al. 2024; Salisbury 2014; Salisbury and Zhao 2020; Stewart 2009). Ideally, consumers would carefully consider their finances and then calculate an appropriate payment amount. For example, when managing multiple credit cards, consumers can minimize their total debt by first paying at least the minimum on all cards and then allocating remaining resources based on interest rates (Hirshman and Sussman 2022). However, given limitations in

attention, memory and processing, consumers may instead rely on heuristics to determine their payments.

In Essay 2, along with my co-authors, I study how consumers use certain cues on credit card statements (i.e., focal payment options) to help them determine their payments. Although anchoring is often assumed to be the heuristic that consumers use to determine their payments, I find that consumers seem to adopt partial payment targets that they aim to meet or exceed. Like in Essay 1, I study credit card management with a series of experiments and data from a large commercial bank.

Essay 2: Anchors or Targets? An Examination of Focal Payment Options on Credit Card Statements

Abstract

Credit card statements often highlight a few partial payment options, like the minimum payment due and the amount needed to pay off the statement balance in three years. Prior research suggests that these focal payment options operate as anchors from which cardholders adjust to determine their payments. Across four experiments and data from a large US commercial bank, the authors find that these values operate more like targets rather than anchors. Although targets and anchors may seem similar, they are psychologically distinct. Most notably, targets have motivational properties, where an outcome on one side of a target is disproportionately preferred to an outcome on the other side of a target, whereas anchors act as motivationally-neutral starting points for judgments. Although focal payment options that currently appear on statements may be better characterized as targets, the authors find a focal payment option framing that produces a typical anchoring effect—placeholder text example payments—that could be introduced to online statements to influence payments. A better understanding of how cardholders respond to a variety of focal payment options can help credit providers structure statements to improve consumer well-being.

Americans carry over a trillion dollars of credit card debt in aggregate (Federal Reserve Bank of New York 2024). Each month, consumers face a decision of how much of their credit card debt to repay. In many cases, cardholders pay their statement balances in full to avoid fees and interest charges. However, the majority of US cardholders with active accounts regularly choose to make partial payments and revolve their balances (Keys and Wang 2019).

Prior research often suggests that cardholders use a heuristic to determine partial payments—they *anchor-and-adjust* from focal payment options on their statements (Agarwal et al. 2015; Guttman-Kenney et al. 2025; Hendy, Slonim, and Atalay 2021; Keys and Wang 2019; McHugh and Ranyard 2016; Medina and Negrin 2022; Navarro-Martinez et al. 2011; Sakaguchi et al. 2024; Salisbury 2014; Salisbury and Zhao 2020; Stewart 2009; Thaler and Sunstein 2009). This anchoring heuristic involves adopting a starting value and adjusting to a final response (Tversky and Kahneman 1974). For example, a cardholder may start by considering paying the minimum and incrementally increase their payment until they arrive at their preferred amount. Importantly, because adjustments from anchors are often insufficient, final judgments are biased toward the anchor (Epley and Gilovich 2006; Simmons, LeBoeuf, and Nelson 2010).

Early evidence for the use of the anchoring heuristic in credit card payments comes from Stewart (2009), who found lower partial payments when minimum payment amounts were included (versus excluded) on credit card statements. This pattern is consistent with participants anchoring and adjusting from the minimum payment to determine their payments. Because minimum payments are relatively small (typically 2-3% of the balance), anchoring on them may reduce payment sizes relative to when the minimum is omitted. Subsequent experiments and

analyses of credit card data replicate the effect of minimums and three-year amounts[6] on partial payments (Hershfield and Roese 2015; Keys and Wang 2019; Salisbury and Zhao 2020).

Although this effect could arise from an anchoring process, it could also arise from cardholders pursuing targets or reference points (Heath, Larrick, and Wu 1999). Anchors and targets share surface-level features, and therefore, can be challenging to tease apart (Bartels, Herzog, and Sussman 2023; Chapman and Johnson 2002; Kahneman 1992); however, they are psychologically distinguishable.

Both anchors and targets can shift average and median responses, but unlike anchors, targets are values that people strive for, like a desired marathon finishing time (Allen et al. 2017; Markle et al. 2018), a baseball batting average of .300, or scoring above multiples of 100 on the SAT (Pope and Simonsohn 2011). Given their motivational properties, there may be a discontinuous (or disproportionate) change in value when targets are met. As a result, responses tend to pile up or "bunch" at and on one side of targets. For example, people are much more likely to finish a marathon in 3 hours and 59 or 58 minutes than 4 hours and 1 or 2 minutes, and they exert more effort as they approach their goals (Allen et al. 2017).

The idea that focal payment options may be perceived as targets stems from the observation that these values have produced significant bunching at and just above these values in payment distributions (Hershfield and Roese 2015; Stewart 2009), which is more characteristic of typical target effects than typical anchoring effects (Bartels, Herzog, and

[6] The amount required to repay a credit card balance in full in three years appears on many US statements because of the CARD act of 2009.

Sussman 2023). In addition, consumers are motivated to pay off their credit card balances in full (Gal and McShane 2012). If they cannot pay off their balances in full, they may look for subgoals (i.e., partial payment targets) to pay each month instead.

The influence of targets on debt repayment has previously been explored in the context of managing multiple debt accounts (Amar et al. 2011; Gal and McShane 2012; Kettle et al. 2016). This literature suggests that cardholders have a superordinate goal of repaying all their debt, and they treat individual account balances as subgoals (i.e., targets). Both partial payments (Kettle et al. 2016) and full payments (Gal and McShane 2012) can affect perceived goal progress and future debt payment decisions.

The current project builds on this literature by considering if and how partial payment targets form when consumers are evaluating a single credit card statement. Specifically, we hypothesize that focal payment options highlighted on credit card statements, like minimums or the three-year amount, may be adopted as targets. Despite the focus on anchoring (Stewart 2009), payment cues (Hershfield and Roese 2015), and salience (Salisbury and Zhao 2020) in the literature, it remains unclear which psychological processes underlie the effect of these focal payment options on payment decisions. We suggest that theories of targets better represent how these values affect payments.

Mechanisms Underlying Focal Payment Option Effects

Prior research suggests that minimums and other salient partial payment options (e.g., the three-year amount) operate as anchors. Further, some researchers have proposed that these focal payment options operate as cues or suggestions for the most appropriate amount to pay

(Hershfield and Roese 2015; Sakaguchi et al. 2022; Thaler and Sunstein 2009). Although these previously proposed mechanisms could operate independently to influence payments, it is also possible that they are related. Thaler and Sunstein (2009) describe minimums as both anchors and nudges for an appropriate payment amount. For example, cardholders may first consider a focal payment option as a suggested starting point that puts them in the ballpark of acceptable payments and adjust from there.

The current project builds on this prior research by considering whether theories of targets better characterize the effect that minimums, three-year amounts, suggested payments, and other values have on partial payment decisions. We suggest that effects that have previously been attributed to anchoring may instead result from cardholders pursuing targets. This distinction matters because it is important for credit issuers and policymakers to know how introducing or changing focal payment options will affects payments. This requires a deeper understanding of the mechanisms at play.

As an example, consider predictions from theories of anchors and targets on how introducing a new "suggested payment" to credit card statements would affect payments. If cardholders anchor-and-adjust from the suggested payment (Tversky and Kahneman 1974), they may start by considering it as a possible appropriate payment but then adjust up or down to come up with a more suitable payment for their financial situation. Further, the suggested payment may activate ideas that are consistent with payments near or at that value being most appropriate (Mussweiler and Strack 2000). Even if the suggestion does not seem relevant to them, it could still influence their payment through an anchoring process because relevance is not required to produce anchoring effects (Tversky and Kahneman 1974).

As we suggest in this project, cardholders may also perceive the suggested payment as a target that they aim to meet or exceed. If they treat this amount like a target, cardholders may feel more motivated to increase their payments to meet or exceed the suggested amount if they were planning to pay an amount just below it (Heath, Larrick, and Wu 1999). Further, after meeting or exceeding this value, they could be disproportionately more satisfied with their payment—even if their payment is only a small fraction of their debt—because they achieved a subgoal. Although motivating consumers to pay at least the suggested amount may sometimes be helpful, it can also backfire if consumers would be better off making smaller payments and spending their resources elsewhere (e.g., on higher interest debt). Lastly, due to a disproportionate change in perceived value, payments will likely bunch at and just above suggested payments if they are perceived as targets.

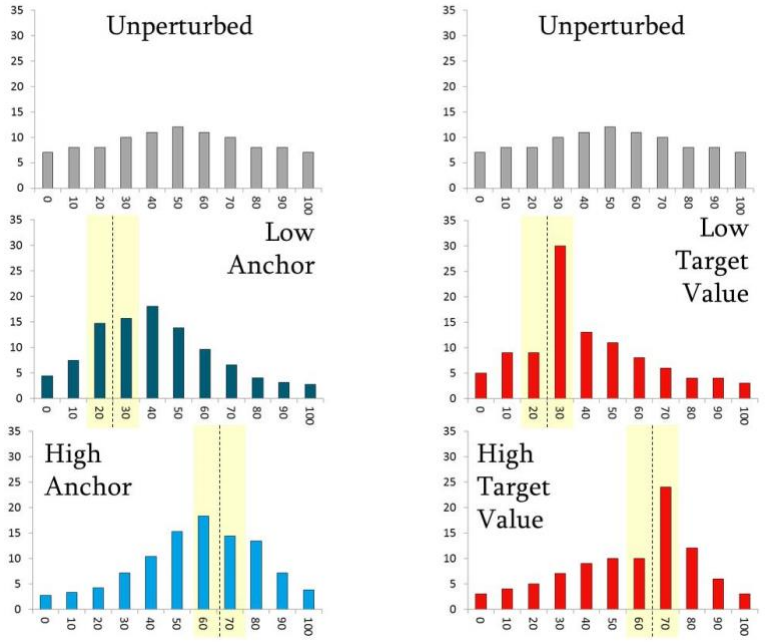
Note that both anchors and targets can affect average and median payments. Therefore, studying how averages or medians change alone does not allow these mechanisms to be distinguished. In the next section, we summarize a method that can help identify target effects. We apply this method throughout the current paper to better understand how focal payment options on credit card statements influence payments.

Method for Identifying Target Effects

Bartels, Herzog, and Sussman (2023) propose a method for distinguishing between anchors and targets that starts with testing for bunching at focal values. As the authors suggest, typical anchors often do not produce bunching, but typical targets do. This follows from the idea that anchors are starting points for judgments and not points at which value changes

disproportionately. In contrasts, targets separate "bad" from "good" outcomes and, therefore, are points at which value changes disproportionately. For a stylized example, Figure 2.1 illustrates expected changes in normal response distributions after introducing low or high anchors and targets.

Figure 2.1: Stylized Representation of Responses to Anchors versus Targets



Notes: Simulated data to depict typical changes in distributions when targets or anchors are present.

If bunching is observed, a second stage may be needed to assess if the bunching is target related. Bunching may occur from target effects (Heath, Larrick, and Wu 1999), but it can also result from, for example, salience effects (Salisbury and Zhao 2020) or default effects (Sakaguchi et al. 2022). In addition, external incentives or punishments associated with some focal payment options, like the minimum, can produce bunching unrelated to the psychological

value of meeting or exceeding a payment value. For instance, consumers might treat the minimum like an anchor from which they adjust, but they may not adjust downward because of penalties, even if that would be their preference in a context without penalties.

To isolate psychological effects from external effects in this paper, we will often focus on "suggested payments". These values will be described as replacing the minimum and not being associated with penalties. Further, they could plausibly operate like anchors (Thaler and Sunstein 2009)—a starting point for an appropriate payment amount—or targets that consumers aim to meet or exceed.

To identify target-based bunching, consumers should report that payments that meet or exceed the focal payment option feel disproportionately better than payments that fall short (Heath, Larrick, and Wu 1999).

In the current project, we apply this method of 1) testing for bunching and 2) measuring satisfaction to shed light on how cardholders perceive focal payment options on credit card statements.

Current Research

We hypothesized that focal payment options on US statements (e.g., minimums and three-year amounts) would produce target effects. In addition, we hypothesized that suggested payments, which may be how minimums and three-year amounts are interpreted (Hershfield and Roese 2015; Thaler and Sunstein 2009), would also produce target effects.

In Study 1, we examined distributions of payments around target values set by cardholders and minimums using data from a large commercial bank, and we found substantial

bunching at both focal payment options. In Study 2, we moved to the lab and compared a variety of focal payment options to typical anchors and targets. Minimums, three-year amounts and suggested payments influenced payment distributions more like typical targets than typical anchors. In Study 3, we introduced a new focal payment option framing—placeholder text example payments—that influenced payments more like typical anchors, which suggests that the way the focal payment option is framed can change the underlying mechanism. Lastly, in Studies 4a and 4b, we examined how consumers expect cardholders to feel when their payments fall above versus below suggested payments. We conclude by discussing implications for financial decision making and choice architecture.

Study 1: Target Payments on Credit Card Statements

In Study 1, we analyzed payment distributions from US cardholders who had payment targets added to their monthly credit card statements. Through a program offered by a large commercial bank, these cardholders elected to include an additional focal payment option on their monthly statements to help them repay their debt. For example, if paying $100 per month allowed a cardholder to achieve their goal of eliminating their debt in 12 months, $100 was presented as a target amount on their statements. Using this dataset, we test our assumption that unambiguous targets produce bunching at or just above the target value in the context of credit card payments.

Data

Our sample includes card-month level data from 16,148 cardholders between January 2011 and September 2014. For each cardholder, we observe 12 months leading up to enrollment and 30 months after enrollment.[7]

Cardholders who selected into this program could choose an amount of time to pay off a fixed amount of their debt, up to their total balance. The monthly target amount was then set by dividing the remaining credit card balance by the number of months selected by the cardholder. This value would appear on the cardholder's credit card statement each month for the duration of their enrollment in the program.[8]

At the card-month level, we observe pre- and post-enrollment periods, target amounts (post-enrollment), credit card balances, minimum payments due, and payments (see Table 2.1 for summary statistics). The pre-enrollment period is 12 months for each cardholder. The post-enrollment period is up to 30 months, although many cardholders are active in the program for a shorter duration.

To study meaningful minimums and targets, we only included card-months with statement balances and targets that were both greater than zero and greater than their minimums. This subsample included 357,946 card-months observations from 16,148 cardholders.

[7] We do not observe cardholders who did not enroll in the program.

[8] The target could vary each month depending on how much cardholders paid in the prior month and their spending.

Table 2.1: Bank Sample Summary Statistics

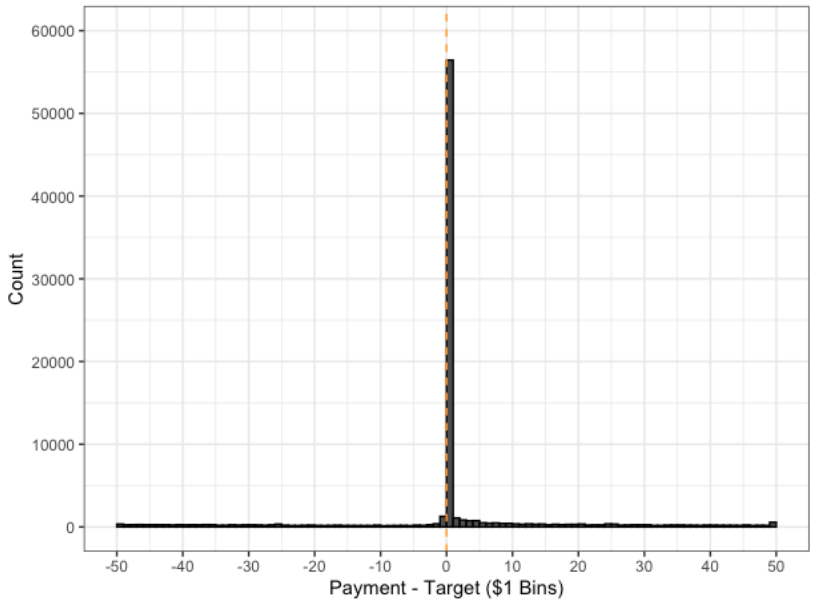
	Mean	SD
Balance	$4,448.91	$4,535.62
Minimum	$99.10	$108.86
Target	$281.44	$357.89
Age	42	14.5
Income	$55,401.79	$27,018.69
Gender	34% Male	

Results

We ask whether introducing a payment target 1) produces payment bunching at or just above the target and 2) changes average payments. Further, since we also have access to minimum payments due, we compared distributions of payments near minimums to distributions of payments near targets. Similar responses to both payment types would offer initial evidence that minimums and targets have shared features.

We first plotted histograms of differences between payments and targets (payments – targets) within $50 above and below the target, in $1 bins (see Figure 2.2). From visual inspection, there appears to be substantial bunching exactly at target values. Just over 28% of all payments during the program (i.e., active post-enrollment period) were equal to the target amount. Further, within $50 above and below the target (n = 85,222), a larger proportion paid more than target (22.2%) versus less than the target (14.7%). This pattern is consistent with our assumption that credit card payments bunch at and just above target values.

Figure 2.2: Payment Differences from Targets Post-Enrollment



Notes: Bins are $1 and include the lower bound.

Like anchors, we also expect targets to affect averages. To formally test if the program helped these cardholders increase their monthly payments, we compared average log payments between pre- and post-enrollment using OLS regression with account (α_i) and month-year (γ_t) fixed-effects, controlling for balance ($X_{i,t}$).

$$Log(Payment + 1_{i,t}) = \beta_0 + \beta_1(PostEnrollment_{i,t}) + \beta_2(X_{i,t}) + \alpha_i + \gamma_t + \varepsilon_{i,t}$$

The key variable of interest is a dummy indicator for post-enrollment ($PostEnrollment_{i,t}$), which captures the effect of introducing targets on log payments. We found a significant increase in log payments in the post-enrollment period ($\beta = 0.169$, $t = 10.38$, $p < .001$). This finding suggests that cardholders set targets that motivated them to increase their payments by 18% on average (see Table 2.2).

In addition, we found a decrease in the probably of paying the minimum in the post-enrollment period, (β = -0.08, t = 18.58, $p < .001$), which further suggests that cardholders are increasing their payments.

Table 2.2: Regression Results for Log Payments Pre- and Post-Enrollment

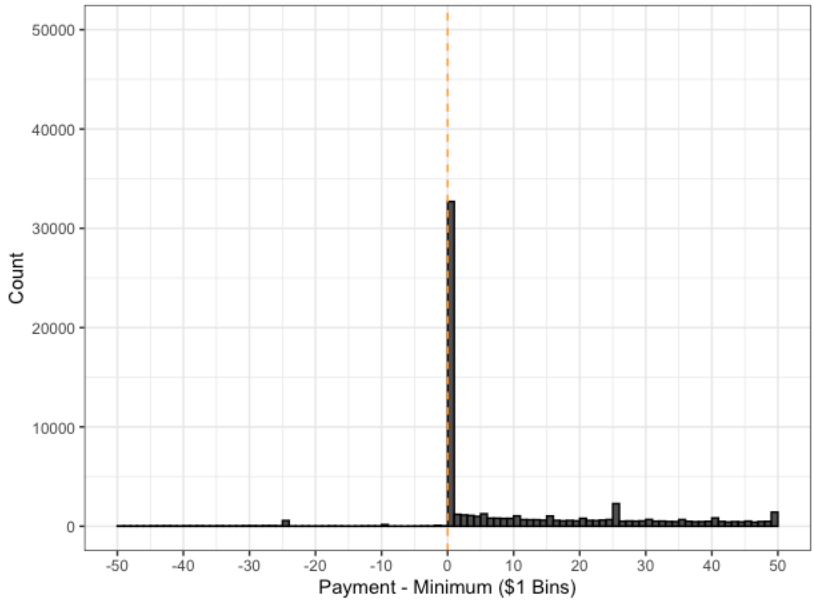
	Log Payment	Minimum Payments
Post Enrollment	0.169***	-0.083***
	(0.016)	(0.004)
Log Balance	0.246***	0.046***
	(0.005)	(0.001)
Num.Obs.	357946	357946
R2	0.440	0.384
R2 Within	0.017	0.008
Std.Errors	by: Account	by: Account
FE: Account	X	X
FE: Month_Year	X	X

Notes: ***$p < .001$, **$p < .01$, *$p < .05$, †$p < .10$. OLS regression estimates with standard errors in parentheses.

Lastly, we plotted histograms of differences between payments and minimums (payments – minimums) in the pre-enrollment period (see Figure 2.3). Like our target histogram, we included observations within $50 above and below the minimum, in $1 bins. Much like targets, minimums produced substantial bunching exactly at minimums (18% of all pre-enrollment payments). We also observed a more extreme asymmetry between payments that are greater than

(50.3%) versus less than (3.6%) minimums within this window, likely due to the added penalties associated with not paying at least the minimum.

Figure 2.3: Payment Differences from Minimums Pre-Enrollment



Notes: Bins are $1 and include the lower bound.

Discussion

Using data from a large commercial bank, we found that including targets on credit card statements, determined by cardholders, was associated with an increase in monthly payments. In line with our assumption about how targets influence distributions more broadly, we see substantial payment bunching at target values in this context. Further, minimums, like targets, produced similar patterns of bunching. Although bunching at minimums may be primarily driven by avoiding external penalties, the psychological effect of minimums may also be better described as a target effect. We provide more direct tests in our subsequent lab studies where we can experimentally manipulate whether a focal payment option is present.

Study 1 also sheds light on the degree of bunching in this credit card payment context. A large fraction of cardholders who paid within $50 of their target (above or below) paid exactly the target amount. Although a general characteristic of targets is that they produce bunching (Bartels, Herzog, and Sussman 2023), the degree of bunching depends on the context. For example, in the context of marathon running, many runners finish a few minutes before their target time, which produces bunching (Allen et al. 2017). However, many runners also finish even earlier or fail to reach their goal by a few minutes. Controlling the exact finishing time is challenging, and as a result, bunching may be somewhat smoother around the target in that context than the payment context, where it is easier to control the exact payment amount.

Study 2: Comparing Focal Payment Options to Typical Anchors and Targets

In Study 2, we moved to the lab to experimentally test a variety of focal payment options that could plausibly operate as anchors or targets. We selected two values that currently appear on US credit card statements (e.g., the minimum and the three-year amount), and have been described as anchors in the literature (e.g., McHugh and Ranyard 2016; Salisbury and Zhao 2020; Stewart 2009). In addition, we selected five focal payment framings that could be introduced to credit card statements (e.g., suggested payments, average payments, previous payments, etc.). We compared these more ambiguous values to a typical target, a typical anchor, and a control condition with no focal payment option present (10 conditions total).

Method

Participants

We recruited 3,062 participants from Prolific. We excluded participants who did not complete the survey (n = 67) or failed the attention check (n = 37), leaving a final sample of 2,968 participants (51% women, M_{age} = 41.12, SD_{age} = 14.02). Within this final sample, 86.9% of participants reported having a credit card, and 95.3% of these cardholders indicated that they (vs. someone else) decided how much to pay each month. Therefore, this sample is largely familiar with the credit card payment context.

Design and Materials

Participants were randomly assigned to one of ten conditions (see Table 2.3). In each condition, participants were presented with a monthly credit card statement that included an account number, a $5,596.12 total balance, and a 21.76% interest rate (avg. US credit card APR in August 2024; Federal Reserve Bank of St. Louis 2025). In the nine experimental conditions, participants observed a focal payment value equal to $213.03. This amount was selected because it equals the three-year amount and is therefore a realistic size for focal payment options that currently appear on US statements.

Participants in the control condition only observed the statement information and decided how much they would pay (i.e., no focal payment option). The control condition was included to test if these focal payment options had any effect on payments. If they do not affect payments (relative to when no value is included) then they are unlikely to operate as either targets or anchors.

The typical anchor and target conditions served as key benchmarks for comparison with the more ambiguous focal payment option conditions. In these conditions, we had reason to believe that these framings were unambiguously perceived as targets or anchors. In the typical target condition, participants were told that they had set a goal to pay at least the focal payment

option (like the real-world payment setting in Study 1). In the typical anchor condition, participants were asked if they would pay more or less than the focal payment option, and then they indicated their exact payments. These "more or less than X" questions are common in studies finding anchoring effects (see Furnham and Boo 2011 for a literature review on anchoring).

Among the seven ambiguous focal payment conditions, two of them are currently on US credit card statements: the minimum and the three-year amount. Further, researchers have argued that cardholders perceive the minimum and three-year amount as suggested payments or appropriate amounts to pay (Hershfield and Roese 2015; Thaler and Sunstein 2009). Suggested payments could operate as either anchors or targets, and they are not associated with external penalties or additional information, like minimums and three-year amounts. Therefore, we also included a suggested payment condition that is explicitly labeled as a suggestion from the credit issuer.

The remaining four conditions were selected because they are potential focal payment options that could be treated like anchors or targets. These include the price of the last purchase, the payment received last month, the average payment for cardholders with similar balances, and an amount framed as a percentage of their credit limits.

Table 2.3: Study 2 Focal Payment Option Framings

Condition	Focal Value Framing
Control	N/A
Typical Anchor	When considering your payment, do you think you would pay more or less than $X
Typical Target	You set a goal to pay at least $X
Minimum	Minimum payment amount: $X
Three-Year Amount	If you make no additional charges using this card and each month you pay: $X You will pay off the balance shown on this statement in about 3 years.
Suggested Payment	Credit card issuer's suggested payment amount: $X
Single Item	Last purchase amount: $X
Payment Last Month	Payment received last month: $X
Average Payment	Average payment amount for customers with a similar balance: $X
Utilization Payment	2% of your credit limit: $X

Procedure

All participants indicated how much they would pay using a text box that accepted any value between $0 and the full balance ($5,596.12). Before indicating their payments, participants were asked to consider how much they can afford to pay and to treat their payment decisions as they would in their everyday lives (modeled after Salisbury and Zhao (2020) Experiment 1). After participants made their payments, they indicated if they had credit cards (yes/no), if they decided how much to pay each month (or someone else), and provided basic demographic information (age, gender, education and income). Lastly, they completed an attention check that required them to type the word “yes” into a text box.

Results

Average Payments

In prior research, anchoring effects have been identified by observing changes in averages or medians relative to a control condition or different sized values (e.g., Strack and Mussweiler 1997). Following prior research, we first tested if focal payment options influenced average payments and could plausibly operate as anchors. We regressed payments on condition dummies with the control condition as the reference group.

All nine focal payment options decreased average payments relative to the control (see Figure 2.4 and Table 2.4). With the focal payment option set at $213.03, a small amount relative to the full balance, these results are consistent with prior research that suggests the minimum and the three-year amount reduce average payments (Hershfield and Roese 2015; Stewart 2009).

Figure 2.4: Average Payment by Focal Payment Option Framing

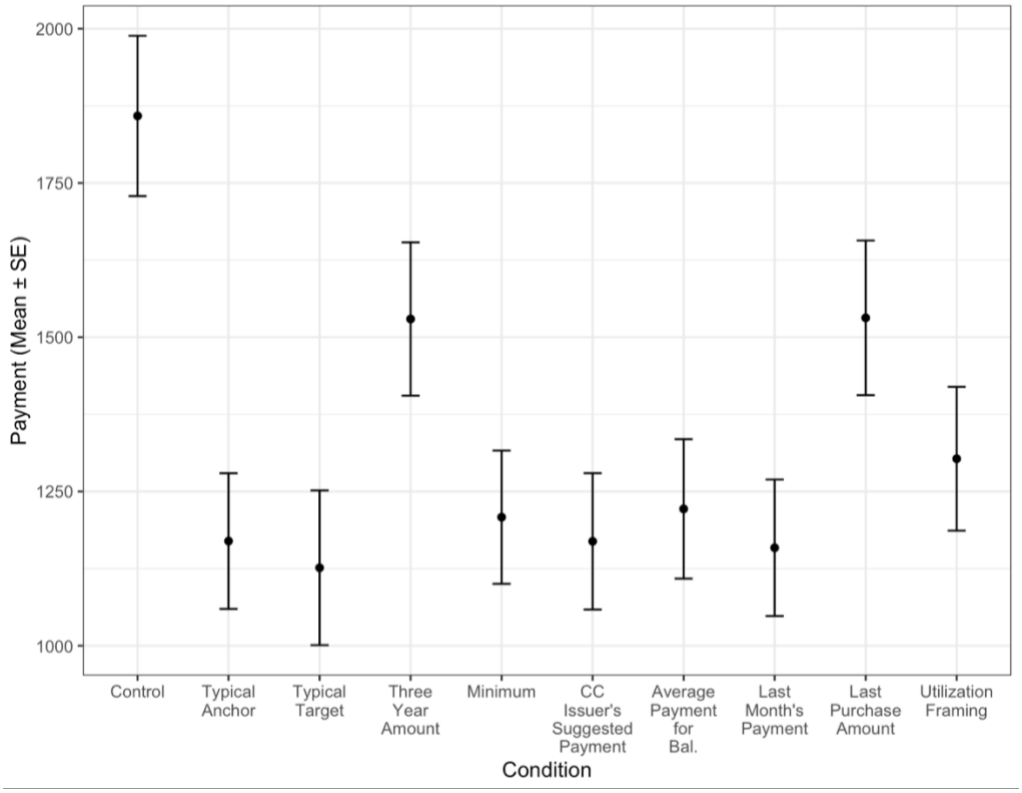


Table 2.4: Regression Results for Average Payments

Typical Anchor	-689.014***
	(165.819)
Typical Target	-732.274***
	(166.517)
Three Year Amount	-329.112*
	(165.957)
Minimum	-650.284***
	(166.376)
CC Issuer's Suggested Payment	-689.451***
	(166.659)
Average Payment for Bal.	-636.895***
	(165.957)
Last Month's Payment	-699.883***
	(166.235)
Last Purchase Amount	-327.282*
	(166.235)
Utilization Framing	-555.626***
	(166.659)
Num.Obs.	2968
R2	0.012

Notes: ***$p < .001$, **$p < .01$, *$p < .05$, †$p < .10$. OLS regression estimates with standard errors in parentheses. The control condition is the reference group.

Distributions Near Focal Payment Options

Anchoring could explain why payments are, on average, smaller than when no focal payment option is present. However, targets also affect averages. For example, average payments in our typical anchor (M = $1,169.62) and typical target (M = $1,126.36) conditions were similar

($t = 0.26$, $p = .795$). To help tease apart anchoring effects from target effects, we tested for bunching at and just above focal payment options.

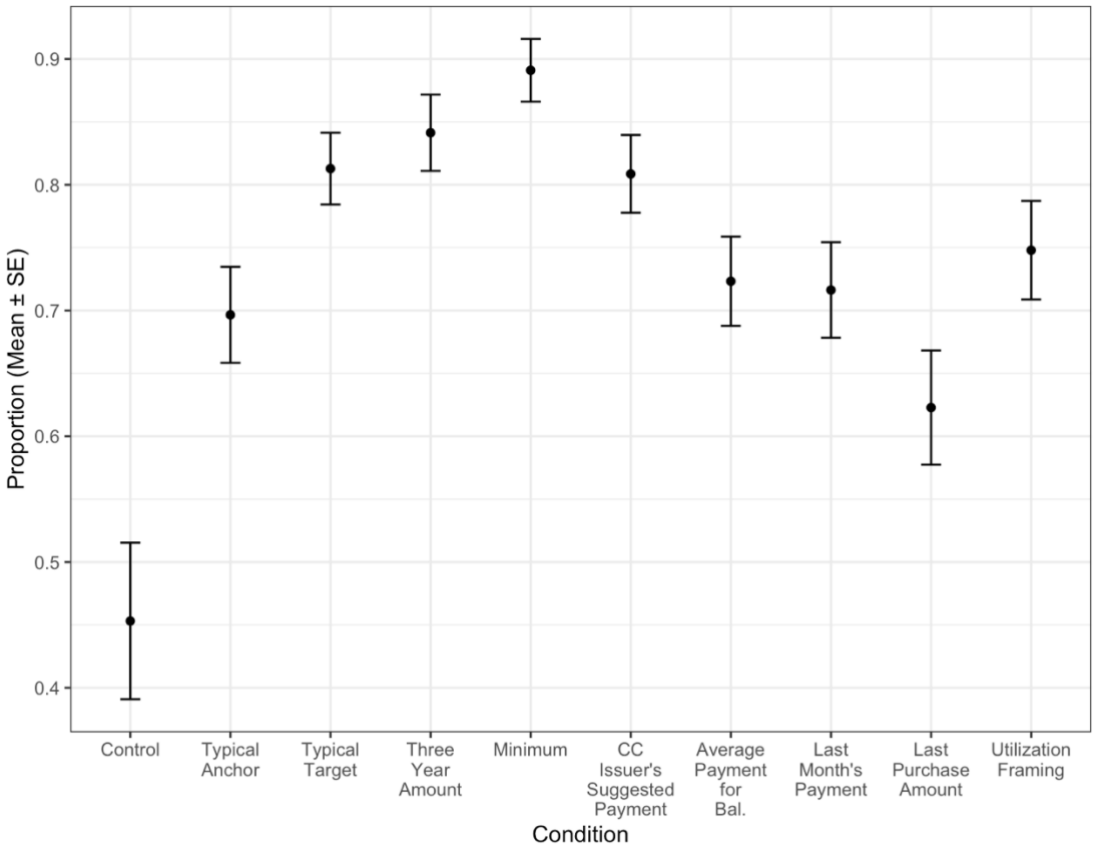
As a simple test of bunching, we pre-registered an analysis that compares the proportion of payments that meet or exceed the focal payment option within $100 above and below the focal payment option. We ran two logistic regressions in which we regressed these proportions on condition dummies. In one model, the typical anchor condition served as the comparison group, and in the other, the typical target condition served as the comparison group (see Table 2.5).

First, we found a significant difference in the proportion of responses that met or exceeded the typical target versus the typical anchor. As expected, the typical target increased the proportion of payments that met or exceeded the focal payment option relative to the typical anchor. Importantly, a similar pattern emerged for the minimum, three-year amount and suggested payment. Each of these values were significantly different from the typical anchor condition. The three-year amount and suggested payment were not significantly different from the typical target condition, while the minimum yielded an even higher proportion of payments that met or exceeded the focal payment option (likely due to the associated external incentives).

When the focal payment option was framed as last month's payment, the last purchase price, the average payment or in credit limit terms, they were either statistically indistinguishable from the typical anchor condition or both the typical anchor and target conditions. Therefore, we cannot reject that these values produce anchoring effects from this test. Although minimums, three-year amounts and suggested payments may operate more like targets than anchors, which stands in contrast to a common assumption in the literature, other focal payment options that could appear on credit card statements may operate more like anchors. However, more work is needed. Visual inspection of histograms reveals some degree of bunching at these four values

(see Appendix D). It is possible that some fraction of cardholders treats these values like targets. Studying which cardholders are more likely to see the same value as an anchor or target is a promising direction for future research.

Figure 2.5: Proportion Paying the Focal Payment Option or More



Notes: This sample only includes payments within $100 above and below the focal payment amount.

Table 2.5: Regression Results for Proportion of Payments ≥ Focal Payment Option

	Target Reference Group	Anchor Reference Group
Control	-1.657***	-1.019***
	(0.313)	(0.309)
Typical Anchor	-0.638*	
	(0.260)	
Typical Target		0.638*
		(0.260)
Three Year Amount	0.200	0.838**
	(0.295)	(0.290)
Minimum	0.633*	1.270***
	(0.318)	(0.314)
CC Issuer's Suggested Payment	-0.027	0.610*
	(0.274)	(0.269)
Average Payment for Bal.	-0.508*	0.130
	(0.258)	(0.253)
Last Month's Payment	-0.542*	0.095
	(0.265)	(0.260)
Last Purchase Amount	-0.967***	-0.329
	(0.269)	(0.265)
Utilization Framing	-0.381	0.257
	(0.280)	(0.275)
Num.Obs.	1396	1396

Notes: ***$p < .001$, **$p < .01$, *$p < .05$, †$p < .10$. Logistic regression estimates with standard errors in parentheses.

Discussion

By comparing both mean payments and distributions near focal payment options, we find initial evidence that focal payment options that are currently on credit card statements (i.e., minimums and three-year amounts), as well as suggested payments, may be better characterized

as targets instead of anchors. Study 2 also suggests that some values may change means and distributions in a way that is more consistent with anchoring, although results are mixed.

One limitation of Study 2 is that the typical anchor is not a focal payment option included on the statement or natural within a payment setting. This manipulation was selected because it reliably produces anchoring effects in a variety of contexts (e.g., Jacowitz and Kahneman 1995). In addition, participants in the typical anchor condition first had to indicate if they would pay more or less than the focal value. This first stage could have discouraged participants from paying the exact focal payment option, which could explain the lack of bunching.

We aimed to address these limitations in Study 3. In this study, we examined a focal payment framing that could be introduced to online payment platforms—example payments in placeholder text. We expected example payments in placeholder text to produce payment distributions that are more consistent with typical anchors than targets. The point of a placeholder text example is to act as a starting point or guide for what should be included and could be seen as less relevant. Anchors are also starting points for subsequent judgments and are often irrelevant (Tversky and Kahneman 1974). By comparing these placeholder text example payments to suggested payments, we shed light on how focal payments can be reframed to produce more target-like or anchor-like effects on payments.

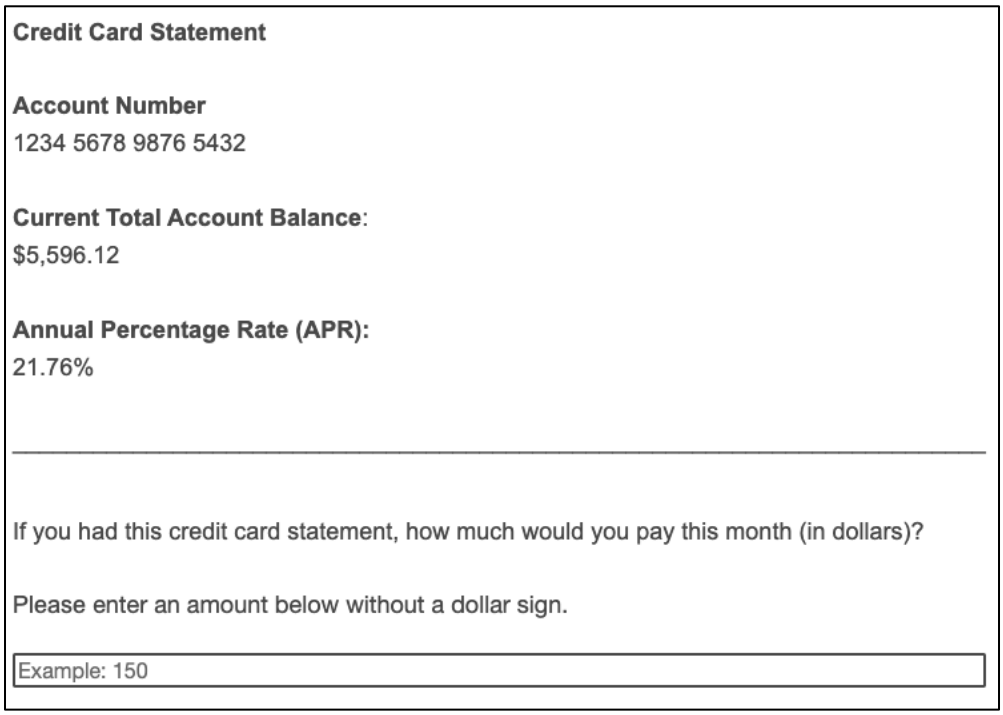
Study 3: Anchoring on Example Payments in Placeholder Text

Placeholder text in text boxes is commonly included as a starting point or guide for what consumers should enter. For example, when consumers are prompted to input login information, they may observe the words “Username” and “Password” in a gray font within the text boxes.

Placeholder text is often not a default option; consumers cannot accept the placeholder value without entering any information. Instead, when consumers click into the text box to enter their information, the placeholder text disappears.

In this study, we manipulated the placeholder text to display smaller and larger example payments (see Figure 2.6). We compared how payments change when placeholder text example payments change versus suggested payments.

Figure 2.6: Credit Card Statement with Placeholder Text



Method

Participants

We recruited 1,231 participants from Prolific. Following our pre-registration (https://aspredicted.org/9t4w-g4ms.pdf), we excluded participants who did not complete the survey (n = 24) or failed the attention checks (n = 98), leaving a final sample of 1,109

participants (53% women, M_{age} = 40.97, SD_{age} =13.54). In line with Study 2, most of these participants are cardholders in charge of making monthly payments: 87.1% of participants reported having a credit card, and 94.0% of these cardholders indicated that they (vs. someone else) decided how much to pay each month.

Design

Participants were randomly assigned to one condition in a 2 (focal value: placeholder text vs. suggested) x 2 (focal value size: low vs. high) between-subjects design. Placeholder text focal values were example payments presented in the payment text box. Suggested focal values were described as a replacement for minimums—they were simply a suggested payment (see Hirshman and Sussman 2022 for a similar focal value framing).

Low focal values were set to $150, and high focal values were set to $850. We selected these values because they fell below or above the median payment in our Study 2 control condition, and they are equally far from the nearest multiple of $100, which consumers often prefer to pay over non-round numbers (Medin and Negrin 2022).

Materials and Procedure

Participants were asked to imagine that they have received their monthly credit card statement. The instructions read, "This statement does NOT have a minimum payment due. You can pay any amount, including $0, and still remain in good standing and avoid penalties" … "Please consider your own finances and decide how much you would pay if you were presented with this credit card statement." In the suggested focal value conditions, participants read one additional line, "Instead, this statement has a suggested payment."

Other than minor formatting changes, the statement in this study was identical to the statement presented in Study 2. The total balance was $5,596.12, and the APR was 21.76%. In

the suggested payment conditions, participants observed a "Suggested Payment" on the credit card statement. In the placeholder text conditions, they observed an example payment within the payment text box (e.g., "Example: 150"). All participants were asked how much they would pay this month, in dollars, if they had this credit card statement, and to enter an amount without a dollar sign.

After they indicated their payments, they answered an attention check about whether the statement had a minimum payment due (True/False), and provided information about their credit card use and demographics. Lastly, they completed the same attention check from Study 2.

Results

Average and Median Partial Payments

To test if example payments in placeholder text and suggested payments influenced partial payments, we pre-registered tests of changes in partial payments between low and high focal values. Just over 89% of payments were partial payments below the full balance of $5,596.12 (n = 955).

Study 2 suggests that these partial payment distributions have a long right tail with outliers. Therefore, we ran two Wilcoxon-Mann-Whitney tests, one for each focal value type, including all partial payments (e.g., payments below $5,596.12). We also compared average partial payments using two independent samples t-tests. To reduce the influence of outliers and focus on the payments we thought would be most affected by these relatively small values, we pre-registered an inclusion rule of payments below $2,500. This inclusion rule keeps just over 94% of the partial payment sample. To test for robustness, we also re-ran the analyses with $2,000 and $1,500 cutoffs, as well as the full partial payment sample. Results do not meaningfully differ with these alternative cutoffs.

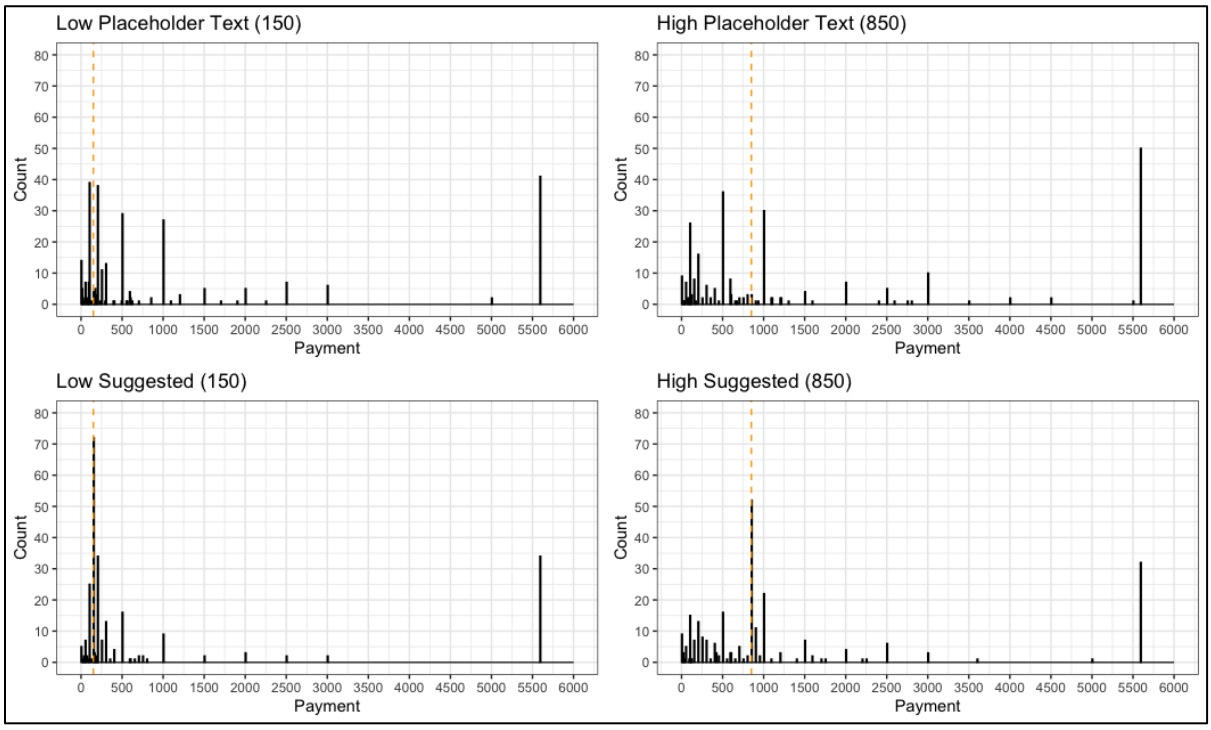
In line with Study 2, suggested payments influenced the size of payments. Higher suggested payments (Median = $850, Mean = $654.23) produced larger partial payments than lower suggested payments (Median = $150, Mean = $277.37), W = 13925, $p < .001$, $t = 9.94$, $p = .003$). In addition, example payments in placeholder text also affected partial payments. Higher placeholder text examples (Median = $500, Mean = $548.41) produced larger partial payments than lower placeholder text examples (Median = $200, Mean = $413.75), W = 24035, $p < .001$, $t = 3.00$, $p < .001$).

Proportion of Payments that Meet or Exceed the Focal Payment Option

As we have suggested, comparing means or medians alone cannot distinguish anchors from targets. To test for bunching, we plotted payment histograms and tested if the proportion of partial payments that met or exceeded the focal values differed between suggested payments and example payments in placeholder text.

From visual inspection of histograms, we once again observed bunching at and just above both low and high suggested payments (see Figure 2.7). Although we see partial payment distributions shift up when the placeholder text example payments increase, we do not observe clear patterns of bunching at these values. Instead, it appears that participants adjusted both up and down from the placeholder text example payments, typically to nearby round numbers.

Figure 2.7: Payment Histograms by Condition

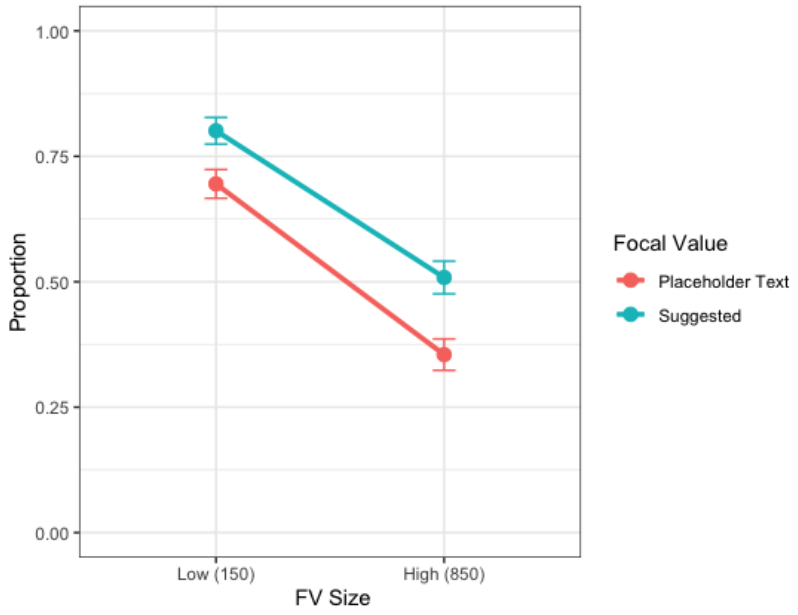


Notes: Bins are $10 and include the lower bound. Orange vertical lines are drawn at the focal value.

As a formal test, we ran a logistic regression predicting whether a payment met or exceeded the focal value by focal value type, size, and their interaction. This analysis supports the idea that suggested payments produce more bunching than example payments in placeholder text. Using effect coding for focal value size (low = -0.5, high = 0.5) and type (placeholder text = -0.5, suggested = 0.5), we found a negative effect of focal value size ($\beta = -1.39$, $z = -9.73$, $p < .001$) and a positive effect of focal value type ($\beta = 0.60$, $z = 4.20$, $p < .001$). The proportion of partial payments that met or exceeded the low suggested payment (80.1%) was greater than the proportion of partial payments that met or exceeded the low placeholder text example payment (69.5%). A similar pattern emerged for the high suggested payment (50.8%) and high

placeholder text example payment (35.5%) (see Figure 2.8). Although this difference is slightly larger for high focal values, the interaction is not significant (β = 0.06, z = 0.22, p = .823)

Figure 2.8: Proportion of Payments Meeting or Exceeding the Focal Payment Option



Notes: Error bars are +/- 1 standard error.

Discussion

Study 3 finds that both suggested payments and example payments in placeholder text can influence average and median payments. However, their impact on payment distributions is distinct. For many consumers, suggested payments appear to operate like targets: payments bunch at and just above suggested payments. In contrast, very few payments bunch at and just above example payments in placeholder text. Instead, a similar number of payments end up at nearby round numbers both above and below these values. These distributions are in line with our expectations of anchors. Cardholders may use them as starting points (or see them as

irrelevant) and ultimately adjust their payments up or down to nearby values. As a result, average and median payments end up closer to these values.

This study also helps rule out salience as an explanation for bunching at suggested payments (Salisbury and Zhao 2020). In all conditions, the focal payment options were more salient than other partial payments and could have increased payments exactly at those amounts because they were more salient. However, we do not observe a similar bunching pattern exactly at placeholder text example payments.

Given that we observed bunching for suggested payments but not placeholder text example payments, we further examined whether bunching at suggested payments is target-driven. One method is simply to ask cardholders how they feel about payment outcomes near focal payment options (Bartels, Herzog, and Sussman 2023). Theories of targets predict that people will feel more satisfied with outcomes that meet or exceed targets than fall just short (Heath, Larrick, and Wu 1999). Theories of anchors do not make clear predictions about how people will feel about outcomes just on either side of anchors (Epley and Gilovich 2005; Frederick and Mochon 2012; Mussweiler and Strack 2000; Tversky and Kahneman 1974; Wegener et al. 2001). Further, anchoring can occur even when people believe that the anchor did not influence their judgments or decisions (Chapman and Johnson 1999). In these cases, reported outcome satisfaction should not explicitly depend on anchors.

In Studies 4a and 4b, we examined perceptions of satisfaction when payments fell short of or exceeded suggested payments. Following Studies 2 and 3, we predicted that these suggested payments are perceived as targets, such that payments that fall short of suggested payments should feel disproportionately less satisfying than payments that reach or exceed suggested payments.

Study 4a: Satisfaction Ratings

To examine if cardholders' satisfaction with payments disproportionately increases when they reach a suggested payment amount—consistent with target effects but not anchor effects—we asked participants how they think cardholders feel about payments that exceed or fall short of a suggested payment. Methods were adapted from Heath, Larrick, and Wu (1999).

Method

Participants

Fifty-one participants were recruited from Prolific. Two participants failed the attention and comprehension checks, leaving a final sample of 49 participants (49% women, M_{age} = 36.78, SD_{age} = 11.28) (see pre-registration: https://aspredicted.org/M54_XS3).

Procedure

Participants read about two cardholders who have credit card statements with suggested payments but no minimum payment due. To ensure comprehension, participants who incorrectly indicated that the credit card had a minimum payment or that interest would not accrue if the balance was not paid in full were excluded.

Next, participants read about two cardholders who had identical balances ($3,211.26) and paid identical amounts ($543.01). One person's payment was above their suggested payment ($209.40), while the other was below their suggested payment ($876.61). The order of suggested payment amounts was counterbalanced. Participants were then asked, "How do you think each of these cardholders feels about his payment?" (1 = Extremely disappointed; 6 = Extremely happy), and provided ratings for both cardholders.

We chose to have participants predict how others would feel, instead of how they would feel, to remove the influence of their typical payment preferences. For example, a participant who typically pays the minimum each month may be extremely pleased with a payment that is much larger ($543.01) than a typical minimum payment for this balance (~$65). However, a participant who typically pays in full ($3,211.26) may be extremely disappointed with the same payment. Using the third-person perspective helps remove some of the noise produced by extremely different personal payment preferences.

Results and Discussion

Despite balances, interest rates, and payments being identical for each cardholder, participants judged the cardholder who had exceeded the suggested payment amount as much happier (M = 5.14, SD = 0.76) than the cardholder whose payment fell below the suggested payment amount (M = 2.31, SD = 0.89, paired-t(48) = 16.60, $p < .001$). The idea that underpayments elicit disappointment is consistent with the notion that the suggested payment acts as a target with motivational properties, rather than an anchor.

Study 4b: Satisfaction Ratings with Various Focal Payment Sizes

Study 4a examined whether consumers believe cardholders would be disproportionately more satisfied with payments just above versus just below suggested payments. In that study, we varied the suggested payment and held the payment constant across cardholders. In Study 4b, we examined, between-subjects, if payments that fell above or below a variety of suggested payment amounts produced similar effects. By manipulating both the size of the suggested payment and the difference between the suggested payment and actual payment, we test the extent to which

perceived payment satisfaction depends on relative differences from the suggested payment. This study design was based on an experiment from Markle et al. (2018) that was designed to test if targets shared features with prospect theory's value function (Kahneman and Tversky 1979)—one proposed model of targets—including loss aversion and diminishing sensitivity.

Method

Participants

We recruited 2,429 participants from Prolific. After excluding participants who failed the attention check (n = 36) or comprehension check (identical to Study 4a; n = 169), the final sample included 2,223 participants (49.8% women, M_{age} = 40.32, SD_{age} =13.56) (https://aspredicted.org/V7H_X5W).

Design

Participants were randomly assigned to a condition in a 4 (suggested payment size: $104.70, $209.40, $573.47, $876.61) x 6 (payment relative to suggested payment: -20%, -10%, -1%, +1%, +10%, +20%) between-subjects design.

Procedure

The first part of the procedure was identical Study 4a. Participants learned about a credit card that had a suggested payment instead of a minimum payment due, and they answered the same comprehension checks. The total card balance was $3,211.26, and the APR was 20.5%.

We tested four suggested payments that varied from low to high ($104.70, $209.40, $573.47, $876.61). To calculate the six possible payments, we added and subtracted 20%, 10% and 1% of the suggested payment to/from the suggested payment. For example, the exact payment 20% below the $209.40 suggested payment was $167.52 (i.e., 209.40 – (209.40*.20).

Participants indicated how they believed the cardholder felt about their payment on a scale from 1 (Extremely disappointed) to 6 (Extremely happy).

Results

We ran a linear regression to test for a jump in satisfaction (Sat) at the suggested payment amount (SPA) and loss aversion. We regressed satisfaction on dummies for suggested payment conditions (medlow, medhigh, high), a dummy for whether the payment was above or below the suggested payment amount (payment≥SPA), payment, and an interaction between payment and the above/below suggested payment dummy. Payments were coded as percent changes from the suggested payment (e.g., -20% to 20%) and included as a continuous predictor. To test for diminishing sensitivity, we added quartic terms by squaring payments in a separate model.

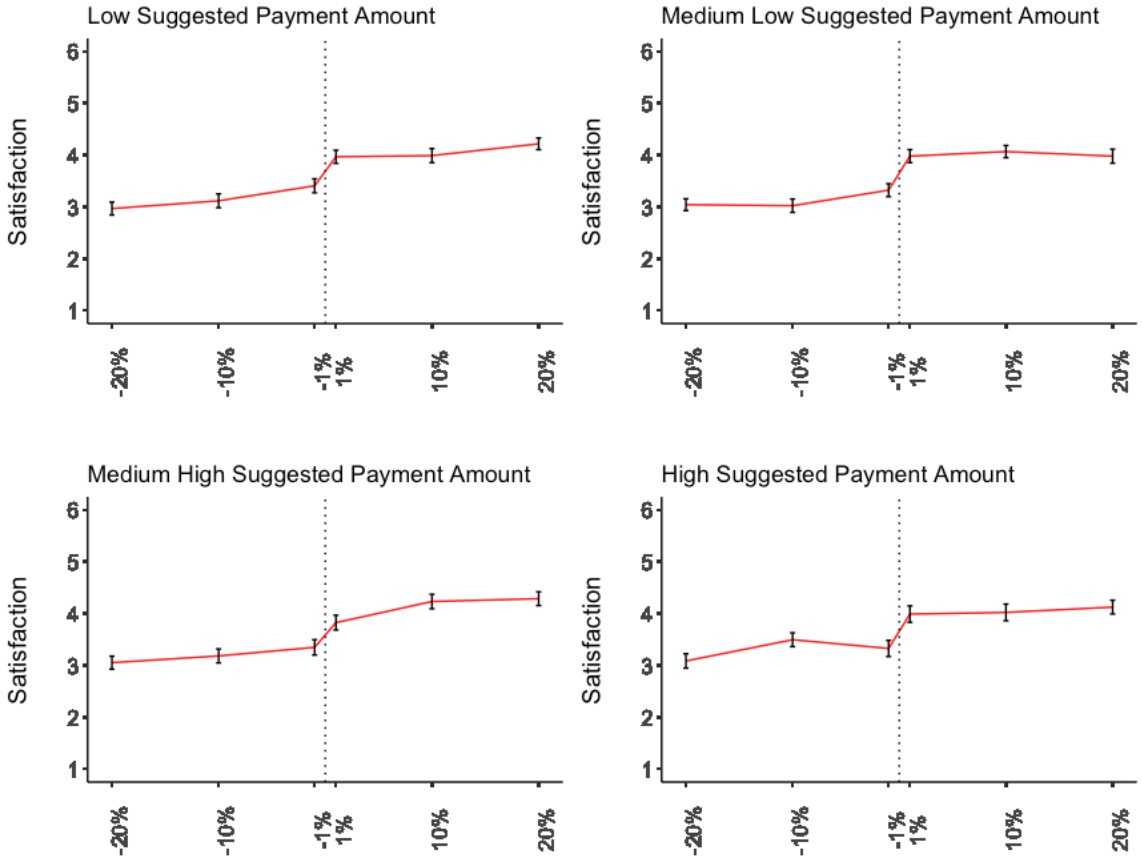
$$Satisfaction = \beta_0 + \beta_1(medlow) + \beta_2(medhigh) + \beta_3(high) + \beta_4(payment) + \beta_5(payment \geq \text{SPA}) + \beta_6(payment \geq \text{SPA} * \text{payment}) + \varepsilon$$

Results are reported in Table 2.6. Participants indicated that cardholders would be significantly more satisfied with their payments when they paid more versus less than the suggested payment (see Table 2.6, Model 1). Although we also found a positive relationship between payment and satisfaction, satisfaction increased disproportionately when payments became greater than the suggested payment. Figure 2.9 presents mean satisfaction ratings for payments around each suggested payment amount. Importantly, these results suggest that payment satisfaction is largely a function of whether the payment is above or below the suggested payment. Despite some payments being hundreds of dollars more when the suggested

payment was high (e.g., $876.61) versus low (e.g., $105.75), participants indicated cardholders would be more satisfied with a smaller payment as long as it exceeded the suggested payment.

We did not find consistent evidence of loss aversion. Collapsing across conditions, slopes did not significantly differ on either side of the suggested payment cutoff. Similarly, we did not find consistent evidence of diminishing sensitivity (see Table 2.6, Model 2). Adding quadratic terms did not improve the fit of the model. As Figure 2.9 illustrates, slopes on either side of the suggested payment cutoff are roughly linear across suggested payment conditions. Although patterns consistent with diminishing sensitivity and loss aversion are present in some suggested payment conditions (Medium Low), this pattern does not arise in aggregate.

Figure 2.9: Average Satisfaction Ratings by Condition



Notes: Error bars are standard errors.

Table 2.6: Study 4b Regression Results for Satisfaction

	Model 1	Model 2
Intercept	3.354***	3.351***
	(0.080)	(0.093)
Medium Low SPA	-0.042	-0.041
	(0.078)	(0.078)
Medium High SPA	0.044	0.044
	(0.078)	(0.078)
High SPA	0.062	0.062
	(0.077)	(0.077)
Payment	0.017***	0.015
	(0.005)	(0.020)
Payment^2		0.000
		(0.001)
Payment > SPA	0.572***	0.553***
	(0.092)	(0.114)
Payment^2 > SPA * Payment		0.000
		(0.001)
Num.Obs.	2223	2223
R2	0.106	0.106

Notes: ***$p < .01$, **$p < .05$, *$p < .10$. OLS regression estimates with standard errors in parentheses.

Discussion

Studies 4a and 4b find a jump in satisfaction at suggested payments, which is not consistent with theories of anchoring but is consistent with theories of target effects (Allen et al. 2017; Heath, Larrick, and Wu 1999). These studies also test for and find mixed evidence for

patterns consistent with prospect theory's value function. Restating, although not all theories of how targets influence perceived value include diminishing sensitivity and loss aversion (Kleven 2016) these properties are not characteristic of anchors (Kahneman 1992; Tversky and Kahneman 1974). Instead, these results provide further evidence that suggested payments operate as targets instead of anchors.

From a practical perspective, these results suggest that cardholders may feel similarly about very different payments. For example, if cardholders feel roughly equally satisfied with paying the suggested payment or $100 more than the suggested payment, they may choose to not increase their payments, regardless of whether that decision is in their best interest.

General Discussion

Across four lab studies and an analysis of credit card data from a large commercial bank, we find evidence that focal payment options that have previously been thought of an anchors (e.g., minimums, three-year amounts, suggested payments) may be better characterized as targets. When these amounts are present, payment distributions do not resemble typical distributions produced by anchors. Instead, we observe consistent bunching—a characteristic of targets. Further, Studies 4a and 4b suggest that reactions to payments that fall short or meet suggested payments are similar to how consumers are expected to react to outcomes near targets more generally (Heath, Larrick, and Wu 1999). Lastly, although some focal payment options may be misclassified as anchors, we also find that placeholder text example payments do affect payments like we would expect anchors to affect payments—by changing medians and averages without producing bunching.

Anchors versus Targets Revisited

Anchors and targets share central characteristics and may be difficult to separate *a priori*. Perhaps the most straightforward point of overlap is that both anchors and targets are likely to shift the overall distribution in the direction of the focal value. In many situations, researchers refer to anchors and targets interchangeably because they focus on changes in means or medians (see Bartels, Herzog, and Sussman (2023) for more detail).

In trying to understand how consumers rely on numeric cues in their environment, it is often important to distinguish whether they react to those values as anchors or targets. For policymakers or credit issuers who hope to nudge cardholders to pay more without having them feel strongly about paying at least some amount, they may prefer introducing a value that produces an anchoring effect. As we observed in Study 3, the majority of cardholders who observed the high anchor and made partial payments paid below the anchor value. If they instead introduce a high focal payment option that cardholders perceive as a target, they may produce a much stronger effect and discourage cardholders from paying amounts just below the target.

For cardholders with additional credit cards or debts that have higher interest rates, increasing their payments to a high target amount may be harmful in the long run. In this case, it may be useful to set low targets on cards with lower interest rates. Low targets on lower interest cards may have the added benefit of being both easy to achieve and satisfying.

Lessons for Credit Card Statements

Ideally, the focal payment option (e.g., anchor or target) and the specific size of a focal payment option should be tailored to each cardholder's situation. For example, consider a cardholder with multiple credit cards at different interest rates. An optimal payment solution likely involves paying minimums on each card and allocating remaining funds based on interest

rates (Hirshman and Sussman 2022). In this case, introducing a high, but achievable, target only on the card with the highest interest rate may help nudge consumers to employ a more optimal repayment strategy.

Although credit issuers could introduce payment targets for cardholders, they may also prefer to have cardholders select their own payment targets. In Study 1, where cardholders were able to generate their own payment targets, payments increased. This finding suggests that people are relatively good at selecting motivational targets for themselves, conditional on selecting into programs that allow them to set payment targets, with more cardholders benefitting from the presence of the target than falling behind as a result of setting an overly ambitious one. Although we see a directional increase in payments when targets are introduced, we do not have sufficient information to observe whether payments would have been even higher if more ambitious, but attainable, targets were set. Therefore, additional research should examine optimal strategies for setting "stretch" targets—those that are higher than the person would otherwise pay, but still low enough that the person could plausibly make the payment with sufficient effort—which should be most effective at increasing payments when that outcome is beneficial for cardholders or credit issuers.

In Study 3, we also found a focal payment option framing that produced a more typical anchoring effect. This finding suggests that credit issuers and policymakers can create more target-like or anchor-like effects on payments depending on how they frame and introduce the focal payment option. To nudge cardholders to pay more without having them adopt a payment target, example payments in the form of placeholder text in payment text boxes could be introduced to online payment platforms.

Limitations and Future Directions

One limitation of the current research is the use of third-person scenarios to study how cardholders feel about payments near suggested payment amounts. Although this method helps reduce noise for extreme differences in payment preferences, researchers would ideally study how cardholders feel about their own payments. To do this, we believe that surveying a large sample of cardholders about their own payments would be particularly insightful. With a large enough sample, researchers can focus in on subsamples of cardholders who pay an amount just above or below the three-year amount. Among cardholders who were aware of this amount, they could ask how they felt about their payments. While correlational, this dataset would have the benefit of measuring feelings toward actual payments among cardholders who may find the three-year amount particularly relevant.

Future research can further examine heterogeneity in how cardholders perceive focal payment options. Although some focal payment options may appear like targets to many cardholders, resulting in overall payment distributions that are consistent with target effects, some fraction of cardholders may treat these same values as anchors (or neither). A promising direction may be to study many payment decisions from cardholders when these focal payment options are present, using card-month level panel data. For example, cardholders with smoother payment distributions near the three-year amount may be using it as a starting point to determine their final payments, instead of a target that they aim to meet or exceed.

Conclusion

Despite an assumption in the literature that focal payment options on credit card statements act as anchors to influence payments, we found that these values act more like targets by assessing payment distributions and reactions to payments near these values. Further, we found that the way focal payment options are framed on statements can influence whether they

operate more like targets or anchors. Essay 2 makes a theoretical contribution by reconsidering the effect of focal payment options on payments, as well as a practical contribution by offering insights that can help guide credit issuers as they continue to restructure credit card statements and assist cardholders in managing their credit cards.

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Appendix A

Essay 1, Study 1 replication with balances that share the leftmost digit

Figure 3.1: Study A1 Recalled Balances

Notes: Distributions of recalled balances. Bins are $50 and include the lower bound.

Table 3.1: Study A1 Regression Results for Overspending

	Purchase Clothes		Recall Error
	Model 1	**Model 2**	**Model 3**
Intercept	-1.099***	-0.970***	85.376***
	(0.125)	(0.130)	(9.606)
Smaller Balance	-0.135	-0.118	14.620
	(0.180)	(0.182)	(13.66)
Recall Errors		-0.002***	
		(0.001)	
R-Squared			0.00
Num. Obs	681	681	681

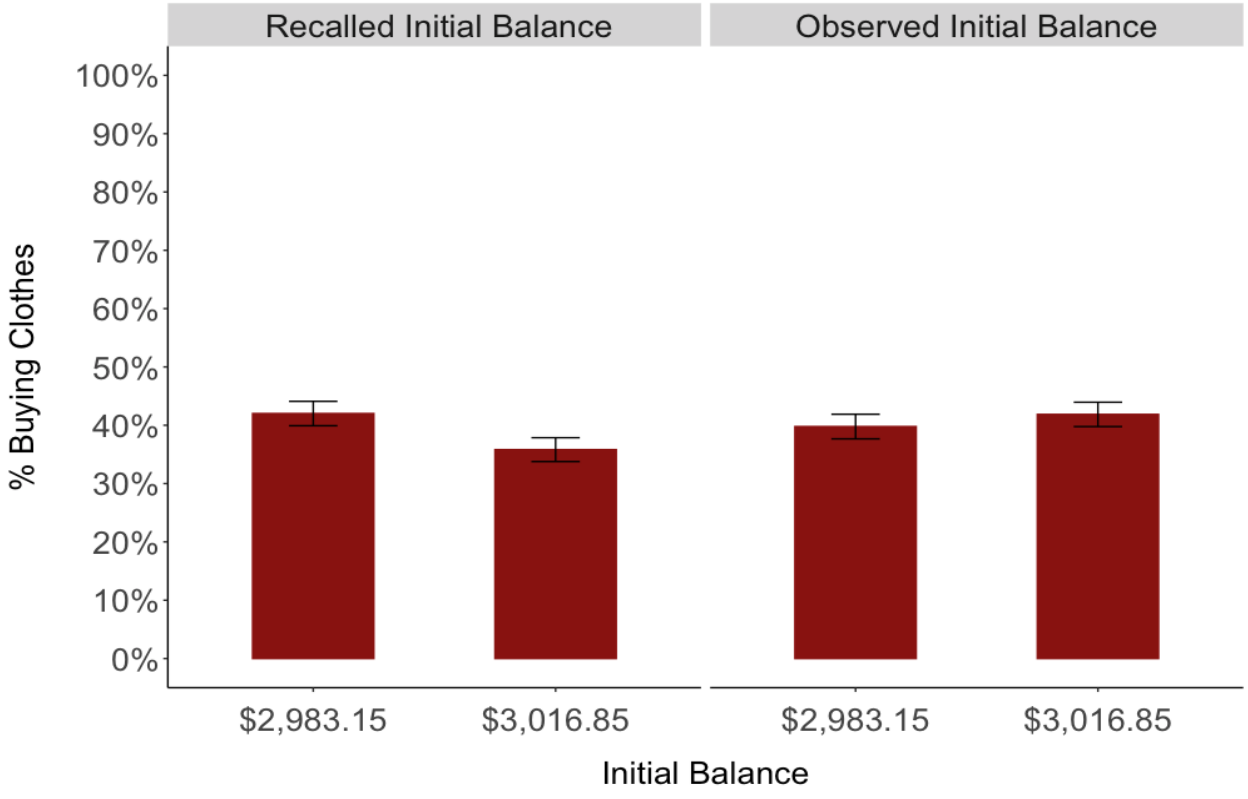
Notes: ***$p < .001$, **$p < .01$, *$p < .05$, †$p < .10$. Standard errors are in parentheses. The decision to purchase the clothes was regressed on condition and recall errors using logistic regression models. Recall errors were regressed on condition using a linear regression model.

Appendix B

Essay 1, Study 2 replication with known budgets

We ran a replication of Study 2 where Prolific participants (n = 2,204) could observe their budgets and current balances together before completing the spending task. Budgets were set to $4,300, and in all conditions, the final expense that participants considered would put them over their budgets and prevent them from earning a bonus.

Figure 4.1: Study A2 Fraction of Participants Who Overspent

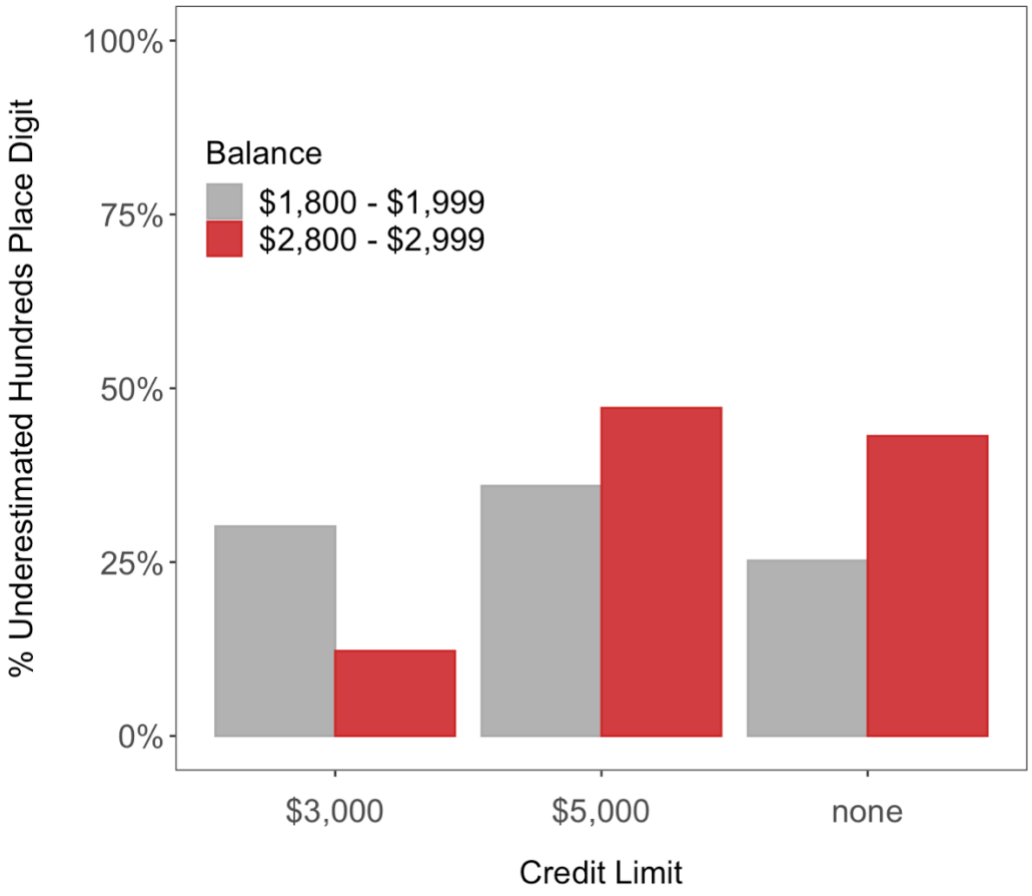


Notes: We found a significant interaction in the predicted pattern: β = -0.347, z-value = -1.99, p = .046, N = 2,204. Error bars are standard errors.

Appendix C

Essay 1, Study 6 alternate figure and replication

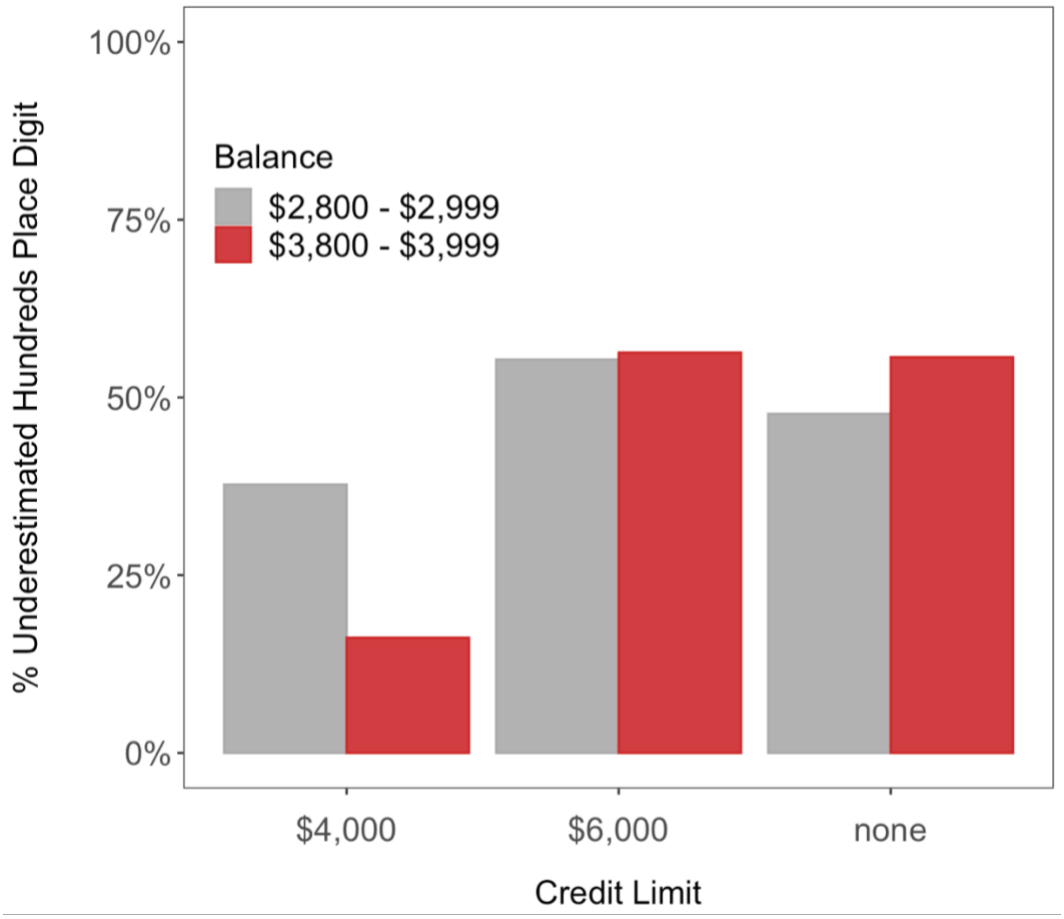
Figure 5.1: Study 6 Fraction of Participants Who Underestimated the Hundreds Place Alternate



Notes: Study 6 interaction excluding participants who entered the exact credit limit.

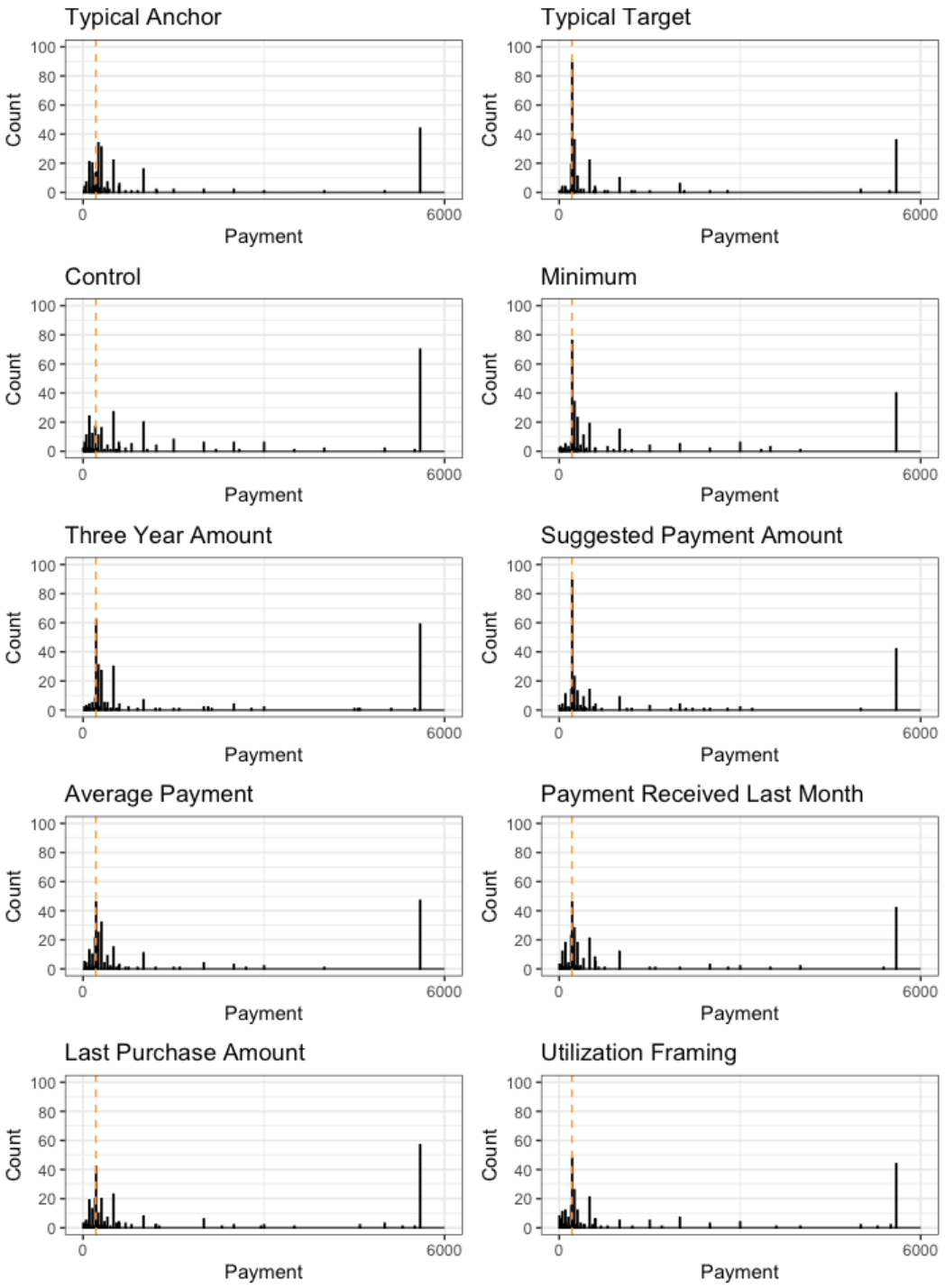
We ran a close replication of Study 6. The method and procedure were identical to Study 6 except for participants recalling the balances and credit limits on the same page to avoid confusion. For stimulus sampling purposes, we also increased balances and limits by $1,000.

Figure 5.2: Study A3 Fraction of Participants Who Underestimated the Hundreds Place (Replication Study)



Appendix D

Figure 6.1: Payment Histograms by Condition



Notes: Bins are $10 and include the lower bound. Orange dotted lines indicate the focal payment amount ($213.03)