The Supply Side of Consumer Debt Repayment*

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Abstract

We study how lender responses to consumer biases affect credit card debt. Using account-level credit bureau data, we document a new fact: many consumers make near-minimum credit card repayments while also overpaying lower-interest installment debt. We estimate an empirical model in which lenders optimally set minimum payments given this behavior. Because some liquid consumers make near-minimum payments, lenders lower minimums to slow repayment, increasing high-interest debt balances and interest revenue. Our model implies that this lender response increases revolving debt by $46 billion. This finding illustrates how optimizing lenders can amplify the effects of consumer biases in equilibrium.

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1 Introduction

Nearly half of U.S. households carry credit card debt from month to month, paying annual interest rates above 21% on average (FRB, 2025; FRB, 2026).[1] Existing research often attributes this high-cost borrowing to borrower-side constraints and behavioral forces.[2] However, lenders also design contract terms that shape repayment, including minimum payment requirements. In practice, these minimum payments are strikingly low: although credit card debt is unsecured, a consumer with a balance of $5,000 is required to repay as little as $50 in a given month. These repayment requirements have drawn policy attention to the role lenders may play in shaping consumer debt and risk (e.g., Tescher and Stone, 2022).

In this paper, we study how lenders choose contract terms in response to consumer behaviors, and how those choices, in turn, affect consumer debt. Using account-level credit bureau data, we show that many consumers make near-minimum credit card payments even when they have the liquidity to overpay other debts. We then develop an empirical model that shows how this behavior creates incentives for credit card lenders to lower minimums, slowing repayment and increasing high-interest debt balances. Our findings illustrate a mechanism through which profit-maximizing lenders amplify the effects of consumer biases.

We begin with a framework that characterizes lenders' incentives when setting minimum payments. In a benchmark setting without default, lenders would prefer to set no minimum and maximize outstanding debt. Intuitively, lenders want to be repaid slowly, earning the spread between high credit card interest rates and their lower cost of funds. With default, there is a tradeoff: slower repayment increases interest revenue, but also raises exposure to default losses. The strength of the interest-revenue channel depends on the repayment behavior of low-risk borrowers. If some borrowers make near-minimum repayments even when they are at low risk of default, reductions in minimums generate substantially more interest revenue, tilting the tradeoff toward lower minimums.

We then document several facts about minimum payments in the U.S. credit card market using a monthly account-level panel from a major credit bureau. First, near-minimum repayment is common: among borrowers with revolving debt, two-thirds pay within $100 of the minimum. Second, minimums themselves are low and often set at a regulatory floor, whereby a borrower choosing the minimum repays only 1% of principal each month. Third, minimums are higher for the lowest credit score borrowers, who typically must repay 5–7% of the principal. Our framework suggests that lower minimums for higher credit score consumers

[1] Following Gibbs *et al.* (2025), we use the term "revolving debt" to describe credit card balances carried over into the next statement. Average credit card debt among revolvers in the Survey of Consumer Finances (SCF) is $6,120. The SCF has been shown to underreport credit card debt levels (Zinman, 2009).

[2] See Zinman (2014) for one discussion of the "credit-card overborrowing puzzle."

may reflect lenders' incentive to generate interest revenue when default risk is low.

To better understand the determinants of consumer repayment—and ultimately lenders' incentives—we examine how borrowers allocate payments intra-temporally across debts. We document a new fact: consumers who revolve credit card debt often make *excess* payments on installment debts in the same month. Among revolvers with a mortgage, student loan, or auto loan, one-fifth of months include an installment overpayment of $25 or above, and nearly 60% of these revolvers make at least one such overpayment over a two-year period. These cross-product repayment patterns are challenging to rationalize with cost-minimization, and imply that many borrowers could pay down credit card debt faster without reducing consumption.

We then explore the potential mechanisms behind these cross-product repayment behaviors. Many behavioral models of credit card debt are primarily intended to target inter-, rather than intra-temporal moments, so cannot directly generate these patterns. A model of mental accounting in which minimum required payments serve as a reference point or "anchor" can explain both the cross-product repayment patterns and near-minimum payments. Consistent with this interpretation, in response to an increase in minimum payments by a lender in the data, borrowers who previously paid just above the old minimum shift to paying just above the new one. This response is strongest among households that had previously overpaid installment debt while revolving credit card debt, directly linking the cross-product and near-minimum payment behaviors. A survey experiment provides additional evidence for this mechanism. We find little support for explanations based on optimal inattention or borrowers making extra installment-loan payments in anticipation of default.

In the second part of the paper, we estimate an empirical model to quantify how these repayment behaviors shape contract design and, in turn, how contract design affects consumer debt. In the model, low credit card payments can arise either from low borrower income or intra-temporal repayment mistakes. We use the term "anchoring" to describe the latter, but identification relies on the observed cross-product repayment patterns rather than a specific psychological mechanism. The model closely fits the distribution of credit card excess payments, spending, and utilization. Model-implied optimal minimums for lenders are also close to those we observe empirically, suggesting the model captures lenders' primary incentives.

The empirical model helps explain why lenders set low credit card minimums, despite the potential losses they face from borrowers defaulting on these unsecured debts. When consumers are anchored, changes in minimums affect relatively liquid borrowers who would otherwise make larger payments. As a result, the marginal revenue from lowering minimums is high. Lenders set low minimums to increase debt balances, even though this also increases default losses. Implicitly, the lender "accepts" more defaults in the long run because they are able to generate much more interest revenue from other low-risk borrowers. By contrast, when consumers are unanchored, payments are closely tied to default risk. The marginal revenue from lowering minimums declines, and lenders instead set higher minimums to increase repayment and mitigate default losses.

Lenders lower minimums in response to borrower anchoring across all credit score bins, but the response is strongest for high-credit-score borrowers. In the top credit score bin, a borrower at the credit limit would face a minimum of \$781 rather than \$100 if consumers in the model were unanchored and prioritized credit card repayment. Paying only the minimum would then fully amortize debt in 5 years instead of 24 years. For lower credit score borrowers, who have lower incomes and whose low payments are more tightly linked to liquidity and default risk, the increase is smaller.[3]

Finally, we show how profit-maximizing lenders' contract choices can amplify the effects of consumer bias on debt. While anchoring directly increases debt in the model, lenders also lower minimum payments in response, generating *more* debt in equilibrium. We quantify these two channels, decomposing the effect of anchoring into a direct behavioral component holding minimum payments fixed and an additional component arising from lenders' re-optimization. Overall, anchoring increases revolving debt by 19%. Roughly three-fourths of this increase reflects the direct effect of anchoring and one-fourth arises from lenders lowering minimum payments in response. Larger balances also lead to more consumer defaults: defaults increase by 7%, with about two-thirds of this effect driven by the lender response. Lenders have an especially large effect on defaults because lower minimums slow repayment most for high-balance borrowers, who are closest to default on average.

Scaled by the size of the credit card market, our estimates imply that lenders' response to anchoring alone increases revolving credit card debt by around \$46 billion. This increase primarily comes from higher-credit-score consumers, from whom lower minimums generate substantial additional interest revenue. More broadly, our results show that consumer behaviors matter not only because they affect repayment and borrowing directly, but also because they lead lenders to choose contract terms that further increase debt in equilibrium.

Our paper makes three main contributions. First, we document an economically significant deviation from cost-minimizing repayment across household debts. Prior work shows that borrowers often fail to optimally borrow or allocate repayments across credit cards (e.g., Stango and Zinman, 2016; Ponce *et al.*, 2017; Gathergood *et al.*, 2019b) and in response to relative rate changes (Katz, 2023), and that repayment decisions can be influenced by impatience, biased beliefs, or inattention to fees (for one overview, see Zinman, 2014). As discussed by Choi (2022), popular advice often promotes non-cost-minimizing excess re-

[3]This result is consistent with Guttman-Kenney (2025), who finds small effects from a de-anchoring intervention among subprime borrowers.

payment strategies but, to our knowledge, no prior work explores the prevalence of these behaviors across many debt products. Unlike the co-holding puzzle, which concerns liquid assets held alongside revolving card debt, the cross-debt repayment patterns we document cannot be explained by demand for liquidity.[4] Instead, our results are consistent with evidence on mental accounting and anchoring (e.g., Keys and Wang, 2019).

Second, we contribute to a literature studying firm behavior in the credit card market. While most revolvers make payments close to the required minimum, relatively little attention has been paid to how lenders optimally set these requirements, as opposed to other contract features such as APRs (Ausubel, 1991; Dempsey and Ionescu, 2024; Nelson, 2025; Drechsler *et al.*, 2025), credit limits (Agarwal *et al.*, 2018; Matcham, 2025), or fees (Agarwal *et al.*, 2015).[5] Prior work has studied borrower responses to discrete changes in minimum payments (Keys and Wang, 2019; Castellanos *et al.*, 2025; Allen *et al.*, 2026), finding increases in payments and decreases in long-term debt levels consistent with our model; however, there is little evidence on the determinants of minimums themselves. We provide evidence using an empirical model which can be transparently estimated from our detailed loan-level data.

Third, we add to a growing literature on behavioral contracting, which studies how profit-maximizing principals design contract terms and target consumers in response to consumer mistakes (see Kőszegi, 2014, for one review). In the credit context, Heidhues and Kőszegi (2010) studies product design when borrowers are naive about self-control; Ru and Schoar (2023) and Robinson *et al.* (2025) provide evidence that lenders target biased credit card borrowers; and Foà *et al.* (2019) and Li (2026) study how non-price channels, such as lender advice, affect mortgage choice. More broadly, a canonical literature studies optimal contracting when consumers make mistakes, such as naivete about present bias (DellaVigna and Malmendier, 2004), limited attention to future prices or contract terms (Gabaix and Laibson, 2006), or overconfidence about future behavior (Grubb and Osborne, 2015).

We provide evidence that profit-maximizing lenders amplify consumer biases through the design of an important contract feature, minimum payments. In contrast to fully exploitative contracting, in which considerations beyond the exploitation of a mistake are non-central (Kőszegi, 2014), in our setting lenders must trade off higher interest revenue against the costs of increased default losses.[6]

[4]For the co-holding puzzle, see, e.g., Gathergood and Olafsson (2024); Vihriälä (2022); Fulford (2015); Telyukova (2013); Gross and Souleles (2002). The cross-product behaviors we document relate to work on mortgage curtailments (Amromin *et al.*, 2007; Adelman *et al.*, 2010; Xu, 2023; Liebersohn *et al.*, 2024).

[5]A number of other papers study aspects of competition in the credit card lending market (Chatterjee *et al.*, 2007; Herkenhoff and Raveendranathan, 2025; Herkenhoff and Morelli, 2026) or, more broadly, the determinants of credit access (Bakker *et al.*, 2025).

[6]In this sense, our setting is related to work that explores how consumer behaviors interact with information frictions in a variety of other contexts (Handel, 2013; Baicker *et al.*, 2015; Veiga and Weyl, 2016).

The rest of the paper proceeds as follows. Section 2 contains a motivating framework to make precise the forces that influence lenders' choice of optimal minimum payments. Section 3 provides background on minimum payments and our data. Section 4 provides evidence on repayment behaviors across credit card and installment debts, and explores potential mechanisms for these behaviors using a natural experiment and survey. Section 5 introduces the empirical model and Section 6 contains counterfactual exercises. Section 7 concludes.

2 Motivating Framework

This section presents a framework that illustrates lenders' incentives when setting required debt payments. Low minimums are optimal when many borrowers are illiquid and unable to make higher payments today, or when default risk is low for borrowers with repayments responsive to the minimum. We use the framework to structure our empirical analysis. Appendix A.1 provides additional details.

Setup. Consider a lender who offers a revolving debt contract with gross interest rate fixed at $R_{cc} > 1$.[7] In period $t = 0$, the lender sets a minimum payment schedule as a function of (statement) balances, B_t, outstanding at the start of period t: $m_t = m(B_t)$. Consumers make spending and repayment decisions, $S_t = S(B_t)$ and $P_t = P(B_t, m_t)$. Repayments increase in minimums, capturing either borrowers' incentive to avoid default or any behavioral responsiveness to the stated minimum. Balances evolve as:

$$B_{t+1} = R_{cc}(B_t - P_t) + S_t \tag{1}$$

Consumers default with probability $\chi_t = \chi(B_t, m_t)$. Default depends on minimums because some borrowers may lack the liquid resources necessary to make minimum payments ("illiquidity defaults"). Default depends on balances because debt burdens may be so high relative to expected future income and default costs that default is optimal ("insolvency defaults").

Lender's Problem. The lender discounts future profits with factor δ, and sets the schedule of minimum payments $m(B_t)$ to maximize the expected present value of profits:

$$\Pi(B_t) = \max_{m} \ \mathbb{E}_t \sum_{j=t}^{\infty} \delta^{j-t}(P_j - S_j) \tag{2}$$

[7]In this illustrative framework, we hold interest rates fixed and allow the lender to make positive profits, consistent with evidence of pricing power in the credit card market (e.g., Ausubel, 1991; Drechsler *et al.*, 2025; Herkenhoff and Morelli, 2026).

The optimal schedule for minimum payments satisfies the Bellman equation:

$$\Pi(B_t) = \max_{m} (1-\chi_t)\left(P_t - S_t + \delta\left[\Pi(B_{t+1})\right]\right) \quad \text{s.t.} \quad B_{t+1} = R_{cc}(B_t - P_t) + S_t \tag{3}$$

Optimal Minimums. In Appendix A.1, we define profits conditional on no default in t as $\tilde{\Pi}(B_t) = P_t - S_t + \delta\Pi(B_{t+1})$ and show that the first order condition can be expressed as:

$$\underbrace{\frac{\partial \chi_t}{\partial m_t}\frac{\tilde{\Pi}(B_t)}{1-\chi_t}}_{\text{Illiquidity Default}} + \underbrace{\frac{\partial P_t}{\partial m_t}\left[(1-\chi_{t+1})\,\tilde{\Pi}'(B_{t+1})\delta R_{cc} - 1\right]}_{\text{Net Interest Revenue}} = \underbrace{\delta R_{cc}\frac{\partial P_t}{\partial m_t}\frac{\partial \chi_{t+1}}{\partial B_{t+1}}\tilde{\Pi}(B_{t+1})}_{\text{Insolvency Default}} \tag{4}$$

Equation 4 equates the marginal costs of raising minimums on the left-hand side to the marginal benefits on the right-hand side. The first term captures that higher minimums can induce default among borrowers with insufficient short-run liquidity, $\frac{\partial \chi_t}{\partial m_t} > 0$, increasing losses. The second term reflects that higher minimums reduce interest-bearing balances through their effect on repayments, $\frac{\partial P_t}{\partial m_t} > 0$, which lowers future interest revenue. The final term shows that by increasing repayments and reducing balances, a higher minimum lowers the costs of future default due to insolvency.[8]

The left-hand side of Equation 4 shows that low required minimums on the supply side and near-minimum repayments on the demand side can arise from two forces. First, consumers might borrow only because they are liquidity-constrained, making small payments today in response to temporary liquidity shocks. Lenders would set low minimums to allow them to borrow against future income and prevent illiquidity defaults. Second, consumers might borrow because of behavioral forces that lead them to make small repayments that are responsive to minimums and not strongly tied to default risk. Lenders would set low minimums to amplify these behaviors and generate more interest revenue.

To illustrate the latter force, suppose consumers never default ($\chi_t = 0$ for all t). Only the net interest revenue term remains. Because credit card interest rates are high relative to the lender discount rate, $\delta R_{cc} > 1$, the lender sets minimums as low as possible, maximizing interest revenue.[9] With default, the relative strength of the interest-revenue channel depends on the repayment of low-risk borrowers. If repayments are responsive to the minimum even when default risk is low (so that $\frac{\partial P_t}{\partial m_t}(1-\chi_{t+1})$ is large), the lender sets lower minimums.

This paper explores the importance of this force. The key object is the relationship between default risk and low credit card repayments. To characterize this relationship,

[8] In Appendix A.1, we add late fees to the lender's problem. Raising minimums may allow lenders to charge additional late fees if borrowers experience very short-run liquidity shocks.

[9] Formally, we assume that $\frac{\partial^2 P_t}{\partial m_t^2} > 0$ with $\frac{\partial P_t(B_t,0)}{\partial m_t} = 0$. Therefore, for Equation 4 to hold when $\chi_t = 0$ for all t, this requires that $\frac{\partial P_t}{\partial m_t} = 0 \Rightarrow m_t = 0$.

we provide new evidence on the determinants of household debt repayments. We use this evidence to inform an empirical model, which allows us to quantify a mechanism through which profit-maximizing lenders amplify the effects of consumer biases.

3 Credit Card Minimums: Background, Data, & Facts

This section provides institutional background, introduces our data, and documents key facts about credit card minimums and repayment. We show that credit card lenders set low minimum payments and many borrowers pay close to these minimums.

3.1 Overview of Credit Card Minimum Payments and Regulations

Credit card minimum payments are the minimum amount a borrower is required to pay in a month to avoid late fees and remain in good standing with the lender. If the borrower fails to make the minimum payment and does not repay in 30 days, a delinquency is reported on their credit report, potentially limiting their access to credit, housing, and employment. The minimum payment is usually substantially less than the statement balance, the consumer's total end-of-month balance. Consumers who pay between the minimum and the statement balance carry a revolving balance that accrues interest to be repaid in later months.

Prevailing Minimum Formula. We use the CFPB Credit Card Agreement Database to explore how lenders set minimums (see Appendix D for details on the database and our analysis). Among 25 large issuers, all use a formula that includes two contract features: a slope, θ, which determines how quickly minimums rise with balances; and a floor, μ, which borrowers pay if their θ-implied minimum is below the floor. The most common formula is:

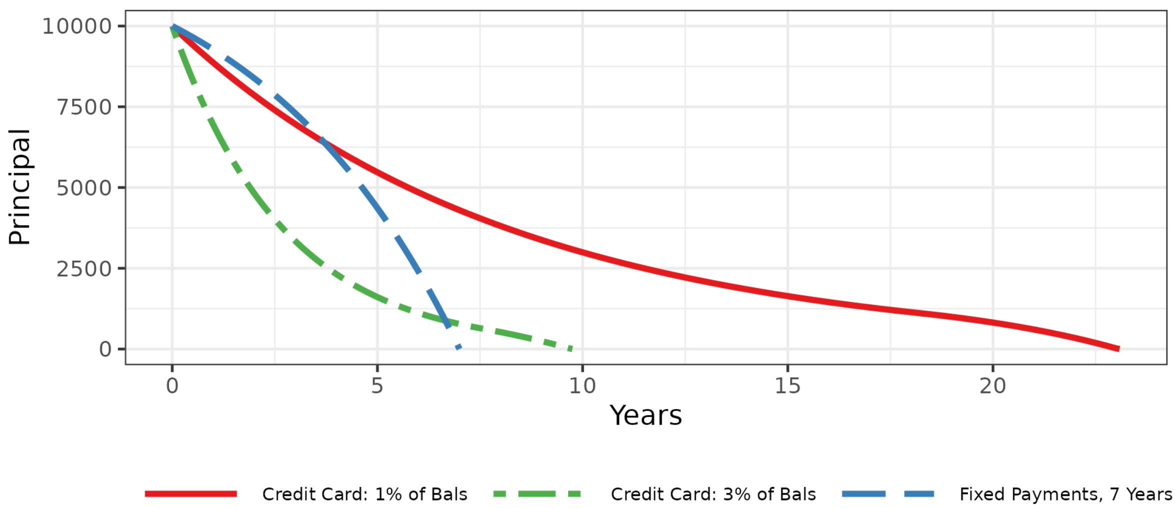
$$\text{Minimum}_t = \max\{\mu,\ \theta \cdot \text{Balance}_t + \text{Interest}_t + \text{Fees}_t\} \tag{5}$$

where Balance_t is the statement balance at the beginning of month t, Interest_t is the one-month interest on the revolving balance accrued from $t-1$ to t, and Fees_t are fees due in period t (e.g., from missing a prior payment).[10] Because the formula explicitly includes any interest and fees generated, it prevents negative amortization for any $\theta \geq 0$. Minimum payment formulas do not typically change over time within accounts.

The prevailing minimum payment formula slows the path of required payments as balances decrease. Figure 1 illustrates this using a debt of \$10,000 and an annual interest rate

[10] If balances fall below the floor, the minimum is the balance. Our notation ignores this for simplicity.

Figure 1: *Implied Debt Repayment Schedules*



Note: Figure shows various amortization schedules of a debt with a \$10,000 principal and 20% annual interest rate. The blue line shows the amortization schedule for a debt with fixed payments over seven years. The red line shows the amortization schedule of a credit card with $\theta = 1\%$ and $\mu = \$30$, as each is defined in Equation 5, when the borrower makes only minimum payments and does not continue spending. The green line shows the amortization schedule for a similar borrower when $\theta = 3\%$.

of 20%. The dashed blue line shows the amortization schedule of a loan with fixed payments over seven years, typical of the longest personal loans in the U.S. The concave amortization schedule contrasts with the credit card in red and green, in which required payments drop as balances decrease, leading to a convex amortization schedule.

Figure 1 also shows that small changes in the slope parameter, θ, can have large impacts on the path of debt repayment. For a borrower paying the minimum, going from θ of 1% to 3% decreases the duration of the credit card debt from 23 years to under 10 years. The total interest paid decreases from \$15,447 to \$5,357.

Law & Regulations. U.S. law and regulatory guidance affect minimum payments in two direct ways. First, regulators have stated that credit card minimums should not cause negative amortization and, in general, should amortize balances over a "reasonable period of time."[11] Lenders have interpreted this to mean $\theta \geq 1\%$. Second, late fees for missing a minimum payment cannot exceed the lesser of the minimum payment itself and a regulatory cap.[12] In practice, lenders often set μ (the minimum floor) equal to the late fee cap, which ensures that they are able to charge the maximum allowable late fee. Consistent with lenders strategically setting floors to maximize late fee revenue, Appendix Figure B.1 shows that bunching at the late fee cap persists even as the regulatory cap shifts over time with inflation.

[11] See FRB (2003), OCC (2003), and OCC (2005) as well as the OCC and FDIC handbooks for examiners.
[12] See the OCC discussion of 12 CFR § 1026 (Regulation Z), available at `https://tinyurl.com/28xjkwc7`.

3.2 Data and Summary Statistics

Our primary data source is a monthly account-level panel of U.S. consumers from a major credit bureau. Importantly, the data allow us to link an individual's repayments across different debts, unlike bank supervision data or data from a single financial institution. We will use this feature to provide a measure of available liquidity that helps us to disentangle the forces in the motivating framework.

Table 1: *Summary of Baseline Sample*

	Mean	SD	p10	p25	p50	p75	p90
Credit Card							
N Open	1.54	0.95	1	1	1	2	3
N Non-Zero Bal.	1.42	0.85	1	1	1	2	2
Total Credit Limit	$12,080	$12,131	$1,000	$3,000	$8,900	$17,300	$26,950
Total Balance	$3,546	$5,556	$117	$405	$1,418	$4,337	$9,611
Total Monthly Amt Due	$98	$156	$20	$27	$52	$115	$237
Total Actual Monthly Pymnt	$872	$2,433	$25	$90	$250	$772	$2,181
N Revolving Bal	0.93	0.99	0	0	1	1	2
Total Revolving Bal	$2,774	$5,202	$0	$0	$535	$3,238	$8,451
Mortgage							
Has 1+ Open	0.34	0.47	0	0	0	1	1
Total Balance	$69,540	$149,681	$0	$0	$0	$97,125	$234,134
Total Monthly Amt Due	$560	$1,654	$0	$0	$0	$925	$1,836
Total Actual Monthly Pymnt	$613	$2,811	$0	$0	$0	$900	$1,947
Total Bal. Cond. on >0	$203,293	$195,719	$51,401	$92,400	$156,986	$256,364	$387,425
Auto Loan							
Has 1+ Open	0.36	0.48	0	0	0	1	1
Total Balance	$7,257	$13,931	$0	$0	$0	$10,826	$24,791
Total Monthly Amt Due	$184	$316	$0	$0	$0	$339	$583
Total Actual Monthly Pymnt	$218	$977	$0	$0	$0	$330	$605
Total Bal. Cond. on >0	$20,158	$16,705	$4,675	$9,272	$16,316	$26,263	$39,458
Student Loan							
Has 1+ Open	0.12	0.32	0	0	0	0	1
Total Balance	$3,528	$17,764	$0	$0	$0	$0	$3,624
Total Monthly Amt Due	$29	$133	$0	$0	$0	$0	$51
Total Actual Monthly Pymnt	$34	$439	$0	$0	$0	$0	$25
Total Bal. Cond. on >0	$30,373	$43,604	$2,686	$6,376	$15,942	$36,565	$71,569
All Four Types							
N Open	2.7	1.98	1	1	2	3	5
N Unique Types	1.82	0.81	1	1	2	2	3
Total Bal	$83,871	$154,709	$290	$1,502	$16,172	$115,161	$257,488
Total Monthly Amt Due	$872	$1,743	$25	$53	$415	$1,305	$2,350
Total Actual Monthly Pymnt	$1,737	$3,991	$60	$260	$863	$2,143	$4,022

Note: Table presents summary statistics on 2017-18 consumer-months in the credit bureau data, as described in Section 3.2. The sample includes only account-months for which we observe actual payments and consumer-months for which there is at least one such credit card. The rows "Total Bal. Cond. on $>$ 0" limit to consumers that have a positive balance for that debt. $N = 6{,}465{,}133$.

The data cover a random sample of one million individuals from 2013 to 2022, and include information on balances, minimum (scheduled) payments, and actual payments made. We focus on general purpose credit cards and the three other largest sources of U.S. household debt: mortgage, student, and auto loans (NY Fed, 2026). We build a sample of consumers who had a positive statement balance on at least one credit card in 2017-18.

Much of our analysis involves studying credit card debt that is carried, or "revolved", between months. Calculating revolving credit card debt requires subtracting actual payments made in month t from the credit card statement balance month $t-1$, as described in Gibbs *et al.* (2025) (see Appendix B.1 for more details). Some credit card providers do not report actual payment information (CFPB, 2020; CFPB, 2023b), which reduces the sample of consumer-months in 2017-18 from 13.4 million to 6.5 million.[13]

Table 1 summarizes our baseline 2017-18 sample, which restricts to account-months for which we can observe payments and consumer-months for which there is at least one such card.[14] Consumers carry revolving balances in 65% of sample months (similar to Grodzicki and Koulayev, 2019). The average revolving balance, conditional on revolving, is $4,250. The median monthly minimum and actual credit card payments are $52 and $250, respectively. The median credit card holder has two different debt types and over $16,000 in total debts.

Borrower Survey. To complement our credit bureau data, we conducted a survey experiment on Prolific in July 2025. The survey targeted individuals in the U.S. with a credit card and mortgage. It included multi-debt repayment scenarios with randomized treatments, along with questions about participants' behaviors, rationales, and beliefs. A pre-registration of our experimental design—including the outcomes, exclusion criteria, and full survey instrument—is available at: `https://www.socialscienceregistry.org/trials/16321/`. The survey yielded 1,598 responses. Appendix E provides additional details.

3.3 Key Facts on Credit Card Minimum Payments

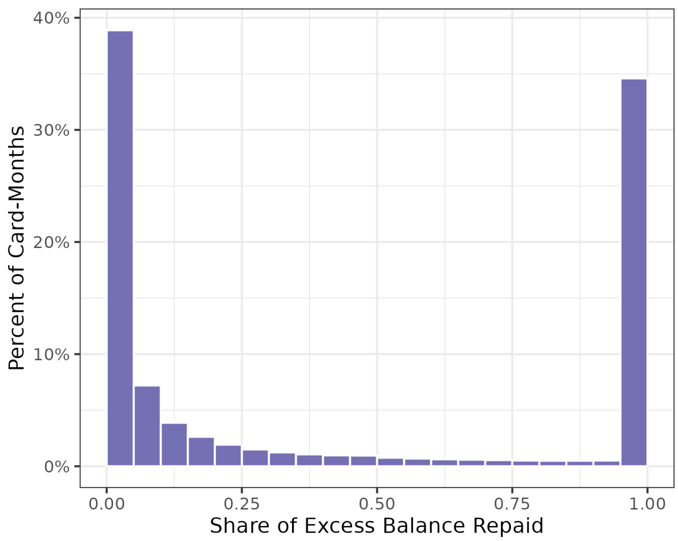
We analyze U.S. credit card repayments and required minimums using our credit bureau data. We summarize our findings in three key facts.

[13] At the card level, we observe actual payments for 34% of credit cards that ever had a positive statement balance in 2017 or 2018 and for 30% of credit card-months with a positive balance. These shares are similar to existing estimates (CFPB, 2020) and (Guttman-Kenney and Shahidinejad, 2023). In Appendix Table B.2 we compare the credit card accounts for which we can and cannot see actual payments. Those without actual payments have slightly higher credit scores and monthly statement balances on average; however, each group includes cardholders across the full credit score distribution.

[14] Appendix Table B.1 summarizes all consumer-months, regardless of reported actual payments. We focus on 2017-18 to avoid the effects of COVID-related stimulus.

Fact 1: Many borrowers pay close to the minimum. Figure 2 plots the distribution of credit card repayments in our sample, measured as the share of the balance above the minimum that a consumer repays. This measure equals zero if the consumer pays only the minimum and one if the consumer pays the full balance. As in Keys and Wang (2019), the distribution is U-shaped, with one group of consumers paying the full balance and another group making payments close to the minimum. Of those below the full balance, two-thirds are within \$100 of the minimum and 53% are within \$50.

Figure 2: *Excess Repayments as Share of Balance*

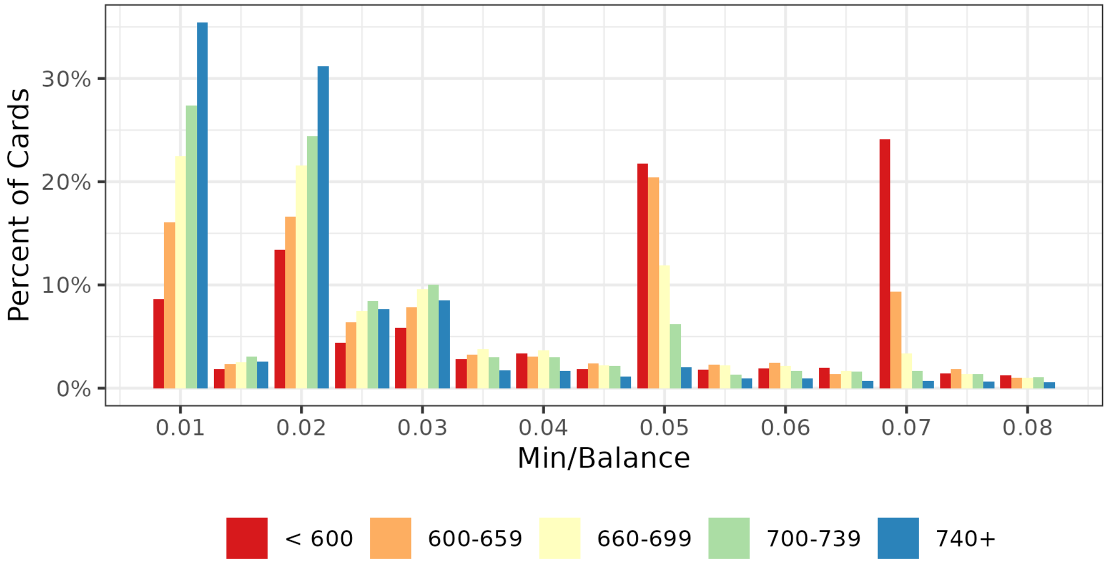


Note: Figure shows the distribution of credit card repayments in months when the borrower did not miss the minimum. The measure is the share of the balance in excess of the minimum the borrower paid. Formally, this is $\frac{\text{actual payment}_t - \text{minimum payment}_{t-1}}{\text{balance amt}_{t-1} - \text{minimum payment}_{t-1}}$. Borrowers who make actual payments above the lagged balance (i.e., are making intra-month payments on recent spending) are given a value of one.

Fact 2: Credit card minimums are often near the lowest allowed by regulators. Figure 3 plots a measure of θ, the rate at which required minimum payments increase with balances, by credit score bin. For each card, we measure θ as the lowest minimum-payment-to-balance ratio in months when the cardholder did not revolve in the prior month, to avoid interest charges, and the minimum exceeded \$40, to avoid the highest floor in our sample period. The darker blue (red) bars show the distribution for high (low) credit score bins. The most common value of θ is 1%, the lowest whole number that ensures non-negative amortization. Two-thirds of accounts have θ of 2.5% or lower.

Fact 3: Minimums are higher for low credit score consumers. While low minimums are common among high credit score consumers, Figure 3 also shows that much higher θ are typical for lower score borrowers. The most common minimums for consumers with credit scores below 600 are 5% and 7% of balances.

Figure 3: *Distribution of Implied Credit Card Minimum θ (Slope) by Credit Score*



Note: Figure shows, across credit score bins, the distribution of cards' smallest $\frac{\text{Minimum}}{\text{Balance}}$. To estimate θ, the rate at which minimums increase in balances, the plot is among months when individuals did not revolve in the prior month and had a minimum larger than \$40. Colors show credit score bins. Each bin sums to one.

Discussion. What do these equilibrium outcomes imply in light of our theoretical framework in Section 2? For the lowest credit score consumers, minimums are high. Our framework suggests this is driven by lenders' incentive to avoid insolvency defaults for these high-risk consumers. For most others, minimums are low. Our framework suggests two possible forces: many of these borrowers are illiquid and would default if required to make higher payments, or many borrowers make near-minimum payments even when they pose little default risk. In the latter case, lower minimums slow repayment and, in turn, increase interest revenue.

In the next section, we use consumers' excess debt repayments to explore the second force. Before doing so, we note two qualitative pieces of evidence consistent with lenders preferring slow repayment from low-risk borrowers. First, a class-action lawsuit against Bank of America, settled in 2021, alleges that the bank offered duplicative autopay options, "Amount Due" and "Minimum Amount Due" to "confuse consumers [into paying the minimum] and inflate the Defendant's profits" (Jette, 2020). Second, in an interview, a former credit card industry consultant described advising a client to reduce minimum payments from 5 percent to 2 percent, explaining that "high-balance accounts will be much more profitable...they're paying interest on a higher balance" (PBS, 2004). While only suggestive, both episodes are consistent with lenders acting on incentives to slow repayment and increase interest revenue.

4 Empirical Evidence on Excess Debt Repayments

Section 3 showed that credit card minimums are low and that many consumers pay close to these minimums. In this section, we explore the determinants of these outcomes. We document a new fact: consumers often carry high-interest credit card debt while paying extra on lower-interest installment debt. This fact shows that some borrowers revolve despite having extra liquidity. We provide evidence tying this behavior to the use of minimum payments as a reference point or anchor, and discuss other potential mechanisms.

4.1 Installment Overpayments Among Credit Card Revolvers

Consumers are typically able to pay extra on their auto, mortgage, and student debts, curtailing the balance and duration of the loan. Such overpayments provide a lower bound on the extra liquidity consumers have to repay debt in a given month without changing their consumption. Installment debts typically carry much lower interest rates than credit cards.[15] Thus, when a consumer is revolving credit card debt, making payments in excess of the required payment on their installment debt generally fails to minimize interest costs.[16] Unlike the co-holding of liquid assets and credit card debt, these behaviors cannot be explained by the need for liquidity to pay for certain goods and services (see e.g., Telyukova, 2013).

Measurement. To measure excess payments, we compare actual and scheduled payments, making a number of conservative adjustments to ensure we capture true overpayments (rather than, e.g., catching up after a missed payment). In particular, we restrict to consumers who were never delinquent during the 2017-18 sample period, and exclude months in which a consumer had prior underpayments or overpayments in the following month. Appendix B.1 provides additional details about our measure and robustness with alternative measures.

Empirical Patterns. We restrict our sample to months in which an individual revolved credit card debt and had an installment debt. To avoid "teaser" 0-APR introductory rates, we only include cards that have been open for at least 24 months.[17] We then ask in what share of months these individuals allocated excess payments to their installment debts rather than their credit card debt.

[15] In 2017-18, the average interest rate on credit cards assessed interest was 15.24%; on 48-month bank auto loans on new vehicles was 4.82%; and on 30-year fixed-rate mortgages was 4.27% (FRED series TERMCBCCINTNS; TERMCBAUTO48NS; MORTGAGE30US). The federal Stafford undergraduate student loan rates for the 2017-18 and 2018-19 years, respectively, were 4.45% and 5.05% (Department of Education, 2023).

[16] We formalize this intuition in Appendix A.2, and discuss default and other potential mechanisms below.

[17] Appendix Figure B.9 shows our results are nearly identical without this adjustment, suggesting that teaser rates are not a major driver of these behaviors.

Table 2: *Credit Card Revolvers Simultaneously Overpay Installment Debts: Summary*

	Mortgage	Auto	Student	Any
Repays \$10+ Extra				
Share Months	0.23	0.15	0.15	0.24
Share Eligible Consumers (2 Yrs)	0.61	0.5	0.49	0.65
Share Months, Cond. on Prior	0.73	0.66	0.71	0.72
Median \$ Extra	\$88	\$47	\$57	\$75
Median Share of Card Repaid	0.04	0.04	0.04	0.04
Repays \$25+ Extra				
Share Months	0.19	0.11	0.12	0.19
Share Eligible Consumers (2 Yrs)	0.56	0.43	0.44	0.59
Share Months, Cond. on Prior	0.71	0.59	0.66	0.68
Median \$ Extra	\$102	\$98	\$90	\$106
Median Share of Card Repaid	0.05	0.04	0.04	0.04
Repays \$50+ Extra				
Share Months	0.15	0.07	0.09	0.15
Share Eligible Consumers (2 Yrs)	0.5	0.38	0.38	0.54
Share Months, Cond. on Prior	0.67	0.5	0.61	0.63
Median \$ Extra	\$161	\$200	\$126	\$175
Median Share of Card Repaid	0.06	0.05	0.04	0.05
Repays \$100+ Extra				
Share Months	0.11	0.05	0.06	0.11
Share Eligible Consumers (2 Yrs)	0.43	0.33	0.28	0.47
Share Months, Cond. on Prior	0.61	0.38	0.54	0.55
Median \$ Extra	\$271	\$311	\$200	\$286
Median Share of Card Repaid	0.07	0.05	0.05	0.06
N Consumer-Months	1,098,275	1,171,240	394,051	1,863,084

Note: Table shows behaviors in consumer-months in which an individual had revolving credit card debt and had a mortgage, auto, or student loan. The sample includes only credit cards that have been open for at least 24 months. Each column restricts to consumer-months in which the individual holds the indicated installment debt. "Share Months" is the share of months with payments of at least \$X in excess of the required amounts on installment debts. "Share Months, Cond. on Prior" is the same measure conditional on the same behavior at the previous revolving month. "Share Eligible Consumers" is the share of consumers who have one or more such payment and revolved for at least six months in 2017-18. "Median \$ Extra" is the median excess payment among consumer-months with overpayments of at least \$X. "Median Share of Card Repaid" is the median share of the excess credit card balance repaid—the measure plotted in Figure 2—among consumer-months with installment overpayments at least \$X.

Table 2 shows that many revolvers do not focus excess repayments toward their credit card debt. Among consumers who revolve and hold installment debt, around one-fifth of months include overpayments of \$25 or more to installment loans, and 59% make one or more such overpayments over two years. Many of these overpayments are much larger than \$25: the median total installment debt overpayment in these months is \$106 and the 75th percentile is \$325. The behavior is also persistent. Conditional on occurring in the previous revolving month, it recurs in 68% of subsequent revolving months. At the same time, these consumers make near-minimum credit card repayments: in installment overpayment months, the median consumer repays only 4% of their balance in excess of the minimum.

Table 3: *Mortgage Overpayment Decomposition*

Prepayment Type	Share	N
1) Stickiness	0.2%	2,271
2) Double	6.8%	69,049
3) Round Up	26%	264,985
4) Total Payment Mult. of 50	19.2%	195,425
5) Excess Payment Mult. of 50	19.4%	197,836
6) Other $<$ 1.25x	12.6%	127,928
7) Other 1.25x - 5x	15.3%	155,529
8) Other $>$5x	0.5%	5,284

Note: Table categorizes mortgage payments in 2017-2018 mortgage-months with an excess payment $\geq$ \$25. Categories are mutually exclusive and assigned in the order listed. "Stickiness" is paying the same as the previous amount due. "Round up" is an amount divisible by 5 that is $\leq$ 1.1x the amount due. "Double" is between 1.95x and 2.05x the amount due. "Total Payment Mult. of 50" is any other payment in which the total payment (excess plus required) is a multiple of 50. "Excess Payment Mult. of 50" is any other payment in which the excess payment is a multiple of 50. The "Other" categories are multiples of the amount due.

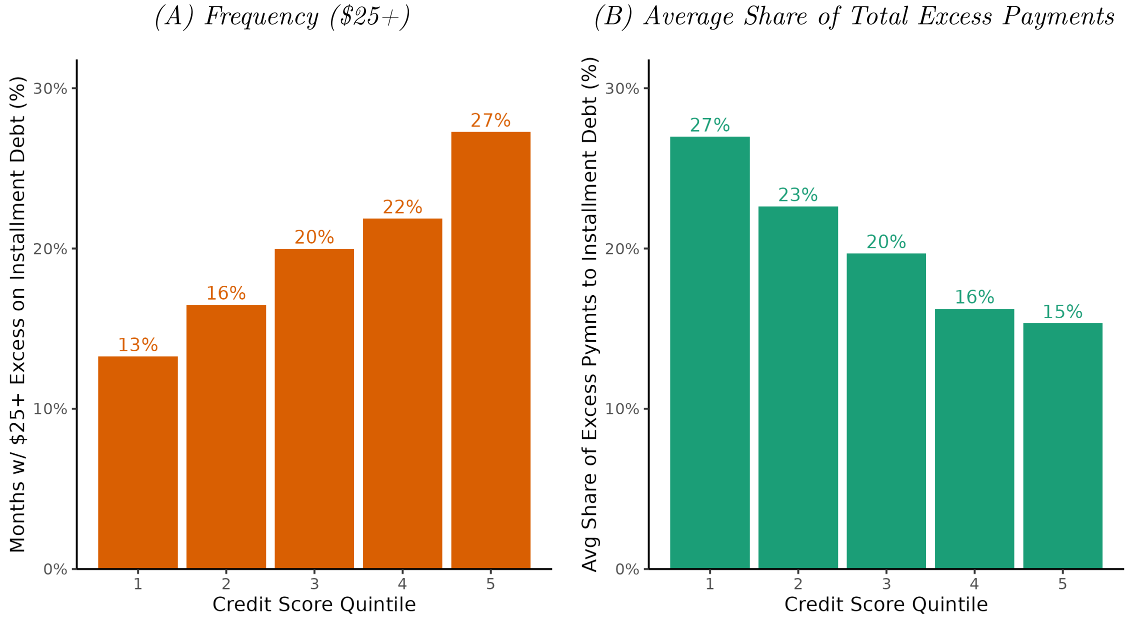
To better understand these patterns, Table 3 decomposes the months in which consumers make mortgage overpayments into categories. Nearly two-thirds of these mortgage overpayment months appear to involve rounding up or adding round amounts to the required payment. These repayments are consistent with the use of heuristics, and are commonly discussed by popular financial advisors.[18]

Figure 4 shows how the cross-product repayment behaviors vary across the credit score distribution. Panel (a) shows that the incidence of these installment debt overpayments while revolving rises with credit score, reaching 27% in the top quintile. Panel (b) shows that the *share* of one's excess payments to installment debt falls with credit score: while higher-score borrowers are more likely to make overpayments, lower-score borrowers allocate a larger share of overpayments to installment debt on the intensive margin.

Appendix B.2 provides additional evidence on the importance of these behaviors for consumers and lenders. Following the steady-state exercise in Gathergood *et al.* (2019b), we estimate that among revolvers with installment debt at the end of 2019, reallocating installment overpayments from the past seven years to credit cards would reduce revolving balances by \$1,817 on average and \$4,926 at the 90th percentile. Compared with the between-card failures to cost-minimize in Gathergood *et al.* (2019a,b), the cross-product failures we

[18] See, for example, Dave Ramsey's advice to "round up your payments so you're paying at least a few extra dollars." Appendix Figure B.2 shows the full distribution of overpayments by debt type.

Figure 4: *Credit Card Revolvers Simultaneously Overpay Installment Debts*



Note: Figure shows behaviors in consumer-months in which an individual had revolving credit card debt and had a mortgage, auto, or student loan. The sample includes only credit cards that have been open for at least 24 months. Panel (a) shows the share of months in which the consumer paid at least $25 in excess of the monthly amounts due on their installment loan. Panel (b) shows these installment debt overpayments as a share of total excess payments (both installment debt overpayments and credit card payments above the minimum). Credit scores are measured as of December 2016.

document are less frequent but larger in dollar terms. Because rate differentials are larger across products than cards, the behaviors we document are also more costly per occurrence.

Anchoring Mechanism. The fact that some consumers revolve credit card debt while making overpayments on installment debt shows that they have the liquidity to pay more on their cards. But what explains these behaviors? One possibility is that consumers use heuristics that depend on required minimums to make repayment decisions, or are effectively "anchored" (e.g., Stewart, 2009; Keys and Wang, 2019; Medina and Negrin, 2022).

Consistent with this, when asked directly in an online survey, participants often describe heuristics that include minimums, such as "I always pay at least $50.00 to $100.00 over the minimum payment due" and "I pay a little extra on the mortgage, and usually double the minimum payment due on the credit card." Using an LLM-assisted coding of responses, we show that respondents who report overpaying installment debt while revolving credit card debt are more likely to describe explicit rules of thumb and budgeting heuristics (Appendix Figure E.11). Appendix E includes additional details and our procedure for coding responses.

To formalize the connection between anchoring and cross-product misallocations, in Appendix A.3 we provide a model in which households make repayment choices that are affected by salient benchmarks, including their minimum payments. The model follows reduced-form frameworks of mental accounting (e.g., Hastings and Shapiro, 2013). When consumers rely on minimum-based heuristics, they fail to fully cost-minimize: their repayments are both anchored to minimums and misallocated across debts.

Anticipation of Default & Other Mechanisms. It is possible that repayment allocations could reflect consumers anticipating default and prioritizing collateralized debts. The pattern we document could then reflect financial hardship, rather than excess liquidity. However, unlike in prior work, the payments we study are made *in excess* of minimums; they are not decisions about which payments to miss (see e.g., Conway and Plosser, 2017).

Three additional pieces of evidence suggest anticipation of default plays at most a limited role. First, in our survey of consumers, only 1% of misallocators mention default when describing their repayment motives, and less than 5% mention a desire to fully own their home or car. Second, overpayment is common even on student loans, which are uncollateralized. Third, Figure 4 shows that the frequency of installment debt overpayments while revolving increases in credit score and, therefore, decreases in default risk. High rates of costly overpayment among low-risk borrowers are challenging to rationalize with default.

In Appendix B.3 we discuss other potential mechanisms. We show that optimal inattention, balance matching, and self-control do not appear to well explain these behaviors, but that intra-household frictions (similar to Vihriälä, 2022) may play a role.

4.2 Evidence from a Minimum Change

To better understand the drivers of the repayment patterns in Section 4.1, we explore the responses to a change in minimum payments. Our results support a model of mental accounting in which minimum required payments serve as a reference point or "anchor." While this specific mechanism is not necessary for our empirical model in Sections 5 and 6, it provides additional evidence that consumer repayments are not fully driven by liquidity constraints.

Empirical Predictions. Our model of mental accounting and anchoring in Appendix A.3 generates two predictions about behavior after a minimum increase. First, repayments may increase even among consumers who are not constrained by the minimum. Second, because this response reflects reliance on minimum-based heuristics rather than cost minimization, it should be stronger among consumers who misallocate excess repayments to their installment debt while revolving. We examine these predictions next.

Borrower response to minimum changes. We explore responses to a minimum change, similar to Keys and Wang (2019). Intuitively, if a borrower pays just above the minimum due to anchoring, when the minimum changes they should continue to pay just above the new minimum. By contrast, if near-minimum repayments are driven by liquidity constraints, borrowers who previously paid below the new minimum should move to paying exactly the new minimum or become delinquent. Empirically, then, an increase in borrowers paying strictly above the new minimum implies anchoring.

We identify a minimum formula change in December 2013 using a shift in the frequency of observed minimums. The credit bureau data include the first digit of a six-digit lender ID, which we use to group lenders. In one group, the frequency of $15 minimums dropped at the same time the frequency of $25 minimums increased, consistent with a major lender raising their formula floor, μ. Panels (a) and (b) of Figure 5 show this variation.

Around this change, we test for anchoring with the difference-in-differences design:

$$Y_{i,t} = \gamma_i + \delta_t + \sum_{\tau \neq 0} \beta_\tau (D_i \times \mathbb{I}\{t = \tau\}) + \epsilon_{i,t} \tag{6}$$

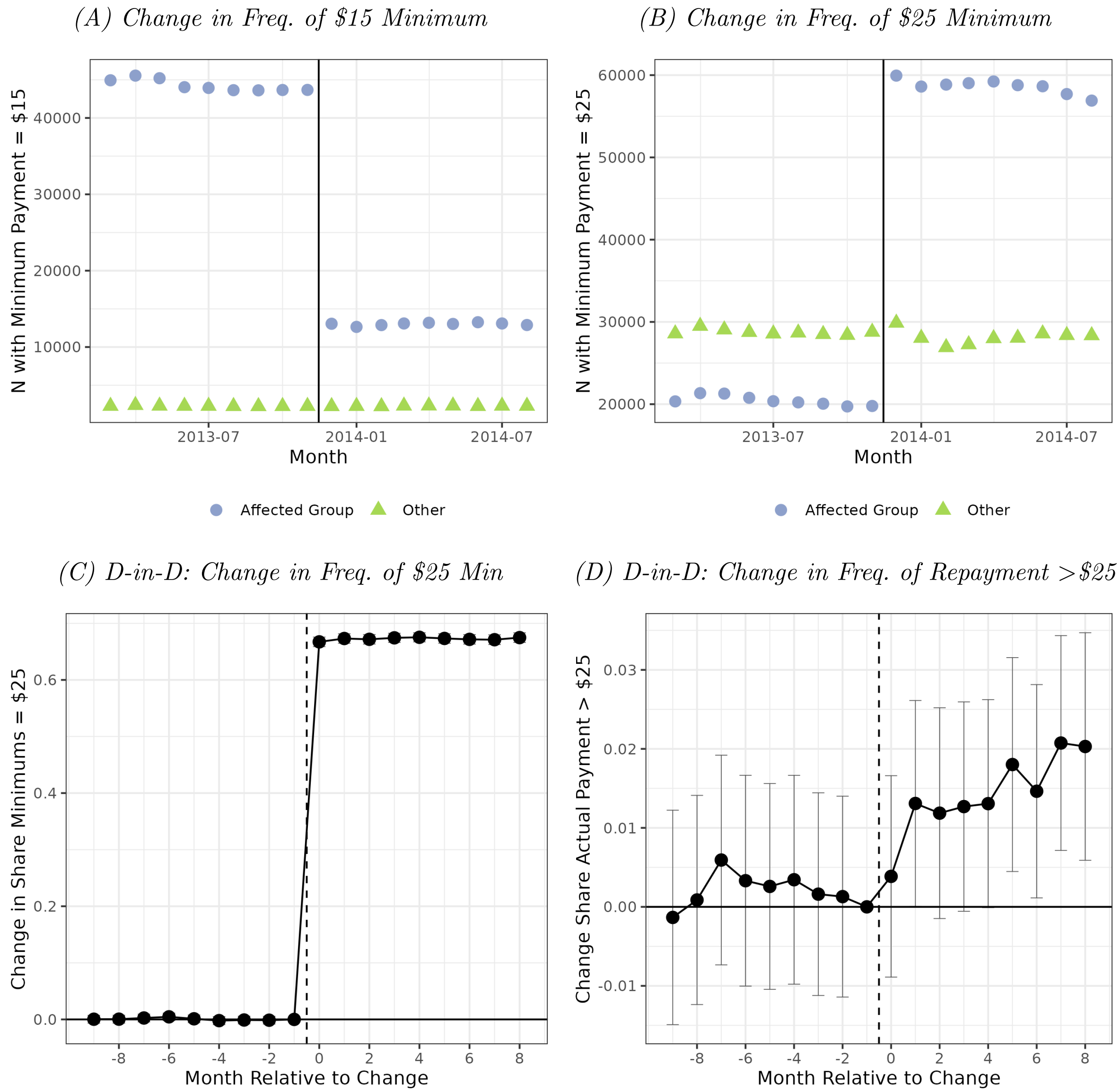
For card i, $Y_{i,t}$ is an outcome at time t, γ_i is a card fixed effect, δ_t is a month fixed effect, and D_i indicates whether card i is in the affected lender group. To isolate observations that would be affected by the change, we restrict to cards that had a minimum of $15 in the pre-period and to months where the minimum is $25 or less. Panel (c) shows the mechanical variation induced by the change: the share of minimums exactly $25 rises by nearly 70%.

Panel (d) shows an increase in payments *strictly* above $25, consistent with anchoring-induced upward adjustment rather than liquidity.[19] Column 3 of Table 4 shows that, intuitively, this effect increases when limiting to borrowers who made a payment of $25 or less in the pre-period, who would most plausibly be affected. In this sample, there is an 8.6% (5.6 pp) increase in the probability borrowers pay strictly greater than $25. This magnitude is large, as a $10 increase in the minimum would only affect borrowers who are closely anchored to the minimum and whose balances are low enough for the floor to bind.

Heterogeneity by Cross-Product Behaviors. We next examine heterogeneity in response to the minimum payment formula change to assess the relationship between cross-product repayments and anchoring. In our mental accounting framework, failing to cost-minimize and moving to repayment strictly above the new minimum both arise from the

[19] Appendix Figure B.10 shows that repayments also increase at other round numbers above $25. Appendix Figure B.11 shows that repayments increase above the threshold, consistent with use of excess payment heuristics (e.g., "I pay the minimum plus $20").

Figure 5: *Minimums and Repayments Around a Formula Change*



Note: Figure shows changes in minimum and actual repayments around a formula change event. Panels (a) and (b) show the frequency of minimum payments by the first digit of a six-digit lender ID, as described in Section 4.2. Panels (c) and (d) show estimates of β_t from the difference-in-differences specification in equation 6. The sample is consumer-months where the minimum is $25 or less. The outcome in panel (c) is an indicator for whether the minimum is exactly $25. The outcome in panel (d) is an indicator for whether the consumer's actual payment is strictly above $25. Error bars show 95% confidence intervals. Standard errors are clustered at the card level.

same behavioral friction. The response to a minimum change, then, should appear most strongly among consumers who had previously overpaid installment debt while revolving.

We test for this heterogeneity using a triple-difference design. We identify a group of borrowers who overpaid an installment loan while revolving credit card debt in the year prior to the change. Letting C_i indicate this group, we estimate:

$$Y_{i,t} = \gamma_i + \delta_t + \alpha_0(C_i \times \text{Post}_t) + \alpha_1(D_i \times \text{Post}_t) + \alpha_2(D_i \times C_i \times \text{Post}_t) + \epsilon_{i,t} \tag{7}$$

where D_i is again an indicator for whether the borrower is in the lender group affected by the minimum change and Post_t is an indicator for whether the month is in the post-period.

Table 4: *Anchoring & Cross-Product Behaviors: Heterogeneity Around a Minimum Change*

	Dependent Var: 100 × Payment > \$25			
	Full Sample		Payment ≤ \$25 in Pre-Period	
	(1)	(2)	(3)	(4)
After Change X Treated	1.00***	0.63*	5.59***	4.45***
	(0.28)	(0.29)	(1.13)	(1.29)
After Change X Treated X Cross-Prod		2.17**		4.38^{+}
		(0.83)		(2.61)
Month FE	✓	✓	✓	✓
Individual FE	✓	✓	✓	✓
After Change X Cross-Prod FE		✓		✓
R^2 Adj.	0.346	0.346	0.340	0.340
Observations	864,685	864,685	110,207	110,207

$^{+}$ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Note: Table shows changes in actual repayments in the months around the formula change event depicted in Figure 5. Column 1 replicates panel (d) of Figure 5, replacing the monthly interaction terms with a single post-period indicator (comparing 8 months pre vs 8 months post). Column 2 presents a triple-difference estimator that compares repayment changes between borrowers who did and did not overpay installment debt while revolving in the year before the event (the behavior documented in Section 4.1). Columns 3 and 4 repeat columns 1 and 2, restricting the sample to individuals who revolved credit card debt and made at least one payment between \$15 and \$25 in the pre-period. Standard errors are clustered at the card level.

Column 2 of Table 4 presents the baseline triple-difference estimate, which shows that the anchoring response is 2.2 percentage points larger for borrowers who overpay an installment debt while revolving in the pre-period. Column 4 shows that, when limiting the sample to those who made a payment of \$25 or less in the pre-period (again, those who are most plausibly affected in both groups), this difference increases to 4.4 percentage points. These results show that cross-product repayment behaviors predict stronger responses to minimum payment changes, consistent with anchoring being more prevalent among these borrowers and helping explain the patterns documented in Section 4.1.[20]

[20]While Keys and Wang (2019) interpret their results as evidence of anchoring, they note they cannot rule out a related alternative interpretation that borrowers solve the intertemporal problem, but make "near-rational" adjustments to round numbers. The contemporaneous installment debt overpayments we document (Section 4.1), and their connection to minimum change responses, are strongly consistent with repayment patterns representing a behavioral response rather than only near-rational rounding.

Additional Evidence from "De-Anchoring" Survey Experiment. In Appendix E we describe a survey experiment in which consumers are presented with bill repayment scenarios involving a credit card and mortgage. In one de-anchor treatment arm, the minimum still appears on the bill, but the button to pay the minimum is removed. The share of respondents who fail to cost-minimize in this treatment falls by around 30%, even when they are given a fixed budget. There is no similar reduction from a cost information disclosure. Our results are consistent with anchoring contributing to cross-product repayment behaviors. The appendix presents a number of additional survey results.

5 Empirical Model

The analysis in Section 4 provides evidence that borrowers fail to focus liquidity on credit cards. This behavior shapes not only repayment, but also lenders' incentives when setting contract terms. This raises two questions. First, how would lenders set minimums if borrowers focused liquidity on credit cards? Second, how would this supply-side change impact consumer debt? In this section, we use our results from Section 4.1 to estimate an empirical model that will allow us to answer these questions.

Key Behavioral Friction. In the model, low credit card payments can arise either from low borrower income or intra-temporal repayment mistakes. We use the term "anchoring" to describe the latter, but identification relies on the observed cross-product repayment patterns rather than a specific psychological mechanism. As discussed in Section 2, any consumer behavior that causes low-risk borrowers' repayments to respond to changes in minimum payments creates an incentive for lenders to lower minimums.

5.1 Model Description

In our model, lenders choose a minimum payment formula to solve the profit maximization problem in Section 2. Consumers make spending, debt repayment, and default choices. We adopt a reduced-form approach, similar to Einav *et al.* (2012), who model consumer behavior in auto loan repayment. This allows us to transparently capture observed patterns relevant for lender profits. Appendix A.4 provides a number of potential microfoundations for our model of consumer behavior.

Setup. Time is discrete, with each period t representing a month. At $t = 0$, the lender sets a minimum payment policy, parameterized by μ and θ (as in Equation 5) and each borrower, i, opens a card with zero balance (we generally omit i subscripts for brevity). The card allows borrowing up to a credit limit $\bar{L}$ at interest rate R_{cc}. In addition to credit card minimum payments, m_t, borrowers also have outside debt obligations (e.g., mortgage, auto, student loans) that require a total monthly minimum payment of m_{other}.

5.1.1 Lender Problem

The lender chooses a minimum payment contract, parameterized by μ and θ, to maximize expected discounted profits. As in Section 2, this is the difference between repayments, P_t, and spending, S_t, given discount factor δ:

$$\max_{\theta,\mu} \mathbb{E}_0 \sum_{t=0}^{\infty} \delta^t [P_t(\theta,\mu) - S_t(\theta,\mu)] \tag{8}$$

In our setup, lenders solve a monopoly problem over minimum payments. In practice, minimums are not revealed to borrowers when choosing credit cards, meaning that unlike interest rates or credit limits, they are shrouded attributes from the perspective of consumers. Consistent with our setup, models of shrouded attributes have producers set the shrouded price to the monopoly price, even if profits are competed away in salient prices (Gabaix and Laibson, 2006).[21] It is theoretically possible that, ex-post, borrowers with high minimums transfer balances to lower minimum formula cards. We believe this to be unlikely, as it would require borrowers to understand that formulas may differ across cards and identify cards with a different contract. Indeed, Castellanos *et al.* (2025) shows that a lender's doubling of minimums in Mexico led to zero borrowing crowd-out.

In Section 6, we conduct counterfactual exercises in which borrowers no longer anchor. While lenders could re-optimize over different contract terms in such a scenario (e.g., interest rates or credit limits), our exercises abstract to a constrained counterfactual that focuses on the direct effects of a change in the behavioral response to a contract feature on that contract feature.[22] Because our model focuses on the choice of minimum in response to a change in anchoring, we do not use it to conduct policy counterfactuals where considering endogenous changes in other contract features would be first-order.

[21] Note that our model does not require lenders to be explicitly aware of anchoring or other consumer bias, only that they set minimums to maximize profits given patterns of repayment and default.

[22] This follows the approach of Agarwal *et al.* (2014) and Agarwal *et al.* (2018), which use the fact that interest rates largely do not adjust to changes in lenders' cost of funds (Ausubel, 1991) to argue that APRs are insensitive to competition and the economic environment.

5.1.2 Consumer Behavior

When setting minimums, the lender considers the relationship between borrowing, which determines interest revenue, and default, which determines costs. We introduce this relationship through consumer income, which is unobserved to the lender, but jointly helps determine repayments and default risk.

Actions & Timing. There are two state variables, income Y_t and credit card statement balances B_t. Each period, the consumer learns their income and decides whether to default. Upon default, lenders recover share Λ of balances. Conditional on no default, consumers may choose to fully repay and close their card. If the consumer does not default or close, they choose repayments across all their debts $\tilde{P}_t$, including P_t on their credit card. Interest accrues on unpaid balances, and if payment falls below m_t late fees F_t apply. Finally, consumers decide how much to spend on their credit card, S_t, and the period advances.

Income. Income is given by $Y_t = \exp(y_t) \cdot \overline{Y}$, where $\overline{Y}$ is mean income and y_t follows an AR(1) process, disciplined with parameters from Guerrieri and Lorenzoni (2017):

$$y_{t+1} = \rho y_t + \epsilon_{t+1} \tag{9}$$

Innovations ϵ_{t+1} are distributed $\mathcal{N}(\mu_y, \sigma_y^2)$, where $\mu_y = -\frac{\sigma_y^2}{2}\frac{1-\rho}{1-\rho^2}$ is a Jensen's inequality correction to prevent mean income growth.[23]

Spending. Consumers decide to use their card for spending with probability $1 - p_{nospend}$.[24] If they use the card, spending follows a lognormal distribution constrained by the remaining credit available, $L_t = \max\{\overline{L} - R_{cc}(B_t - P_t) - F_t,\ 0\}$. Therefore, $S_t = 0$ with probability $p_{nospend}$ and otherwise log spending is:

$$s(B_t, Y_t; m_t) = s_0 + \epsilon_t^s \tag{10}$$

subject to the constraint that spending cannot exceed the remaining credit limit $S_t \leq L_t$. ϵ_t^s is distributed $\mathcal{N}(0, \sigma_s^2)$.

[23]This income calibration is similar to Lee and Maxted (2023). Appendix Table B.12 shows that our results do not substantially change when using an income process with additional transitory shocks. Residual volatility in expense and income shocks that affect repayment (and vary by credit score bin) can be captured in our calibration of total repayments, as we describe below.

[24]This captures the empirical fact that many borrowers hold multiple cards (as shown in Table 1) and may change which card they spend on in a given month.

Total Repayment. We parameterize consumers' log total debt repayment according to:

$$\tilde{p}(B_t, Y_t; m_t) = \beta_y y_t + \beta_b b_t + \epsilon_t^p \tag{11}$$

where y_t and b_t are log income and statement balances, respectively. ϵ_t^p is distributed $\mathcal{N}(0, \sigma_p^2)$. Total repayments are increasing both in borrowers' income and the size of their debt balances. Conditional on not missing a credit card payment (discussed below), they are bounded below by total minimum payments, $\tilde{P}_t \geq m_t + m_{\text{other}}$.

Anchoring. If borrowers minimized interest costs in each period, they would repay $P_t^R = \tilde{P}_t - m_{\text{other}}$ on their credit card. Our analyses in Section 4 show that many borrowers do not cost-minimize, instead making overpayments on their installment debts while revolving credit card debt. We parameterize this behavior, subject to $P_t \in [m_t, B_t]$, as:

$$P(B_t, Y_t; m_t) = (1 - \gamma)P_t^R + \gamma m_t \tag{12}$$

The parameter γ controls the degree of anchoring: when $\gamma = 1$ borrowers pay only the minimum, regardless of their income; when $\gamma = 0$ borrowers cost-minimize. Appendix A.4 shows this linear parameterization can be microfounded with models of mental accounting (e.g., Hastings and Shapiro, 2013) or cognitive uncertainty (Enke and Graeber, 2023).

This setup allows us to transparently link the model to the evidence in Section 4.1. Because Equation 12 is linear, if payments are interior ($P_t < B_t$ and $\tilde{P}_t > m_{other} + m_t$), then:

$$P_t = (1 - \gamma)(\tilde{P}_t - m_{other}) + \gamma m_t \Rightarrow \gamma = \frac{P_{other} - m_{other}}{\tilde{P}_t - m_{other} - m_t} \tag{13}$$

so the moment identifying γ is:

$$\gamma = \mathbb{E}\left[\frac{P_{other} - m_{other}}{\tilde{P}_t - m_{other} - m_t}\middle| \tilde{P}_t > m_t + m_{other} \text{ and } P_t < B_t\right] \tag{14}$$

Equation 14 is the share of total excess payments allocated to installment debt rather than credit card debt, the result in panel (b) of Figure 4.

Default. We parameterize the probability of default according to the logistic decision rule:

$$\mathbb{P}(\chi(B_t, Y_t; m_t) = 1) = \frac{1}{1 + \exp\{-(d_0 + d_m m_t + d_u u_t + d_y y_t)\}} \tag{15}$$

where χ is an indicator for default, utilization is given by $u_t = B_t/\overline{L}$, the consumer's credit limit utilization.[25] This default rule captures different potential drivers of default: high balances (insolvency), high minimums (illiquidity), and low income. If the borrower defaults in t, they are cut off from future borrowing ($P_{t'} = 0$ for all $t' \geq t$ and $S_{t'} = 0$ for all $t' > t$).

Other Repayment Behaviors. Consumers may also close their card, or miss a payment and incur a late fee. In our baseline model, these events occur iid.[26] Borrowers close their card with probability p_{close} each period. Upon closure in period t, the borrower fully repays their balance ($P_t = B_t$) and ceases future spending ($P_{t'}, S_{t'} = 0$ for all $t' > t$). With probability p_{nomin}, a borrower misses the minimum payment. In such cases, the borrower does not make a repayment and a late fee, set to $\min(F_{\max}, m_t)$, is due next period.

Discussion. Our reduced-form approach allows us to transparently capture observed patterns relevant for lenders' choice of contract parameters without making functional form assumptions on borrower primitives, which the data may be less suited to inform (Einav *et al.*, 2012). In Appendix A.5, we discuss how our approach can be seen as an approximate parameterization of consumer policy functions.

We model anchoring as intra-temporal misallocation that holds total debt repayment fixed. In reality, consumers may also use installment debt minimums as a reference point when deciding repayment, lowering total debt repayment. Appendix Table B.12 shows that such a response would increase the effect of anchoring on minimums. Our baseline model is therefore conservative, focusing only on the allocation of liquidity consumers have to repay debts. We view this as an advantage of our approach, which allows us to avoid taking a normative stance on how consumers make inter-temporal tradeoffs.[27]

5.2 Calibration & Estimation

We estimate the model separately for five credit score groups (<600, 600-659, 660-699, 700-739, 740+). The model is estimated in two stages. First, we calibrate and estimate many of our parameters by matching observed data. Second, we estimate parameters correlated with unobserved income jointly using simulated minimum distance (indirect inference).

[25] We use utilization instead of balances to capture the empirical fact that the probability of default increases quickly at high utilization, as shown in Figure 7.

[26] Appendix Table B.12 reports results from models incorporating upper-bound sensitivities of closures and late fees to minimum payments. Our conclusions are qualitatively unchanged.

[27] More broadly, a potential concern with our approach is that other aspects of behavior may not realistically be held invariant to changes in γ, our counterfactual exercise in Section 6. However, if consumers are "naive" about anchoring—i.e., they do not internalize how anchoring affects their broader intertemporal optimization—then their policy functions will not adjust with γ, mitigating this concern. In Appendix A.6, we discuss the plausibility of this assumption and the implications of potential violations.

In each credit score group, there are 24 parameters associated with the consumer's problem: calibrated fixed parameters of the credit card contract and lender's problem $(R, \overline{L}, \mu, \theta, F_{\max}, m_{other}, \delta, \Lambda)$, calibrated parameters of the income process $(\overline{Y}, \rho, \sigma_y)$, and estimated parameters relating to spending $(p_{nospend}, s_0, \sigma_s)$, default (d_0, d_u, d_y, d_m), card closure (p_{close}), and repayments $(p_{nomin}, \beta_y, \beta_b, \sigma_p, \gamma)$. We calibrate and estimate 15 parameters Θ_1 in the first stage, and jointly estimate 9 parameters $\Theta_2 = (\beta_y, \beta_b, \sigma_p, s_0, \sigma_s, d_0, d_u, d_y, d_m)$ in the second stage.

Table 5: *Calibrated and First Stage Parameters*

Description	Parameter	Moment or Value	Source
Fixed Parameters			
APR	$(R-1)*12$	Estimated APR	CFPB (2021)
Credit limit	$\overline{L}$	Average credit limit	Our data
Minimum floor ⋆	μ	25	Our data
Minimum slope	θ	Median estimated θ	Our data
Max late fee ⋆	$F_{\max}$	25	Regulation
Monthly installment min	m_{other}	Median installment min	Our data
Annual discount rate ⋆	$1-\delta^{12}$	0.05	Cost of equity
Chargeoff recovery rate ⋆	Λ	0.25	8-K Filings
Income			
Average annual income ($'000)	$\overline{Y}*12$	Mean household income	Albanesi *et al.* (2022)
Persistence ⋆	ρ	0.989	GL (2017)
Standard deviation ⋆	σ_y	0.078	GL (2017)
Spending			
No spending probability	$p_{nospend}$	Share of months zero spend	Our data
Card Closure			
Card closing probability	p_{close}	Monthly probability of closing	Our data
Repayments			
Missed min probability	p_{nomin}	Share of months missed minimums and no default	Our data
Anchoring	γ	Share of excess payments on other debts	Our data

Note: Table presents values of first stage parameters. GL (2017) is Guerrieri and Lorenzoni (2017). The cost of equity is obtained from https://pages.stern.nyu.edu/adamodar/. The chargeoff recovery rate comes from credit card ABS issuance filings, including Citigroup Inc. (2024). All parameters marked with a ⋆ *do not* vary by credit score. For values of first stage parameters that vary by credit score, see Table B.9.

5.2.1 First Stage Parameters

We briefly describe the first stage parameters below, providing more detail in Appendix C. Table 5 shows the source of all first stage parameters.

Fixed Contract Parameters. We use APRs by credit score from CFPB (2021) (Section 3, Figure 3). We estimate the average credit limit and median installment minimum within credit score group in our data. We use the median slope on credit card minimums and set the floor and maximum late fee to $25, the regulatory maximum at the time of our sample. We set the lender's annual discount rate at 5% and assume they recover 25% of defaults.[28]

Calibrated Income Process. We follow Guerrieri and Lorenzoni (2017) in parameterizing the income process, converting their quarterly AR(1) income process into a monthly one, which yields a monthly persistence of 0.989 and standard deviation of 0.078. We use average income levels across credit scores from Albanesi *et al.* (2022), as in Nelson (2025).

Estimated Spending & Repayment Parameters. We directly match the estimated probability of nonzero spending, card closure, and missed minimums from our data. For closures, we match the average share of cards that transition into being unused for a full year or more. For missed minimums, we match the proportion of borrower-months where the borrower misses a minimum but makes some payment in the future.[29]

Following Equation 14, we identify the anchoring parameter γ using our result in Figure 4, panel (b). In our baseline model, we assume representative consumers with mean γ in each credit score bin. Appendix Table B.12 shows results that allow γ to vary across individuals, and across both individuals and time. In both, our conclusions are largely unchanged.

Table 6: *Second Stage Parameters and Moments*

Description	Parameter	Moment
Total debt repayment on income	β_y	Mean utilization
Total debt repayment on balances	β_b	Corr(log balances, log total repayment)
SD total repayment shock	σ_p	Within-person SD log total repayments
Mean spending shock	s_0	Mean log spend
SD spending shock	σ_s	SD log spend
Default intercept	d_0	Monthly probability of default
Default on utilization	d_u	Utilization six months before default
Default on income	d_y	Log total repayment in six months before default
Default on minimums	d_m	d'Astous and Shore (2017) implied elasticity

Note: Table presents second stage parameters and corresponding identifying moment. While all parameters are estimated jointly (so all parameters are sensitive to all the moments), the "Moment" column provides intuition for where the identifying variation comes from. Section 5.1.2 provides more detail on the parameters.

[28]See, for example, 2024 Citibank credit card trust 8-K filings (Citigroup Inc., 2024) which reports recoveries as a share of gross chargeoffs between 17% and 32% over the prior four years. Appendix Table B.12 shows that assuming a 0% recovery rate increases the lender-optimal θ, but does not change our conclusion that lenders substantially raise minimums in the counterfactual where borrowers are unanchored.

[29]In Appendix Table B.7 we show that, at the card level, the likelihood of missing a minimum we observe is similar to the likelihood of paying a late fee over a year in administrative Y-14 data (CFPB, 2022).

5.2.2 Second Stage Simulated Minimum Distance

We estimate the 9 remaining parameters $\Theta_2 = (\beta_y, \beta_b, \sigma_p, s_0, \sigma_s, d_0, d_u, d_y, d_m)$ using just-identified simulated minimum distance, minimizing the sum of squared deviations between sample moments $\hat{m}$ and modeled moments $m(\Theta_1, \Theta_2)$:

$$\Theta_2^* = \arg\min_{\Theta_2} (\hat{m} - m(\Theta_1^*, \Theta_2))'(\hat{m} - m(\Theta_1^*, \Theta_2)) \tag{16}$$

where Θ_1^* are the first stage parameters in Section 5.2.1. We calculate bootstrapped standard errors that account for simulation error and uncertainty in first stage estimated parameters.

Table 6 shows our empirical moments, $\hat{m}$, and how each is intended to provide variation to identify a parameter in the joint estimation. The targeted moments depend on each targeted parameter in intuitive ways. For example, β_b governs the relationship between repayments and balances so helps match the empirical correlation between the two. To estimate our default parameters, we match overall default rates (d_0), the correlation between utilization and default (d_u), the correlation between log average total payments in the prior six months and default (d_y),[30] and the elasticity of defaults to the minimum implied by d'Astous and Shore (2017) (d_m). Following Andrews *et al.* (2017), we present formal sensitivity analysis of parameters to moments to support these arguments in Appendix Figure B.13.

Our just-identified model matches targeted moments exactly, as shown in Appendix Table B.11. Appendix C contains more details on our estimation procedure.

5.3 Baseline Estimation Results

We present our parameter estimates and show that our baseline model can fit unmatched moments such as the distribution of utilization, spending, and excess repayments. Additionally, optimizing lenders in the model set minimum payments similar to those we observe empirically, suggesting the model captures the key forces that determine this choice.

5.3.1 Parameter Estimates

Table 7 presents our estimates Θ^*, with standard errors in parentheses. Our estimates are generally precise and reasonable. For example, our model implies that, on average, around 30-50% of income goes toward total debt repayment. These estimates are similar to the

[30]Because payments rise with income, borrowers with lower payments have lower income on average. To account for the fact that borrowers mechanically do not make credit card payments in the months before a default in the data, we define default as the month after the final month the borrower makes a payment.

Table 7: *Values of Estimated Parameters*

	< 600	600-659	660-699	700-739	740+
First Stage					
γ	0.259	0.26	0.244	0.232	0.184
	(0.007)	(0.006)	(0.006)	(0.005)	(0.005)
p_{nomin}	0.122	0.106	0.091	0.079	0.05
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
p_{close}	0.008	0.009	0.011	0.011	0.014
	(2e-04)	(2e-04)	(2e-04)	(2e-04)	(2e-04)
$p_{nospend}$	0.104	0.138	0.207	0.205	0.15
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
$\overline{Y} * 12$ ('000)	28.5	53.0	69.0	82.5	111.3
	(0.171)	(0.162)	(0.202)	(0.232)	(0.278)
Second Stage					
β_y	0.643	0.61	0.687	0.732	0.814
	(0.013)	(0.012)	(0.007)	(0.005)	(0.004)
β_b	0.122	0.165	0.153	0.144	0.129
	(0.013)	(0.012)	(0.007)	(0.004)	(0.003)
σ_p	0.817	0.652	0.385	0.298	0.128
	(0.038)	(0.029)	(0.012)	(0.01)	(0.014)
s_0	4.34	4.352	4.743	5.02	5.541
	(0.023)	(0.023)	(0.029)	(0.028)	(0.023)
σ_s	2.213	2.265	2.393	2.295	2.017
	(0.017)	(0.015)	(0.017)	(0.016)	(0.016)
d_0	8.23	8.403	0.271	-4.102	5.67
	(2.213)	(7.677)	(22.68)	(31.866)	(55.42)
d_u	6.584	17.635	43.041	60.435	55.938
	(1.806)	(5.637)	(6.664)	(4.012)	(28.353)
d_y	-2.583	-3.859	-6.069	-7.767	-8.46
	(0.086)	(0.263)	(1.862)	(4.08)	(9.721)
d_m	1e-03	7e-04	5e-04	4e-04	2e-04
	(1e-04)	(1e-04)	(1e-04)	(1e-04)	(1e-04)

Note: Table shows estimated first and second stage parameters with standard errors in parentheses.

debt-to-income ratio of 30-40% common for auto-loans and mortgages.[31] The variance of log total debt repayment, σ_p, decreases with credit score, consistent with lower-credit-score consumers facing more volatile marginal utility of consumption. The sensitivity of default to minimums, d_m, also falls with credit score, consistent with lower-credit-score consumers being more prone to liquidity-driven default. By contrast, the sensitivity of default to income and utilization, d_y and d_u, generally increases with credit score.

[31] Note also that DTI ratios are based on minimums, and many of our payments (especially for high credit score borrowers) are above the minimum.

5.3.2 Model Fit & Lender-Optimal Minimums

To verify that the model captures meaningful relationships between variables that influence repayment decisions, we next analyze its fit to several pieces of evidence that were not targeted in the estimation, including the lender's chosen minimum.

Distributions of Borrower Outcomes. Figure 6 plots the distribution of utilization, spending, and excess repayments in the model versus data by credit score. As in the data, high credit score borrowers have lower utilization, and overall, the shares of borrowers in each utilization bin align well with the data. The distribution of spending also aligns with the data, suggesting our log-normal approximation is reasonable. Finally, the model replicates the U-shaped distribution of excess repayments documented in Section 3.3.

Figure 7 plots the probability of default within different horizons by utilization. As in the data, the likelihood of default at any given utilization is monotonically decreasing in credit score. Additionally, within each credit score bin the probability of default increases sharply for borrowers near the credit limit.

Lender-Optimal Minimums. We find lender-optimal minimums by searching for the value of θ that maximizes lender profits. Panel (a) of Table 8 shows that the model reproduces the key features of lender-optimal minimums described in Section 3.3. First, consistent with Fact 2, the optimal minimum for the highest credit score borrowers is the lowest allowed by regulation, 1% of balances, implying the 20+ year amortization schedules for a $10,000 debt shown in Figure 1.[32] Second, consistent with Fact 3, the optimal θ increases for lower credit score borrowers, reaching 6.7% for the lowest credit score group. As in our framework, this pattern is driven by the sensitivity of default to debt balances and the fact that low credit score borrowers default at higher rates, making them less profitable revolvers.[33]

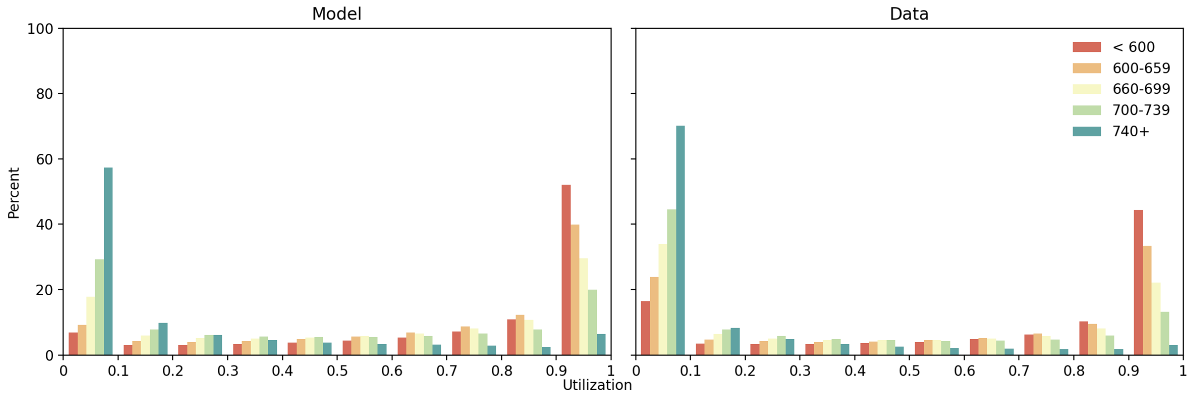
Responses to Minimum Changes. In the appendix, we conduct two simulations to assess how our model predicts consumers will respond to a change in minimums. Appendix Figure B.14 shows responses to a simulated minimum floor change calibrated to match the change in Figure 5. The model response is similar to the data, though slightly weaker; by contrast, there is no response when $\gamma = 0$. Appendix C.4 describes an exercise in which we

[32] Appendix Figure B.17 shows that even at $\theta = 0.01$ marginal revenues exceed marginal costs for this group, suggesting that lenders would set lower minimums if able. This is consistent with the existence of negatively amortizing contracts prior to regulations discussed in Section 3.1.

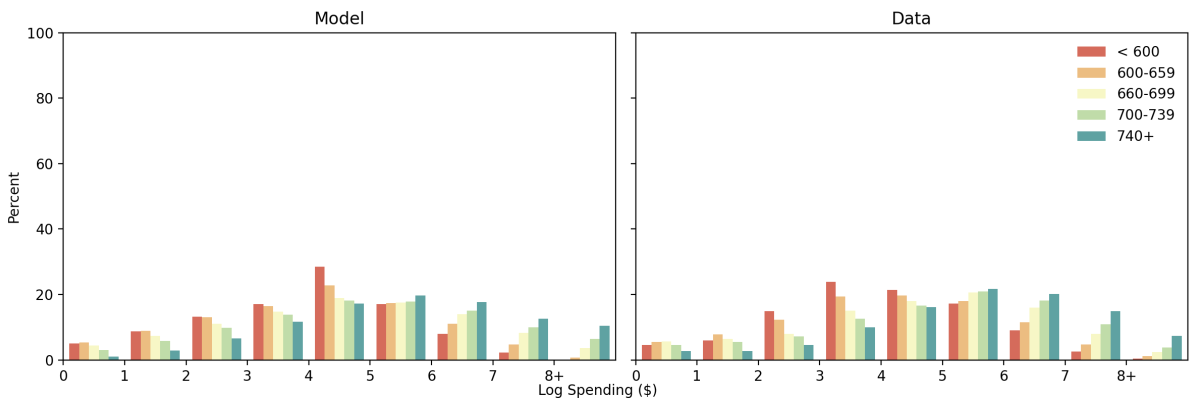
[33] Appendix Table B.10 shows how expected profits vary with the floor, μ. Without a floor, lenders cannot always charge the maximum late fee. With a floor above the late fee maximum, interest revenue falls. In both cases, profits decrease. These results help explain why minimum formulas are piecewise linear.

Figure 6: *Utilization, Spending, and Repayment in the Model vs. Data*

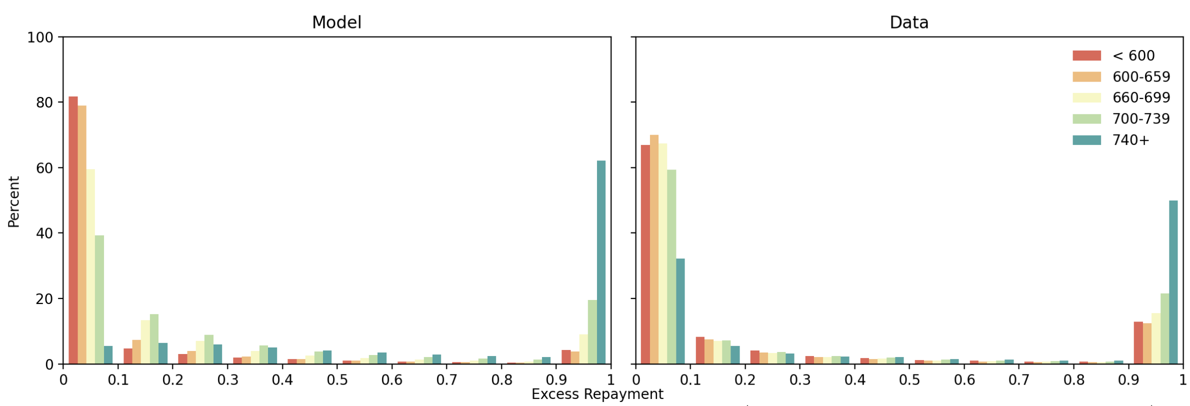
(A) Utilization



(B) Spending



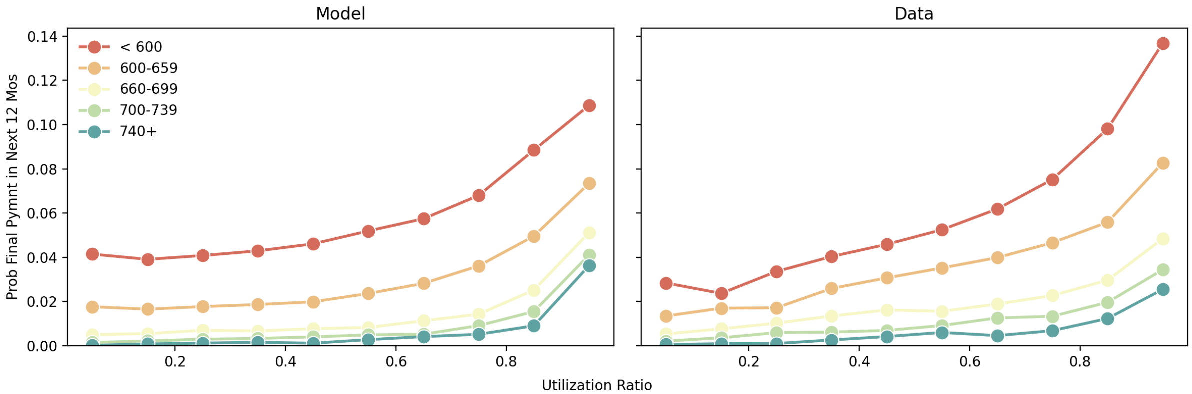
(C) Excess Repayment



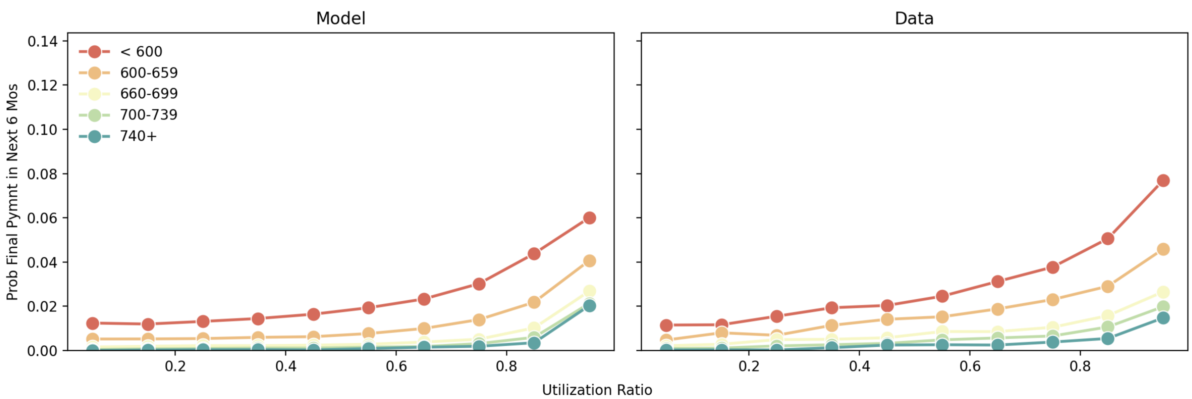
Note: Figure shows the distribution of utilization, log spending (in months with non-zero spending), and excess repayment in the model vs. data. Utilization is the statement balance divided by the credit limit. Excess repayment is defined as in Figure 2.

Figure 7: *Default and Utilization in the Model vs. Data*

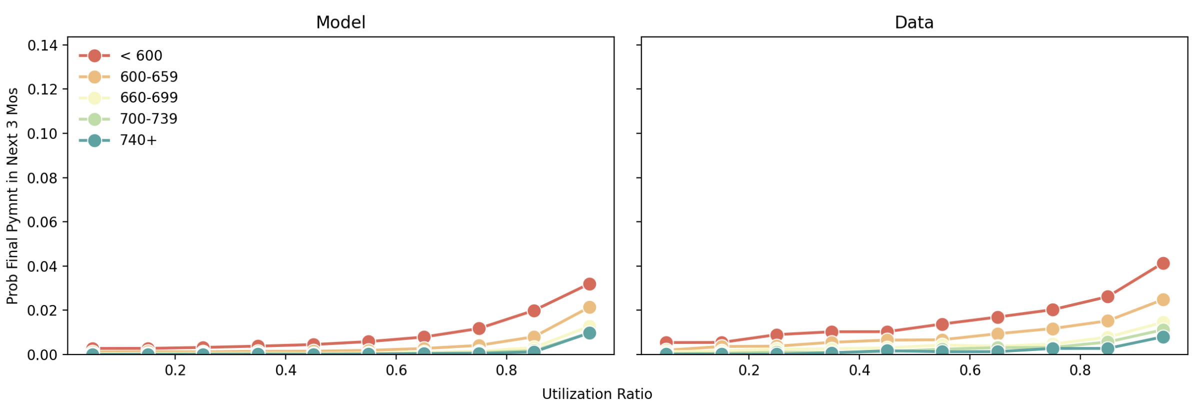
(A) Final Payment Within 12 Months



(B) Final Payment Within 6 Months



(C) Final Payment Within 3 Months



Note: Figure shows the probability of default at different horizons by utilization and credit score bin in the model vs. data. The outcome is the share of borrowers who permanently stop making payments prior to a chargeoff. Utilization is the statement balance divided by the credit limit.

Table 8: *Model-Implied vs. Observed Minimums*

	< 600	600-659	660-699	700-739	740+
Panel A: Baseline Model					
θ Model	0.067	0.056	0.032	0.025	0.01
θ Real (25th)	0.03	0.02	0.015	0.01	0.01
θ Real (Median)	0.05	0.035	0.025	0.02	0.02
θ Real (75th)	0.065	0.05	0.045	0.03	0.025
Panel B: Counterfactuals					
Counterfactual θ	0.074	0.061	0.043	0.041	0.078
Min at CL (Behavioral)	\$113	\$188	\$174	\$176	\$100
Min at CL (Rational)	\$125	\$205	\$234	\$288	\$781

Note: Panel A shows model-implied and real-world θs in credit card minimums. Panel B shows counterfactual θ when there is no anchoring. "Min at CL" is the minimum amount due at the credit limit, defined as the credit limit and multiplied by the model-implied optimal θ with and without anchoring.

simulate a policy implemented in Quebec that required lenders to increase their minimums. Our model implies that revolving balances decrease by 1.44% after 24 months, smaller, but within the confidence interval of the estimated effect in Allen *et al.* (2026).[34]

6 Impacts of Lender Responses on Consumer Outcomes

In this section, we use the model to study how consumer behavior shapes lenders' minimum-payment choices and how those choices affect consumer debt. In counterfactual simulations in which consumers are *un*anchored, lenders set higher minimums, consistent with our framework in Section 2. Holding minimums fixed, anchoring increases credit card debt and default; lenders' response to anchoring (low minimums) amplifies these effects.

6.1 Effects of Consumer Bias on Credit Card Contracts

We first ask how anchoring affects lenders' choice of credit card minimums. To answer this question, we conduct a counterfactual exercise in which all consumers are unanchored, with $\gamma = 0$. We then find the lender's new optimal minimum payment contract. Our results help explain why lenders set low credit card minimums, despite the potential losses they face from borrowers defaulting on these unsecured debts.

Panel B of Table 8 shows when consumers are unanchored, minimums would be higher in all credit score bins. This increase is strongest in the top credit score bin: before interest

[34]The weaker response in both analyses is consistent with γ being a conservative estimate of anchoring, identified only from intra-temporal allocations (see the discussion in Section 5.1.2).

and fees, a borrower at the credit limit would have a minimum of $781 in the counterfactual instead of $100. Minimum payments in this case would fully amortize their debt in 5 years instead of 24 years. For lower credit score borrowers, where existing minimums are already higher, the increase is meaningful but smaller, ranging from 10 to 70%.

Our framework in Section 2 helps explain these outcomes. Low minimums increase balances and interest revenue, but can also raise default losses. Without anchoring, only high-risk borrowers are responsive to changes in minimums, weakening the interest-revenue channel and the incentive to set low minimums. This change in behavior most affects the minimums of higher credit score consumers: because these consumers tend to have higher incomes and lower-volatility repayments, when $\gamma = 0$, near-minimum repayments strongly signal that they have experienced large negative income shocks. For lower credit score consumers, baseline risk levels are higher so the change in γ is relatively less impactful.

6.2 Demand- and Supply-Side Effects on Consumer Debt

We next ask how much anchoring increases total debt and default, separating between the role of consumer biases, a *demand-bias* effect, and lenders' response to these biases, a *supply-side amplification* effect. This decomposition allows us to quantify a mechanism through which profit-maximizing lenders amplify the effects of consumer bias.

For our decomposition, we first simulate the model in a counterfactual setting where borrowers are unanchored, with $\gamma = 0$. In this setting, we find the optimal lender minimums: $m^*_{\gamma=0}$. We then estimate the demand-side bias and supply-side amplification effects as changes in outcomes (revolving debt and default) across two alternative settings:

- *Demand-side bias* is the change in outcomes when we re-introduce anchoring, $\gamma > 0$, while holding minimums fixed at $m^*_{\gamma=0}$.
- *Supply-side amplification* is the additional change in outcomes when we allow lenders to re-optimize minimums in response to anchoring.

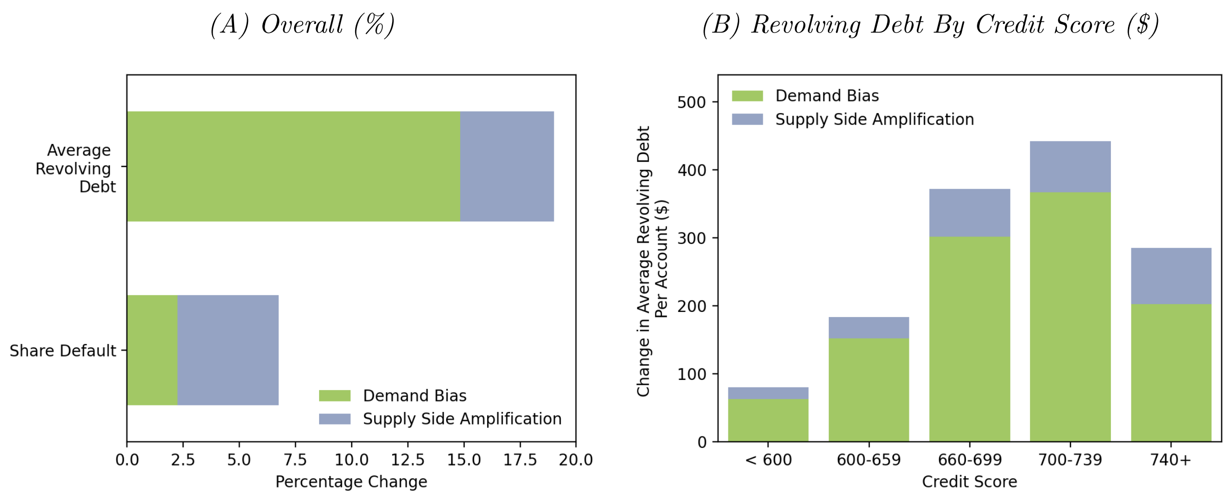
This exercise allows us to separately capture the direct effects of consumer bias and the additional effect generated by lenders' response.

Results. Figure 8 shows how demand-bias and supply-side amplification shape consumer debt and default. The green portions of the bars show the direct demand-side effect of anchoring before allowing lenders to re-optimize. The top bar of panel (a) shows that demand-bias increases revolving debt levels by 15%.[35] Larger balances due to anchoring also increase long-run default: the bottom bar shows the share of consumers who default rises by 2%.

[35] To aggregate across credit score bins, we weight by the mass of borrowers in each bin.

The purple portions of the bars show the extent to which the supply-side amplifies anchoring in the model. The top bar in panel (a) shows the increase in revolving debt is 30% larger once we allow the supply-side to lower minimums. When scaled by total revolving credit card debt outstanding, our estimates imply that the lender response increases revolving debt by $46 billion (4.2%).[36] Lower minimums also amplify the effects on default: combined, the demand- and supply-side effects raise defaults by nearly 7%.

Figure 8: *Increase in Revolving Debt and Defaults Due to Anchoring*



Note: Figure shows the change in revolving debt and default in a counterfactual exercise in which consumers change from unanchored to anchored (see Section 6). The "Demand Bias" is the change that would occur without the supply-side re-optimizing minimums. The "Supply Side Amplification" is additional debt or defaults incurred after the supply-side re-optimizes. Panel (a) shows the overall percentage change in debt and default. Panel (b) shows the average dollar change in revolving debt per account by credit score bin.

Panel (b) of Figure 8 shows heterogeneity in the revolving debt effect by credit score group.[37] In dollar terms, middle- and high-credit-score consumers are most affected by lenders' re-optimization of minimum payments. Intuitively, low-credit-score consumers tend to have lower incomes and are more likely to borrow due to low liquidity. Despite experiencing the largest change in minimums, the highest-credit-score consumers are also somewhat less affected than those just below them: they have high incomes and stable repayments, often using their card only to transact even when $\gamma > 0$.

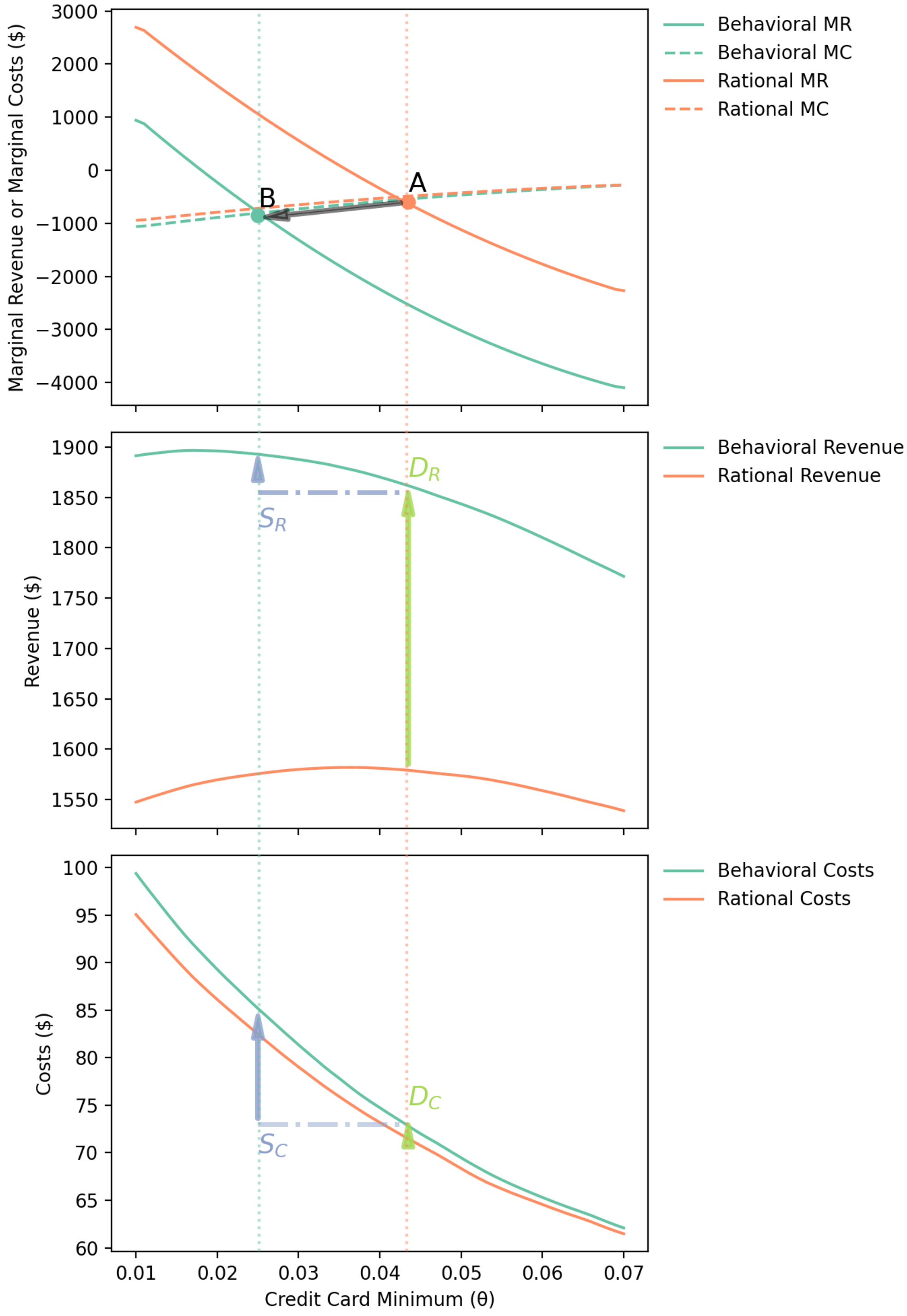
6.3 Drivers of Amplification

We use our model to show why lenders lower minimums when borrowers are anchored. This illustrates a mechanism through which optimizing lenders amplify consumer biases.

[36] Total credit card debt outstanding in Q4 2025 was $1.28 trillion (NY Fed, 2026) with 85% of this debt representing revolving balances (Drechsler *et al.*, 2025).

[37] Appendix Figure B.15 shows the analogous plot for default.

Figure 9: *Revenue and Cost Curves for Example Credit Score Group (700-739)*



Note: Figure shows marginal revenue and marginal cost curves by credit score bin, with and without anchoring ("behavioral" versus "rational" respectively). Revenue is given by discounted repayments and chargeoffs, less spending (i.e., interest revenue). Costs are given by discounted chargeoffs. To smooth simulation error, the line in the top plot shows the numerical derivative of a spline fitted to the marginal cost and revenue curves.

Anchoring Weakens the Correlation Between Balances and Risk. Holding minimums fixed, anchored borrowers have more debt and higher credit limit utilization on average. However, *conditional* on utilization, they are less likely to default. For example, Appendix Figure B.16 shows that in the 700-739 credit score group, anchored consumers are 15% more likely to reach near-limit utilization (defined as >90% of the credit limit), but, conditional on doing so, are 12% less likely to ever default. With anchoring, small repayments and large balances are less strongly tied to negative income shocks.

A Weaker Correlation Shifts the Marginal Revenue Curve. The framework in Section 2 suggests that when correlation between balances and risk falls, lenders have an incentive to set lower minimums. Figure 9 shows this effect in our model. The top panel shows that anchoring shifts the lender's marginal revenue curve to the left, as an increase in minimums leads revolving interest to fall more steeply. The optimal minimum thus falls from point A, where the rational marginal (interest) revenue and marginal (chargeoff) cost curves intersect, to point B, where the analogous behavioral curves intersect. The middle and bottom panels illustrate the demand- and supply-side contribution to revenue and costs. The supply-side contribution is larger for chargeoffs, in line with Figure 8. Chargeoff losses decline steeply in the minimum-formula θ: in levels, an increase in θ raises payments most when balances are large, decreasing debt fastest among the accounts most likely to default.

7 Discussion and Conclusion

A large literature studies household financial behavior, often emphasizing settings in which consumers appear to make systematic mistakes (Beshears *et al.*, 2018). There is concern that profit-maximizing firms design consumer financial products that exacerbate these mistakes (Campbell and Ramadorai, 2025; Akerlof and Shiller, 2015). This paper studies one such mechanism in the U.S. credit card market.

A possible policy response would be to restrict contract terms. For example, a policymaker could impose a floor on minimum payments, requiring lenders to set payments high enough that borrowers repay debt more quickly. Such restrictions are not unprecedented. Negatively amortizing credit cards were common in the U.S. until regulatory guidance issued in the early 2000s (see Section 3.1), and stricter regulations exist in a range of countries, including Canada, Mexico, Taiwan, Chile, and Indonesia (Castellanos *et al.*, 2025).

Our paper is not intended to provide a full policy analysis, which would require modeling lender responses along a number of dimensions, such as interest rates and fees, on which our data have little to say. Nevertheless, our results suggest that requiring lenders to set higher minimum payments could reduce consumer debt by partially undoing the effects of consumer bias. Because the behavior we document appears to reflect a mistake, rather than intertemporal tradeoffs, it is less likely to represent consumers' "normative preferences," potentially strengthening the case for such an intervention (Beshears *et al.*, 2008). Additionally, because minimum payments are already higher for consumers with the lowest credit scores, such a policy would likely be less binding for the most liquidity-constrained consumers. This contrasts with, for example, interest rate caps, another widely proposed intervention (NPR, 2026). Yet, minimum payment restrictions could affect the price and availability of credit for some consumers, even if it corrects the mistakes of others. Studying these tradeoffs is an important avenue for future work.

More broadly, our findings help explain outcomes in the credit card market, where half of U.S. households revolve high-interest debt. We show that equilibrium debt outcomes reflect not only household preferences, liquidity needs, or mistakes, but also lenders' responses to consumer behavior. In ongoing work, we explore the extent to which lenders target consumer bias (Robinson, Russel and Shi, 2025) and the factors driving differences in debt behaviors across households (Bakker, Russel and Shi, 2026).

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Online Appendices (Not for Publication)

A Theoretical Appendix

A.1 Derivation of Equation 4

Notation:

- Default: $\chi_t = \chi(B_t, m_t)$
- Repayments: $P_t = P(B_t, m_t)$
- Spending: $S_t = S(B_t)$
- Fees: $F_t = F(m_t)$
- Statement balance: $B_{t+1} = R_{cc}(B_t - P_t) + S_t + F_t$

B_{t+1} is the statement balance received in the beginning of period $t+1$. $B_t - P_t$ is the revolving balance after period t and accumulates interest from $t \to t+1$. S_t is new spending in period t that is due in $t+1$. F_t are fees accumulated in period t that are due in $t+1$. Expected total profits are:

$$\Pi(B_t) = \max_m (1-\chi_t)\left(P_t - S_t + \delta\left[\Pi(B_{t+1})\right]\right) \quad \text{s.t.} \quad B_{t+1} = R_{cc}(B_t - P_t) + S_t + F_t \tag{A.1}$$

Define $\pi_t = P_t - S_t$ as flow profits and $\tilde{\Pi}(B_t) = \pi_t + \delta\Pi(B_{t+1})$ as profits in t conditional on no default in t. Then the first order condition is:

$$(1-\chi_t)\left[\frac{\partial P_t}{\partial m_t} - \delta\Pi'(B_{t+1})\left(R_{cc}\frac{\partial P_t}{\partial m_t} - \frac{\partial F_t}{\partial m_t}\right)\right] = \frac{\partial \chi_t}{\partial m_t}\tilde{\Pi}(B_t) \tag{A.2}$$

The envelope condition is:

$$\Pi'(B_t) = (1-\chi_t)\left[\frac{\partial P_t}{\partial B_t} - \frac{\partial S_t}{\partial B_t} + \delta\Pi'(B_{t+1})\left(R_{cc} - R_{cc}\frac{\partial P_t}{\partial B_t} + \frac{\partial S_t}{\partial B_t}\right)\right] - \frac{\partial \chi_t}{\partial B_t}\tilde{\Pi}(B_t) \tag{A.3}$$

$$= (1-\chi_t)\left[\frac{\partial \pi_t}{\partial B_t} + \delta\Pi'(B_{t+1})\frac{\partial B_{t+1}}{\partial B_t}\right] - \frac{\partial \chi_t}{\partial B_t}\tilde{\Pi}(B_t) \tag{A.4}$$

Iterate forward:

$$\Pi'(B_{t+1}) = (1-\chi_{t+1})\left[\frac{\partial \pi_{t+1}}{\partial B_{t+1}} + \delta\Pi'(B_{t+2})\frac{\partial B_{t+2}}{\partial B_{t+1}}\right] - \frac{\partial \chi_{t+1}}{\partial B_{t+1}}\tilde{\Pi}(B_{t+1}) \tag{A.5}$$

Substitute into the FOC and simplify by noticing that $\frac{\partial \tilde{\Pi}(B_{t+1})}{\partial B_{t+1}} = \frac{\partial \pi_{t+1}}{\partial B_{t+1}} + \delta \Pi'(B_{t+2}) \frac{\partial B_{t+2}}{\partial B_{t+1}}$:

$$(1-\chi_t)\left[\frac{\partial P_t}{\partial m_t} - \delta\left\{(1-\chi_{t+1})\frac{\partial \tilde{\Pi}(B_{t+1})}{\partial B_{t+1}} - \frac{\partial \chi_{t+1}}{\partial B_{t+1}}\tilde{\Pi}(B_{t+1})\right\}\left(R_{cc}\frac{\partial P_t}{\partial m_t} - \frac{\partial F_t}{\partial m_t}\right)\right] = \frac{\partial \chi_t}{\partial m_t}\tilde{\Pi}(B_t) \tag{A.6}$$

This implies that the Euler equation is:

$$\underbrace{(1-\chi_t)\frac{\partial P_t}{\partial m_t}}_{\text{current pmt}} \underbrace{- \delta(1-\chi_t)(1-\chi_{t+1})\frac{\partial \tilde{\Pi}(B_{t+1})}{\partial B_{t+1}}\left(R_{cc}\frac{\partial P_t}{\partial m_t} - \frac{\partial F_t}{\partial m_t}\right)}_{\text{future payments + fees}} \tag{A.7}$$

$$= \underbrace{\frac{\partial \chi_t}{\partial m_t}\tilde{\Pi}(B_t)}_{\text{illiquidity defaults}} \underbrace{- \delta(1-\chi_t)\frac{\partial \chi_{t+1}}{\partial B_{t+1}}\tilde{\Pi}(B_{t+1})\left(R_{cc}\frac{\partial P_t}{\partial m_t} - \frac{\partial F_t}{\partial m_t}\right)}_{\text{insolvency defaults + fees}} \tag{A.8}$$

Rearranging gives us Equation 4 (with fees) as wanted.

$$\underbrace{\frac{\partial P_t}{\partial m_t}\left[(1-\chi_{t+1})\tilde{\Pi}'(B_{t+1})\delta R_{cc} - 1\right]}_{\text{Net Interest Revenue}} + \underbrace{\frac{\partial \chi_t}{\partial m_t}\frac{\tilde{\Pi}(B_t)}{1-\chi_t}}_{\text{Illiquidity Default}} = \underbrace{\delta R_{cc}\frac{\partial P_t}{\partial m_t}\frac{\partial \chi_{t+1}}{\partial B_{t+1}}\tilde{\Pi}(B_{t+1})}_{\text{Insolvency Default}} \tag{A.9}$$

$$+ \underbrace{\delta\frac{\partial F_t}{\partial m_t}\left[(1-\chi_{t+1})\tilde{\Pi}'(B_{t+1}) - \frac{\partial \chi_{t+1}}{\partial B_{t+1}}\tilde{\Pi}(B_{t+1})\right]}_{\text{Future Fee Revenue}} \tag{A.10}$$

A.2 Cost-Minimizing Repayment

This appendix illustrates why, conditional on total repayments, an individual minimizes costs by allocating excess repayments toward their higher-interest debt.

Setup. Consider an agent who has credit card debt D_t, mortgage balance $D_{o,t}$ and a path of repayments $\{(P_\tau, P_{o,\tau})\}_{\tau \geq t}$ that follows until both balances are zero in period k and k_m respectively.[38] The credit card interest rate is R_{cc}, the mortgage has interest rate $R_m < R_{cc}$. The credit card minimum is M_t and the mortgage minimum is $M_{o,t}$.

Overpaying mortgage debt fails to minimize the present-value of total debt. Suppose there is a period $t = j$ where $R_{cc}D_{j-1} > P_j$ and $P_{o,j} > M_o$. In words, suppose the

[38]This assumption implies that the agent cannot default. In Section 4.1 we present evidence that anticipation of default plays at most a limited role in explaining the patterns we document.

individual is revolving in period j while making excess payments on their mortgage. This implies there is an $\epsilon > 0$ such that $R_{cc}D_{j-1} > P_j + \epsilon$ and $P_{o,j} - \epsilon \geq M_o$.

Consider a perturbation of repayments $(\hat{P}_j, \hat{P}_{o,j}) = (P_j + \epsilon, P_{o,j} - \epsilon)$ which is feasible (i.e., satisfies the minimum payment and full balance constraints) by construction of ϵ. Since the borrower repays ϵ more on their card in j under the perturbation, by period $j + 1$, their credit card balance is $R_{cc}\epsilon$ lower and their mortgage balance is $R_m\epsilon$ higher. Since the total debt balance has fallen by $(R_{cc} - R_m)\epsilon > 0$, the present value of the agent's debt decreases.

Overpaying mortgage debt fails to minimize the present-value of total debt repayments. Consider the same perturbation. Intuitively, the present-value of repayments also falls because, after period j, the borrower can finish repaying their credit card more quickly and use the interest saved to more than cover their (now larger) mortgage debt.

Formally, some assumptions are necessary to ensure that the future repayments path is feasible. Assume that credit card minimums are weakly increasing in credit card balances; that mortgage minimums are constant at M_o until mortgage debt is repaid ($D_{o,t} = 0$); and that credit card debt is repaid before the mortgage along the original repayment path ($k < k_m$).[39] Then, there is a feasible perturbation from $\{P_\tau, P_{o,\tau}\}_{\tau \geq j}$ to $\{\hat{P}_\tau, \hat{P}_{o,\tau}\}_{\tau \geq j}$ that, for all periods $\tau \geq j$, the borrower has weakly lower total repayments in all periods and strictly lower total repayment in at least one period.

Consider $\{\hat{P}_\tau, \hat{P}_{o,\tau}\}_{\tau \geq j}$:

- $\hat{P}_j = P_j + \epsilon$, $\hat{P}_{o,j} = P_{o,j} - \epsilon$.
- $\hat{P}_k = P_k - R_{cc}^{k-t}\epsilon$, $\hat{P}_{o,k} = P_{o,k} + R_m^{k-t}\epsilon$.
- $\hat{P}_\tau = P_\tau$ and $\hat{P}_{o,\tau} = P_{o,\tau}$ for $\tau \neq j, k$.

where $\epsilon > 0$ is such that $R_{cc}D_{j-1} > P_j + \epsilon$, $P_{o,j} - \epsilon \geq M_o$, and $P_k > R_{cc}^{k-t}\epsilon$. Clearly under $\{\hat{P}_\tau, \hat{P}_{o,\tau}\}_{\tau \geq j}$, the borrower has weakly lower total repayments in all periods and strictly lower total repayments in period k because $(R_{cc}^{k-t} - R_m^{k-t})\epsilon > 0$.

We must also check feasibility. Starting in period j, ϵ is chosen so that mortgage payments weakly exceed the minimum payment and credit card payments are less than the statement balance. In periods $\tau \in [j + 1, k)$, payments are unchanged so $\hat{P}_{o,\tau}$ is feasible because $P_{o,\tau}$ is feasible and minimums are constant. For the credit card, $\hat{P}_\tau$ is feasible because $\hat{D}_\tau < D_\tau$ (an extra ϵ dollars was repaid on the card in j), so $\hat{P}_\tau = P_\tau \geq M_\tau \geq \hat{M}_\tau$ because credit card minimums are weakly increasing in balances. In period k, the credit card balance is repaid because $\hat{D}_k = R_{cc}D_{k-1} - R_{cc}^{k-t}\epsilon - P_k + R_{cc}^{k-t}\epsilon = D_k = 0$; and the mortgage balance is

[39]These assumptions are sufficient but not necessary.

restored because $\hat{D}_{o,k} = R_m D_{o,k-1} + R_m^{k-t}\epsilon - P_{o,k} - R_m^{k-t} = D_{o,k}$. So, $\hat{P}_k$ is feasible because it completely repays outstanding debt, and $\hat{P}_{o,k}$ is feasible because $\hat{P}_{o,k} > P_{o,k} \geq M_o$. For $\tau > k$, $\hat{P}_{o,\tau} = P_{o,\tau}$ which must be feasible since $\hat{D}_{o,k} = D_{o,k}$, as desired.

A.3 A Theoretical Framework of Mental Accounting & Anchoring

This appendix contains a theoretical mental accounting framework, similar to Hastings and Shapiro (2013). Motivated by our evidence in Section 4, consumers make repayment choices that are affected by salient benchmarks, including their minimum payments.[40] The framework generates both the cross-product repayment patterns we document and "anchoring" on minimums that has been documented in several existing works. It also generates predictions about consumer behavior after a minimum increase, which we explore in Section 4.2.

Setup. Consider a discrete consumption-savings model. Each consumer has a checking account, credit card, and installment debt. They receive income each period into their checking account, which follows a first-order Markov process. As a result, there are four state variables: checking account balances X_t, credit card statement balances B_t, installment debt balances B_{ot}, and income Y_t. Given the state variables, each period the consumer chooses how much to repay on the credit card, P_t, and installment debts, P_{ot}. They must also choose their credit card spending S_t and their non-credit card consumption C_t.

Individuals receive interest rate R_a in their checking account, R_{cc} on their credit card balances, and R_o on installment debt. Assume that $R_a < R_o < R_{cc}$. For simplicity, there is no default, so credit card payments must be no less than the minimum payment m_t and no bigger than the statement balance B_t. Similarly, for installment debt, payments must be no less than $m_{o,t}$ and no more than $B_{o,t}$.

Individuals maximize expected discounted utility. Flow utility is given by $u(C_t + S_t)$ and a mental accounting disutility term, Γ. As in Hastings and Shapiro (2013), Γ is the generic disutility individuals receive from deviating from repayment benchmarks. These benchmarks could arise from a variety of forces such as debt aversion or cognitive uncertainty.[41]

Continuation utility given the state variables is $V_{t+1}(X_{t+1}, B_{t+1}, B_{o,t+1}, Y_{t+1})$. We place no restrictions on V_{t+1}, except that it is continuous and twice-differentiable in the state variables, and that its Hessian is negative definite. We do not define V_{t+1} recursively or explicitly write down a Bellman equation. This allows our model to incorporate a broader

[40] While we focus primarily on minimum payments, the framework could be extended to incorporate other benchmarks including the credit limit (see e.g., Gross and Souleles, 2002; Agarwal *et al.*, 2018).

[41] We discuss a model of the latter in Appendices A.4.3 and A.4.4.

set of behaviors that could lead to debt repayment mistakes, for example present-focused preferences or Dave Ramsey's "snowball" method.[42]

Each period, the household's problem is:

$$\max_{C_t, S_t, P_t, P_{ot}} u(C_t + S_t) + \Gamma(P_t, P_{o,t}, \cdot) + \delta \mathbb{E}_t \left[V_{t+1} \left(X_{t+1}, B_{t+1}, B_{o,t+1}, Y_{t+1} \right) \right] \tag{A.11}$$

where resource transitions are:

$$X_{t+1} = R_a(X_t - C_t - P_t - P_{o,t}) + Y_{t+1} \tag{A.12}$$

$$B_{t+1} = R_{cc}(B_t - P_t) + S_t \tag{A.13}$$

$$B_{o,t+1} = R_o(B_{o,t} - P_{o,t}) \tag{A.14}$$

subject to the constraints:

$$[\alpha] \quad X_{t+1} \geq 0 \tag{A.15}$$

$$[\kappa] \quad S_t \geq 0 \tag{A.16}$$

$$[\beta] \quad P_t \geq B_t - L_t = m_t \tag{A.17}$$

$$[\mu] \quad B_t \geq P_t \tag{A.18}$$

$$[\lambda] \quad P_{o,t} \geq B_{o,t} - L_{o,t} = m_{o,t} \tag{A.19}$$

$$[\omega] \quad B_{o,t} \geq P_{o,t} \tag{A.20}$$

where brackets indicate positive Lagrange multipliers and L_t is the maximum allowable balance that can be carried forward into the next period.

Rational benchmark. Suppose $\Gamma = 0$ and V_t defined recursively so that the solution to problem (A.11) is dynamically optimal. This will yield two predictions.

Proposition 1. *Under the rational benchmark, no individual will make "cross-product misallocations" ($P_t < B_t$ and $P_{o,t} > m_{o,t}$).*

Proof. Taking the first order conditions with $\Gamma = 0$ implies:

$$[P_t] : \delta \mathbb{E}_t \left[\frac{\partial V_{t+1}}{\partial X_{t+1}} R_a + \frac{\partial V_{t+1}}{\partial B_{t+1}} R_{cc} \right] = -\alpha_t R_a + (\beta_t - \mu_t) \tag{A.21}$$

$$[P_{o,t}] : \delta \mathbb{E}_t \left[\frac{\partial V_{t+1}}{\partial X_{t+1}} R_a + \frac{\partial V_{t+1}}{\partial B_{o,t+1}} R_o \right] = -\alpha_t R_a + (\lambda_t - \omega_t) \tag{A.22}$$

[42] See, for example, the discussion following Claim 3 in Katz (2023).

$$[C_t] : \delta \mathbb{E}_t R_a \frac{\partial V_{t+1}}{\partial X_{t+1}} = u'(C_t + S_t) - \alpha_t R_a \tag{A.23}$$

$$[S_t] : -\delta \mathbb{E}_t \frac{\partial V_{t+1}}{\partial B_{t+1}} = u'(C_t + S_t) + \kappa_t \tag{A.24}$$

We can also show that $\mathbb{E}_t \frac{\partial V_{t+1}}{\partial B_{t+1}} = \mathbb{E}_t \frac{\partial V_{t+1}}{\partial B_{o,t+1}}$. In particular, the envelope theorem implies that:

$$\frac{\partial V_{t+1}}{\partial B_{t+1}} = \delta \mathbb{E}_{t+1} R_{cc} \left[\frac{\partial V_{t+2}}{\partial B_{t+2}} \right] - \beta_{t+1} + \mu_{t+1} \tag{A.25}$$

$$\frac{\partial V_{t+1}}{\partial B_{o,t+1}} = \delta \mathbb{E}_{t+1} R_o \left[\frac{\partial V_{t+2}}{\partial B_{o,t+2}} \right] - \lambda_{t+1} + \omega_{t+1} \tag{A.26}$$

Iterating the FOC for P_t and $P_{o,t}$ one period forward and plugging into $\partial V_{t+2}/\partial B_{t+2}$ and $\partial V_{t+2}/\partial B_{o,t+2}$ implies that:

$$\frac{\partial V_{t+1}}{\partial B_{t+1}} = -\delta R_a \mathbb{E}_{t+1} \left[\frac{\partial V_{t+2}}{\partial X_{t+2}} \right] - \alpha_{t+1} R_a < 0 \tag{A.27}$$

$$\frac{\partial V_{t+1}}{\partial B_{o,t+1}} = -\delta R_a \mathbb{E}_{t+1} \left[\frac{\partial V_{t+2}}{\partial X_{t+2}} \right] - \alpha_{t+1} R_a < 0 \tag{A.28}$$

As a result, $\mathbb{E}_t \frac{\partial V_{t+1}}{\partial B_{t+1}} = \mathbb{E}_t \frac{\partial V_{t+1}}{\partial B_{o,t+1}}$ as wanted. Subtracting (A.22) from (A.21) and plugging in for $\mathbb{E}_t \frac{\partial V_{t+1}}{\partial B_{t+1}} = \mathbb{E}_t \frac{\partial V_{t+1}}{\partial B_{o,t+1}}$ implies:

$$\delta (R_{cc} - R_o) \mathbb{E}_t \left[\frac{\partial V_{t+1}}{\partial B_{t+1}} \right] = (\beta_t - \mu_t) - (\lambda_t - \omega_t) \tag{A.29}$$

Since $\frac{\partial V_{t+1}}{\partial B_{t+1}} < 0$ and $R_{cc} > R_o$, the right-hand side must be negative. Consequently, if $\mu_t = \lambda_t = 0$ (i.e., $P_t < B_t$ and $P_{o,t} > m_{o,t}$), Equation (A.29) cannot hold so cross-product behaviors cannot occur under $\Gamma = 0$ as wanted. □

Proposition 2. *Under the rational benchmark, the elasticity of repayments to (a one-period change) in the credit card minimum is zero if* $P_t > m_t$.

Proof. We want to show that if $\Gamma = 0$ and $P_t > m_t$, then $\partial P_t / \partial m = 0$.

If $P_t > m_t$, then $\beta_t = 0$. If $\mu_t > 0$, that implies $P_t = B_t + S_t$, so $\partial P_t / \partial m_t = 0$ as wanted. Suppose $\omega_t > 0$. In this case, $P_{o,t} = B_{o,t}$ and we know from Proposition 1 that if $P_{o,t} = B_{o,t}$ then $P_t = B_t + S_t$ in which case $\partial P_t / \partial m_t = 0$ as wanted. As a result, going forward we'll consider the case where $\beta_t = \mu_t = \omega_t = 0$.

In addition, $\alpha_t R_a$ in Equations (A.21)-(A.24) (which comes from $\alpha_t \cdot \frac{\partial X_{t+1}}{\partial Z_t}$ where Z_t is a choice variable) is equal to zero because if $\alpha_t > 0$ then $X_{t+1} = 0$, so $\partial X_{t+1} / \partial Z_t = 0$.

Therefore, the implicit function theorem applied to Equations (A.21)-(A.24) is:

$$[P_t] : \delta \mathbb{E}_t \left[\frac{d}{dm_t} \frac{\partial V_{t+1}}{\partial X_{t+1}} R_a + \frac{d}{dm_t} \frac{\partial V_{t+1}}{\partial B_{t+1}} R_{cc} \right] = 0 \tag{A.30}$$

$$[P_{ot}] : \delta \mathbb{E}_t \left[\frac{d}{dm_t} \frac{\partial V_{t+1}}{\partial X_{t+1}} R_a + \frac{d}{dm_t} \frac{\partial V_{t+1}}{\partial B_{o,t+1}} R_o \right] = \frac{d}{dm_t} \lambda_t \tag{A.31}$$

$$[C_t] : u''(C_t + S_t) \left(\frac{\partial C_t}{\partial m_t} + \frac{\partial S_t}{\partial m_t} \right) = \delta \mathbb{E}_t R_a \frac{d}{dm_t} \frac{\partial V_{t+1}}{\partial X_{t+1}} \tag{A.32}$$

$$[S_t] : u''(C_t + S_t) \left(\frac{\partial C_t}{\partial m_t} + \frac{\partial S_t}{\partial m_t} \right) = -\delta \mathbb{E}_t \frac{d}{dm_t} \frac{\partial V_{t+1}}{\partial B_{t+1}} - \frac{d}{dm_t} \kappa_t \tag{A.33}$$

Expanding, notice that:

$$\mathbb{E}_t \frac{d}{dm_t} \frac{\partial V_{t+1}}{\partial B_{t+1}} = \tag{A.34}$$

$$\mathbb{E}_t \left(V_{BB} \frac{\partial B_{t+1}}{\partial P_t} \frac{\partial P_t}{\partial m_t} + V_{BB} \frac{\partial B_{t+1}}{\partial C_t} \frac{\partial C_t}{\partial m_t} + V_{BB} \frac{\partial B_{t+1}}{\partial S_t} \frac{\partial S_t}{\partial m_t} + V_{BB} \frac{\partial B_{t+1}}{\partial P_{o,t}} \frac{\partial P_{o,t}}{\partial m_t} \right) \tag{A.35}$$

$$+ \mathbb{E}_t \left(V_{BX} \frac{\partial X_{t+1}}{\partial P_t} \frac{\partial P_t}{\partial m_t} + V_{BX} \frac{\partial X_{t+1}}{\partial C_t} \frac{\partial C_t}{\partial m_t} + V_{BX} \frac{\partial X_{t+1}}{\partial S_t} \frac{\partial S_t}{\partial m_t} + V_{BX} \frac{\partial X_{t+1}}{\partial P_{o,t}} \frac{\partial P_{o,t}}{\partial m_t} \right) \tag{A.36}$$

$$+ \mathbb{E}_t \left(V_{BB_o} \frac{\partial B_{o,t+1}}{\partial P_t} \frac{\partial P_t}{\partial m_t} + V_{BB_o} \frac{\partial B_{o,t+1}}{\partial C_t} \frac{\partial C_t}{\partial m_t} + V_{BB_o} \frac{\partial B_{o,t+1}}{\partial S_t} \frac{\partial S_t}{\partial m_t} + V_{BB_o} \frac{\partial B_{o,t+1}}{\partial P_{o,t}} \frac{\partial P_{o,t}}{\partial m_t} \right) \tag{A.37}$$

So:

$$\mathbb{E}_t \frac{d}{dm_t} \frac{\partial V_{t+1}}{\partial B_{t+1}} = R_{cc} \mathbb{E}_t V_{BB} \left(-\frac{\partial P_t}{\partial m_t} + \frac{1}{R_{cc}} \frac{\partial S_t}{\partial m_t} \right) - R_a \mathbb{E}_t V_{BX} \left(\frac{\partial C_t}{\partial m_t} + \frac{\partial P_t}{\partial m_t} + \frac{\partial P_{o,t}}{\partial m_t} \right) \tag{A.38}$$

$$- R_o \mathbb{E}_t V_{BB_o} \frac{\partial P_{o,t}}{\partial m_t} \tag{A.39}$$

and analogously for

$$\mathbb{E}_t \frac{d}{dm_t} \frac{\partial V_{t+1}}{\partial X_{t+1}} = R_{cc} \mathbb{E}_t V_{XB} \left(-\frac{\partial P_t}{\partial m_t} + \frac{1}{R_{cc}} \frac{\partial S_t}{\partial m_t} \right) - R_a \mathbb{E}_t V_{XX} \left(\frac{\partial C_t}{\partial m_t} + \frac{\partial P_t}{\partial m_t} + \frac{\partial P_{o,t}}{\partial m_t} \right) \tag{A.40}$$

$$- R_o \mathbb{E}_t V_{XB_o} \frac{\partial P_{o,t}}{\partial m_t} \tag{A.41}$$

and:

$$\mathbb{E}_t \frac{d}{dm_t} \frac{\partial V_{t+1}}{\partial B_{o,t+1}} = R_{cc} \mathbb{E}_t V_{B_o B} \left(-\frac{\partial P_t}{\partial m_t} + \frac{1}{R_{cc}} \frac{\partial S_t}{\partial m_t} \right) - R_a \mathbb{E}_t V_{B_o X} \left(\frac{\partial C_t}{\partial m_t} + \frac{\partial P_t}{\partial m_t} + \frac{\partial P_{o,t}}{\partial m_t} \right) \tag{A.42}$$

$$- R_o \mathbb{E}_t V_{B_o B_o} \frac{\partial P_{o,t}}{\partial m_t} \tag{A.43}$$

If $\lambda_t = 0$, Equations (A.30) and (A.31) combined with $\mathbb{E}_t \frac{\partial V_{t+1}}{\partial B_{o,t+1}} = \mathbb{E}_t \frac{\partial V_{t+1}}{\partial B_{t+1}}$ implies:

$$\delta(R_{cc} - R_o)\mathbb{E}_t \left[\frac{d}{dm_t} \frac{\partial V_{t+1}}{\partial B_{t+1}} \right] = 0 \tag{A.44}$$

So $\mathbb{E}_t \left[\frac{d}{dm_t} \frac{\partial V_{t+1}}{\partial B_{t+1}} \right] = 0$. If $\mathbb{E}_t \left[\frac{d}{dm_t} \frac{\partial V_{t+1}}{\partial B_{t+1}} \right] = 0$, Equation (A.30) implies that $\mathbb{E}_t \left[\frac{d}{dm_t} \frac{\partial V_{t+1}}{\partial X_{t+1}} \right] = 0$ and Equation (A.32) implies $\frac{\partial C_t}{\partial m_t} + \frac{\partial S_t}{\partial m_t} = 0$. Thus, we have the following system of equations from Equations (A.39)-(A.43):

$$\underbrace{\mathbb{E}_t \begin{bmatrix} V_{BB} & V_{BX} & V_{BB_o} \\ V_{XB} & V_{XX} & V_{XB_o} \\ V_{B_oB} & V_{B_oX} & V_{B_oB_o} \end{bmatrix}}_{H} \begin{bmatrix} -\frac{\partial P_t}{\partial m_t} + \frac{1}{R_{cc}} \frac{\partial S_t}{\partial m_t} \\ -R_a\left(\frac{\partial C_t}{\partial m_t} + \frac{\partial P_t}{\partial m_t} + \frac{\partial P_{o,t}}{\partial m_t}\right) \\ -R_o \frac{\partial P_{o,t}}{\partial m_t} \end{bmatrix} = 0 \tag{A.45}$$

Since H is invertible (principal sub-matrix of the Hessian of V_{t+1} which is negative definite), this implies that:

$$-\frac{\partial P_t}{\partial m_t} + \frac{1}{R_{cc}} \frac{\partial S_t}{\partial m_t} = 0 \tag{A.46}$$

$$\frac{\partial C_t}{\partial m_t} + \frac{\partial P_t}{\partial m_t} + \frac{\partial P_{o,t}}{\partial m_t} = 0 \tag{A.47}$$

$$\frac{\partial P_{o,t}}{\partial m_t} = 0 \tag{A.48}$$

$$\frac{\partial C_t}{\partial m_t} + \frac{\partial S_t}{\partial m_t} = 0 \tag{A.49}$$

This system of equations implies that $\frac{\partial S_t}{\partial m_t} = 0$ which implies $\frac{\partial P_t}{\partial m_t} = 0$ as wanted.

If $\lambda_t > 0$, this implies that $P_{o,t} = m_{o,t}$ so $\frac{\partial P_{o,t}}{\partial m_t} = 0$. Notice that if we also have $\kappa_t > 0$, then $S_t = 0$ so $\frac{\partial S_t}{\partial m_t} = 0$. In this case, Equations (A.30) and (A.32) imply:

$$\underbrace{\mathbb{E}_t \begin{bmatrix} u'' - \delta R_a R_{cc} V_{XB} & u'' + \delta R_a^2 V_{XX} \\ R_a R_{cc} V_{XB} + R_{cc}^2 V_{BB} & -R_a^2 V_{XX} - R_a R_{cc} V_{XB} \end{bmatrix}}_{H_2} \begin{bmatrix} -\frac{\partial P_t}{\partial m_t} \\ \frac{\partial C_t}{\partial m_t} + \frac{\partial P_t}{\partial m_t} \end{bmatrix} = 0 \tag{A.50}$$

H_2 has a non-zero determinant because $u'' < 0$ and $\det \begin{bmatrix} V_{BB} & V_{BX} \\ V_{XB} & V_{XX} \end{bmatrix} = V_{BB}V_{XX} - V_{BX}^2 \geq 0$

(by Sylvester's Criterion). Therefore:

$$\det(H_2) = \delta R_a^2 R_{cc}^2 \left(V_{XB}^2 - V_{XX}V_{BB}\right) - u'' \cdot \left(R_a^2 V_{XX} + 2R_a R_{cc} V_{XB} + R_{cc}^2 V_{BB}\right) < 0 \quad \text{(A.51)}$$

As a result, H_2 is also invertible, so $\frac{\partial P_t}{\partial m_t} = 0$, as wanted.

If instead, $\lambda_t > 0$ and $\kappa_t = 0$, Equations (A.32) and (A.33) imply that:

$$\delta \mathbb{E}_t R_a \frac{d}{dm_t} \frac{\partial V_{t+1}}{\partial X_{t+1}} = -\delta \mathbb{E}_t \frac{d}{dm_t} \frac{\partial V_{t+1}}{\partial B_{t+1}} \quad \text{(A.52)}$$

However, since $R_{cc} > 0$ Equation (A.30) implies that $\mathbb{E}_t \frac{d}{dm_t} \frac{\partial V_{t+1}}{\partial B_{t+1}} = 0$. As a result, we can return to Equation (A.45) in the previous case and the same conclusion follows.[43] □

Propositions 1 and 2 motivate two empirical predictions.

Prediction.

1. *When $\Gamma \neq 0$, unconstrained consumers may change their payments in response to a minimum increase. Consumers who originally paid below the new minimum may end up paying strictly above the new minimum (as in Keys and Wang, 2019).*

2. *If consumers overpay installment debt while revolving credit card debt, then $\Gamma \neq 0$. The same consumers, therefore, should be more likely to respond to a change in credit card minimums (i.e., "cross-product misallocations" should predict minimum change responses).*

A.4 Microfoundations for Empirical Model Repayment Friction

In our empirical model, consumers make repayments as a weighted average of the cost-minimization approach and only paying the credit card minimum (Equation 12). In this appendix, we extend our framework from Appendix A.3 to provide several possible microfoundations for this parameterization.

A.4.1 Mental Accounting with Quadratic Loss

The weighted-average repayment rule can be microfounded with a model of mental accounting in which individuals receive quadratic disutility from repaying far from the minimum.

[43] Note that this proof requires a one-time change in the minimum. Even if $\Gamma = 0$, a permanently higher minimum could introduce a precautionary motive to increase payments. In our empirical analysis we assume that these forward-looking precautionary effects—which require consumers to understand their minimum formula and internalize its effects on a future constraint—are second-order.

Assumptions.

- A1: C_t and S_t are chosen under the rational benchmark.
- A2: Define total debt repayment $\tilde{P}_t = P_t + P_{o,t}$ and $\tilde{P}_t^R$ to be total debt repayments under the rational benchmark. Then, let

$$\Gamma = \theta_1 \left| \tilde{P}_t - \tilde{P}_t^R(\cdot) \right| + \frac{\theta_2}{2}(P_t - m_t)^2 \tag{A.53}$$

  and assume there exists a $\theta_1 > \overline{\theta}_1$ such that $\tilde{P}_t = \tilde{P}_t^R$.

- A3: As in the case under the rational benchmark, $\frac{\partial V_{t+1}}{\partial B_{t+1}} = \frac{\partial V_{t+1}}{\partial B_{o,t+1}}$.

The assumptions imply that individuals have different mental accounts for debt repayments and consumption (for example, using dollars "left over" after spending for debt repayment). They also imply that individuals use credit card minimums as a repayment anchor. There is work in psychology to support both assumptions. For example, Prelec and Loewenstein (1998) provide suggestive evidence that credit card repayments are "decoupled" from credit card spending because specific payments are usually not assigned to cover specific purchases. Martínez-Marquina and Shi (2024) find that in a lab setting, individuals do not jointly minimize costs across positive and negative balance accounts. A number of recent works suggest consumers use credit card minimums as a repayment anchor or target, including Stewart (2009); Keys and Wang (2019); Medina and Negrin (2022); Bartels *et al.* (2023).

Proposition 3. *Under Assumptions A1-A3 and strong mental accounting ($\theta_1 > \overline{\theta}_1$), optimal credit card repayments are (to a first-order) $P_t = \gamma m_t + (1-\gamma)P_t^R$, where P_t^R are repayments under the rational benchmark. As a result:*

$$\frac{\partial P_t}{\partial m_t} = \gamma + (1-\gamma)\frac{\partial P_t^R}{\partial m_t} \tag{A.54}$$

Proof. Since C_t and S_t are chosen under the rational benchmark, P_t and P_{ot} are chosen to solve:

$$\max_{P_t, P_{ot}} \; u(C_t + S_t) - \theta_1 \left| \tilde{P}_t - \tilde{P}_t^R(\cdot) \right| - \frac{\theta_2}{2}(P_t - m_t)^2 + \delta \mathbb{E}_t V_{t+1}(P_t, P_{ot}; \cdot) \text{ s.t. (A.12)-(A.20)} \tag{A.55}$$

With θ_1 sufficiently high $\tilde{P}_t^* = \tilde{P}_t^R(\cdot)$, so the problem is equivalent to:

$$\max_{P_t} \; -\frac{\theta_2}{2}(P_t - m_t)^2 + \delta \mathbb{E}_t V_{t+1}(P_t, \tilde{P}_t^R - P_t; \cdot) \tag{A.56}$$

The FOC (with respect to P_t) is:

$$-\theta_2(P_t - m_t) + \delta R_o \mathbb{E}_t \frac{\partial V_{t+1}}{\partial B_{o,t+1}} - \delta R_{cc} \mathbb{E}_t \frac{\partial V_{t+1}}{\partial B_{t+1}} - \alpha_t R_a + (\beta_t - \mu_t) = 0 \tag{A.57}$$

Since $\frac{\partial V_{t+1}}{\partial B_{t+1}} = \frac{\partial V_{t+1}}{\partial B_{o,t+1}}$:

$$\theta_2(P_t - m_t) = -\delta(R_{cc} - R_o)\mathbb{E}_t \frac{\partial V_{t+1}}{\partial B_{t+1}} - \alpha_t R_a + (\beta_t - \mu_t) \tag{A.58}$$

This expression implies if $R_{cc} - R_o$ is large, then $P_t - m_t$ is also large. That is, people pay more than the minimum, even given the cost of deviating from it. Take a first-order approximation of $\mathbb{E}_t \frac{\partial V_{t+1}}{\partial B_{t+1}}$ around P_t^R:

$$\mathbb{E}_t \frac{\partial V_{t+1}}{\partial B_{t+1}} \approx \theta_0 + \theta_3(P_t - P_t^R(\cdot)) \tag{A.59}$$

where $\theta_0 := \mathbb{E}_t \frac{\partial V_{t+1}}{\partial B_{t+1}}(P_t^R; \cdot)$. Since $P_t = P_t^R$ if $\theta_2 = 0$, this implies the FOC evaluated at P_t^R is:

$$\delta(R_{cc} - R_o)\mathbb{E}_t \frac{\partial V_{t+1}}{\partial B_{t+1}}(P_t^R; \cdot) = \delta(R_{cc} - R_o)\theta_0 = -\alpha_t R_a + (\beta_t - \mu_t) \tag{A.60}$$

Then:

$$\theta_2(P_t - m_t) = -\delta(R_{cc} - R_o)(\theta_0 + \theta_3(P_t - P_t^R)) - \alpha_t R_a + (\beta_t - \mu_t) \tag{A.61}$$
$$\theta_2(P_t - m_t) = \alpha_t R_a - (\beta_t - \mu_t) - \delta(R_{cc} - R_o)\theta_3(P_t - P_t^R) - \alpha_t R_a + (\beta_t - \mu_t) \tag{A.62}$$
$$\theta_2(P_t - m_t) = -\delta(R_{cc} - R_o)\theta_3(P_t - P_t^R) \tag{A.63}$$
$$(\theta_2 + \delta(R_{cc} - R_o)\theta_3)P_t = \theta_2 m_t + \delta(R_{cc} - R_o)\theta_3 P_t^R \tag{A.64}$$

Thus:

$$P_t = \gamma_t m_t + (1 - \gamma_t)P_t^R \tag{A.65}$$

where $\gamma_t := \frac{\theta_2}{\theta_2 + \delta(R_{cc} - R_o)\theta_3}$, as wanted. Notice that, γ_t depends on t because Equation (A.59) approximates $\mathbb{E}_t \frac{\partial V_{t+1}}{\partial B_{t+1}}$ around P_t^R which is time-varying. Empirically, we find γ_t is persistent within person (Table 2), and use constant γ as an approximation in Equation (12). □

A.4.2 Mental Accounting Over Repayment Shares

Alternatively, the weighted-average repayment rule can be microfounded with a model of mental accounting in which individuals mental account over repayment shares. First, make a change of variables. Instead of choosing P_t and $P_{o,t}$, households choose:

- Total debt repayment $\tilde{P}_t := P_t + P_{ot}$.
- The share of excess payments made towards other installment debt, rather than credit cards: $\gamma_t := \frac{P_{ot} - m_{ot}}{\tilde{P}_t - m_{ot} - m_t}$.

Given the change of variables, we have:

$$\begin{aligned}
P_{o,t} &= m_{o,t} + \gamma_t \cdot (\tilde{P}_t - m_{o,t} - m_t) && \text{(A.66)}\\
&= (1-\gamma_t) \cdot m_{o,t} + \gamma_t \cdot (\tilde{P}_t - m_t) && \text{(A.67)}\\
P_t &= \tilde{P}_t - P_{o,t} && \text{(A.68)}\\
&= \tilde{P}_t - (1-\gamma_t) \cdot m_{o,t} - \gamma_t \cdot (\tilde{P}_t - m_t) && \text{(A.69)}\\
&= (1-\gamma_t) \cdot (\tilde{P}_t - m_{o,t}) + \gamma_t \cdot m_t && \text{(A.70)}
\end{aligned}$$

Then, the consumer solves:

$$\max_{C_t, S_t, \tilde{P}_t, \gamma_t} u(C_t + S_t) - \theta_1 \cdot \left| \tilde{P}_t - \tilde{P}_t^R(\cdot) \right| - \theta_2 \cdot |\gamma_t - \gamma| + \delta \mathbb{E}_t \left[V_{t+1}(\cdot) \right] \text{ s.t. constraints.} \tag{A.71}$$

i.e., $\Gamma = \theta_1 \left| \tilde{P}_t - \tilde{P}_t^R(\cdot) \right| + \theta_2 |\gamma_t - \gamma|$. In this model, borrowers have different mental accounts for debt repayment and consumption (similar to Section A.4), and target excess repayment shares. Psychologically, the latter assumption is supported by Gathergood *et al.* (2019a) who show that borrowers often use heuristics such as balance matching (where repayments are proportional to balances) to repay different credit cards.

For high enough θ_1, θ_2, the optimal path has $\tilde{P}_t = \tilde{P}_t^R$ and $\gamma_t = \gamma$ which implies $P_t = (1-\gamma)(\tilde{P}_t^R - m_{o,t}) + \gamma m_t = (1-\gamma) P_t^R + \gamma m_t$ as wanted.

A.4.3 Bayesian Cognitive Noise with Beta-Binomial

The weighted-average repayment rule can also be microfounded using a Bayesian cognitive noise model following Enke and Graeber (2023).[44]

[44] This microfoundation can also be seen as capturing the intuition of "anchoring-and-adjustment" in Tversky and Kahneman (1974).

Assumptions.

- The borrower has already solved for total debt repayments $\tilde{P}_t$.
- The utility-maximizing credit card repayment is P_t^R and the default is m_t.

Individuals solve for the share of balances to repay (in excess of the minimum) with a beta prior and binomial signal. Let $a_t^* = \frac{P_t^R - m_t}{B_t - m_t} \in [0, 1]$, the utility-maximizing action, represent the share of excess balances repaid on the card (0 = minimum, 1 = full balance). The borrower does not know a_t^*, but depending on cognitive effort N, receives the following mental simulation:

$$S_t \sim \frac{1}{N} \text{Bin}(N, a_t^*) \tag{A.72}$$

The borrower's prior for the utility-maximizing action is a Beta distribution over their "cognitive default" action. Since the default repayment is m_t, this implies that as a share of excess balances repaid the default is zero. If n is confidence in the prior, $a_t^* \sim \text{Beta}(0, n)$. Assuming the borrower takes an action that is the mean of their posterior (as in Enke and Graeber (2023)), by the Beta-Binomial conjugacy this implies that the observed action is:

$$a_t^{ob} = \mathbb{E}[a_t^* | S_t = s_t] = \frac{N s_t}{n + N} = (1 - \gamma) s_t \tag{A.73}$$

where $\gamma = n/(n + N)$. The expected action as a share of excess balances repaid is therefore:

$$\mathbb{E}[a_t^{ob}] = (1 - \gamma) a_t^* = (1 - \gamma) \frac{P_t^R - m_t}{B_t - m_t} \tag{A.74}$$

Thus, expected dollars repaid are:

$$(1 - \gamma)(P_t^R - m_t) + m_t = \gamma m_t + (1 - \gamma) P_t^R \tag{A.75}$$

as wanted.

A.4.4 Bayesian Cognitive Noise with Normal-Normal

Alternatively, suppose individuals solve for the amount to repay with a normal prior and normal signal. Let the utility-maximizing action be $A_t^* = P_t^R$. The individual has the following prior and mental simulation:

$$A_{prior,t} \sim \mathcal{N}(m_t, 1/n) \qquad \text{and} \qquad S_t \sim \mathcal{N}(P_t^R, 1/N) \tag{A.76}$$

Then, the expected action is:

$$\mathbb{E}[A_t^{ob}] = \frac{n}{n+N} m_t + \frac{N}{n+N} P_t^R = \gamma m_t + (1-\gamma) P_t^R \tag{A.77}$$

as wanted.

A.5 Empirical Model as Linearized Policy Functions

This appendix shows how our empirical model of consumer behavior in Section 5 can be seen as an approximate parameterization of policy functions in a consumption-repayment model. We describe the setup in Appendix A.5.1 and our approximation in Appendix A.5.2.

A.5.1 Model Setup

We begin the timing and actions of the framework in Appendix A.3. We add default, closure, fees, and credit limits. If a consumer defaults on their credit card, $\chi_t = 1$, they are shut out from credit markets and receive total utility $V_{\chi,t}(\cdot) + \epsilon_t^{\chi}$, where ϵ_t^{χ} can capture, for example, time-varying idiosyncratic expense shocks that make default more attractive. Conditional on not defaulting, borrowers can close their card and receive outside value ϵ_t^c, which captures borrowers' time-varying idiosyncratic benefits of a card, such as rewards.

We make two additional changes. First, rather than modeling liquid savings and non-credit card consumption explicitly, we assume flow utility depends on net liquidity, $Y_t - P_t - P_{o,t}$, similar to Einav *et al.* (2012). This allows us to avoid taking a stance on aspects of consumer behavior not observed in our data. Second, we treat installment debt as a fixed payment obligation. This allows us to avoid tracking balances that evolve slowly relative to the horizon of credit card spending and repayment decisions. Together, these assumptions improve tractability, make our model estimation more transparently tied to the data, and focus attention on the forces most relevant for credit card lender profits.

The value function in period t conditional on no default or closure this period is:[45]

$$V_t(B_t, Y_t) = \max_{S_t = S_t^R, P_t, P_{ot}} u(S_t, Y_t - P_t - P_{o,t}) + \Gamma(P_t, P_{o,t}, .) + \tag{A.78}$$

$$+ \delta \mathbb{E}_t \left[\max\{V_{t+1}, V_{\chi,t+1}(\cdot) + \epsilon_{t+1}^{\chi}, \epsilon_{t+1}^c\} \mid B_t, Y_t \right] \tag{A.79}$$

[45]We slightly abuse notation for the continuation value, since the continuation value equals $V_\chi(\cdot) + \epsilon_{t+1}^{\chi}$ if $V_\chi(\cdot) + \epsilon_{t+1}^{\chi} > V(\cdot)$, regardless of the value of ϵ_{t+1}^c.

such that:

$$B_{t+1} = R_{cc}(B_t - P_t) + S_t + F_t \tag{A.80}$$

and the following inequalities are satisfied:

$$\max\{\overline{L} - R_{cc}(B_t - P_t) - F_t, 0\} \geq S_t \geq 0 \tag{A.81}$$

$$P_t \geq m_t(B_t, F_t) \tag{A.82}$$

$$B_t \geq P_t \tag{A.83}$$

$$P_{o,t} \geq m_{o,t} \tag{A.84}$$

where $\overline{L}$ is the credit limit, and F_t are fees accumulated in period t that are due in $t+1$. The borrower also forgets to repay their credit card with some probability each period, in which case $P_t = 0$ and $F_t > 0$.

A.5.2 Policy Function Approximation

The problem in Equation A.79 gives rise to three policy functions that govern consumer behavior: spending, repayments, and default. We discuss these policy functions below.

Spending. In the model, consumers receive flow utility over their spending on the given card. Empirically, many borrowers hold multiple cards (as shown in Table B.1) and frequently change both whether they use a card at all in a given month and, conditional on using the card, how much they use it. Any parameterization intended to speak to lender profits must therefore accommodate this extensive- and intensive-margin variation in card usage. Equation 10 can be seen as directly parameterizing this behavior as independent of state variables, up to the constraint that spending, S_t, cannot exceed the remaining credit limit L_t. With probability $1 - p_{nospend}$,

$$s(B_t, Y_t; m_t) = s_0 + \epsilon_t^s \tag{A.85}$$

where $\epsilon_t^s \sim \mathcal{N}(0, \sigma_s^2)$.

Repayment. Conditional on spending, total debt repayment decisions determine borrowers' inter-temporal tradeoff. Any calibration would require functional form assumptions that determine this tradeoff. Equation 11 can be seen as directly parameterizing total debt repayment as log-linear in the two state variables, income Y_t and balances B_t. Intra-temporal repayment allocations can be represented as a weighted average of cost minimization and minimum payments under a variety of microfoundations (see Appendix A.4). Equation 12 parameterizes repayment allocations accordingly, up to the constraint that $\tilde{P}_t \geq m_t + m_{other}$ and $P_t \in [m_t, B_t]$.

$$\tilde{p}(B_t, Y_t; m_t) = \beta_y y_t + \beta_b b_t + \epsilon_t^p \tag{A.86}$$

$$P(B_t, Y_t; m_t) = (1-\gamma)(\tilde{P}_t - m_{other}) + \gamma m_t \tag{A.87}$$

where $\epsilon_t^p \sim \mathcal{N}(0, \sigma_p^2)$, $\tilde{p}_t$ are log total debt repayments, and P_t are credit card repayments.

Default. In the model, consumers default according to:

$$\chi_t(B_t, Y_t; m_t) = \mathbf{1}\left[V_{\chi,t}(B_t, Y_t; m_t) + \epsilon_t^\chi > V_t(B_t, Y_t)\right] \tag{A.88}$$

Any calibration would require functional form assumptions on the costs of default (e.g., psychic and hassle costs) and their relationship to the benefits (e.g., debt discharge and short-term liquidity) conditional on the state variables. We instead parameterize the borrower's value of default with the linear approximation:

$$V_{\chi,t}(B_t, Y_t; m_t) - V_t(B_t, Y_t; m_t) = d_0 + d_m m_t + d_u u_t + d_y y_t \tag{A.89}$$

where utilization is given by $u_t := B_t/\overline{L}$, the consumer's credit limit utilization.[46] This default rule captures different potential drivers of default: high balances (insolvency) and high minimums (illiquidity), as well as low income. Under the assumption that ϵ_t^χ is iid logistic, the probability of default is given by the decision rule in the empirical model:

$$\mathbb{P}(\chi_t(B_t, Y_t; m_t) = 1) = \mathbb{P}(V_{\chi,t} > V_t) = \frac{1}{1 + \exp\{-(d_0 + d_m m_t + d_u u_t + d_y y_t)\}} \tag{A.90}$$

A.6 Policy Function Invariance in Counterfactual Exercise

In Section 6, we use our empirical model to conduct a counterfactual exercise in which we change repayment prioritization, γ, holding all else fixed. In the exercise, we assume that the policy functions that govern other aspects of consumer behavior remain unchanged as the behavioral parameter changes. This appendix discusses psychological plausibility and implications of this assumption.

[46] We use utilization instead of balances to capture the empirical fact that the probability of default increases quickly at high utilizations, as shown in Figure 7.

A.6.1 Invariance Under Naivete

If consumers are "naive" about anchoring—specifically, they do not internalize the effects of anchoring when solving other aspects of their intertemporal maximization problem—their policy functions will not change with γ.[47] As we show below, the microfoundation in Appendix A.4.1 implies naivete with respect to total debt repayments and spending.

This naivete assumption is consistent with work in psychology and economics that suggests anchoring arises from context-dependent cognitive processes that individuals do not consciously perceive (e.g., Tversky and Kahneman, 1974; Ariely *et al.*, 2003; Epley and Gilovich, 2006; Englich *et al.*, 2006). Without this assumption, agents would neglect a relatively simple intra-temporal rule (pay the higher-interest-rate debt first) while simultaneously internalizing its implications in a more complex intertemporal problem. Additionally, the notion that consumers do not internalize the costs of their intra-temporal choices is consistent with our survey evidence that borrowers who fail to cost minimize are no less likely to report that their repayment allocations minimize costs (Appendix Figure E.11).

Importantly, this naivete assumption and our empirical model still allow anchoring to indirectly affect repayment choices through its impact on state variables. For instance, because the repayment policy function increases in balances, our parameterization allows borrowers to "undo" the effects of anchoring by repaying more after anchoring leads to higher balances. This concern relates to work showing individuals may undo the effects of nudges or default options over time (e.g., Guttman-Kenney *et al.*, 2023; Choukhmane, 2025).[48]

Naivete in Mental Accounting Microfoundation. From the consumer optimization problem in Appendix A.4.1, the counterfactual with no anchoring would be to set $\theta_1 = \theta_2 = 0$. In this case, $\tilde{P}_t = \tilde{P}_t^R$ (by definition of $\tilde{P}_t^R$) and since $\gamma = \frac{\theta_2}{\theta_2+\delta(R_{cc}-R_o)\theta_3}$, this implies that $\gamma = 0$ so $P_t = P_t^R$. As a result, under this microfoundation, the total repayments policy function is invariant to setting $\gamma = 0$. Spending continues to be S_t^R, so the spending policy function is also invariant.

A.6.2 Implications of Alternative Models

We discuss the implications of two alternative models in which total debt repayment, $\tilde{P}_t^R$, is affected by behavioral frictions.

[47]This assumption is similar to models of naive present-bias (Laibson *et al.*, 2024), in which the agent fails to internalize certain aspects of their behavior while otherwise maximizing utility.

[48]In our counterfactual, removing anchoring ($\gamma = 0$) decreases balances, suggesting that this secondary response is not strong enough to fully offset anchoring. This result, that minimum-payment-related consumer biases can affect long-run balances, is consistent with empirical studies in Canada and Mexico that show increases in minimums significantly reduced balances (Allen *et al.*, 2026; Castellanos *et al.*, 2025).

Anchoring on Installment Debt Minimum Payments. Consumers have required minimum payments on installment debts, and they may also use these minimums as a reference point when deciding repayment. Such a response would suggest that behavioral frictions also affect total debt repayment. In particular, a reduction in repayments in response to a decrease in credit card minimums may not be offset by an increase in installment debt overpayment, unlike in our baseline empirical model.

Intuitively, Appendix Table B.12 shows that if total repayments do respond to the minimum, the effect of anchoring on minimums becomes stronger. Our baseline model conservatively abstracts away from this response, focusing only on the effects of biases that impact intra-temporal tradeoffs. We view this as an advantage of our approach, which allows us to avoid taking a normative stance on how consumers make inter-temporal tradeoffs.

Internalizing the Effects of One's Own Bias. In a model in which consumers are fully cognizant of their current and future biases, total debt repayment may be affected by a behavioral change in consumers' intra-temporal repayment allocations. The direction of this effect is ambiguous, mirroring standard income and substitution effects. The substitution effect captures the fact that mis-allocation decreases returns to repayment, leading consumers to repay less. The income effect captures the fact that mis-allocation increases one's lifetime debt burden, leading consumers to repay more. As discussed above, both effects would require consumers to neglect a simple intra-temporal rule, while simultaneously internalizing its implications in a more complicated inter-temporal problem.

B Empirical Appendix

B.1 Additional Details About Credit Bureau Measures

In this appendix we provide additional details about measures in our credit bureau data.

Revolving balances. To measure revolving balances in the credit bureau data we subtract the actual payments made in month t from the statement balance in the prior month, $t-1$. When this measure is negative (because of intra-month repayments), we assign a zero balance. The use of the lagged balance captures the time between the statement being issued and the payment being due, typically 30 days. This measure is the same as the one in Guttman-Kenney and Shahidinejad (2023) and described by Gibbs *et al.* (2025). A similar approach is used in Bornstein and Indarte (2023).

This measure is consistent with Metro 2, the industry-standard electronic format used for credit reporting in the United States.[49] In the Metro 2 format, furnishers report:

- "Actual payment," which is the total amount paid during the one-month period prior to the "Date of Account Information."
- "Current balance," which is the outstanding balance on the account as of the "Date of Account Information."

For credit cards, "Date of Account Information" is "the date of the current month's billing cycle" (p.69), so current balances are statement balances. As a result, we observe the statement balance in month t alongside actual payments made in response to the statement balance issued in month $t-1$. This timing implies that when actual payments in month t are less than the statement balance reported in month $t-1$, the account holder is revolving a balance rather than paying the statement in full.

Installment debt excess payments. We measure excess payments by comparing actual payments to scheduled monthly payments. We take several steps to isolate true overpayments rather than variation driven by reporting timing or payment scheduling.

We first restrict attention to non-delinquent accounts to avoid conflating excess payments with "catch-up" payments. We further exclude small overpayments (below $25, measured after all cleaning steps) to eliminate rounding discrepancies and other minor reporting noise. We define excess payments as the difference between the actual payment in month t and the scheduled monthly payment in month $t-1$. To address potential timing discrepancies in

[49] A version of the guidelines is available at https://tinyurl.com/h8ev4fjv.

how these fields are reported across installment debt furnishers, we set excess payments to zero whenever the actual payment in month t equals the scheduled payment in month t.

There remain instances in the data in which we observe a large payment in one month accompanied by zero or below-scheduled payments in adjacent months. These patterns may reflect reporting discrepancies or "pay-ahead" behavior, in which borrowers prepay in one period and make reduced payments in the subsequent period.

We consider three approaches to addressing these cases. First, in our baseline method, we construct a running deficit that accumulates whenever a consumer's actual payment falls below the scheduled payment, only resetting to zero once they make a full payment or more. We define excess payments as actual payments net of both the current scheduled payment and any accumulated deficit. To account for forward-looking shortfalls, we also subtract any payment deficit in the subsequent period from measured excess payments.

Second, as an alternative, we subtract any payment deficits within a three-month window centered on the current month (and, conservatively, do not incorporate payment surpluses from other months). As in our baseline approach, this approach captures both backward- and forward-looking adjustments. However, it can overstate excess payments when multiple zero payments are followed by a single large payment.

Third, we implement the second approach using a five-month window. This removes cases in which two zero payments are followed by a single large payment or vice versa. However, it may understate true excess payments by attributing any deficit within the five-month window to the current month (even if that deficit is offset elsewhere within the window).

Appendix Figure B.5 shows the distribution of excess payments implied by these different methods, as well as the raw comparison of actual payments and lagged scheduled monthly payments. All three adjustment methods reduce the share of months with excess payments. Our baseline method is more conservative than the quarterly window and nearly as conservative as the five-month window, which we find tends to remove true excess payments.

Our estimates are similar to two sets of analyses that use data on Fannie Mae-owned mortgages. In particular, Liebersohn *et al.* (2024) finds 21% of Fannie Mae-owned mortgages were curtailed by \$20 or more each month between January 2022-February 2023 and Xu (2023) finds that 22% of Fannie Mae mortgages originated from 2009-2018 were curtailed by \$30 or more in a given quarter. Our measure is more conservative than the credit bureau measure presented in Liebersohn *et al.* (2024), which directly compares actual and scheduled monthly payments without adjustments.

Aggregating student loans. Even when a borrower has a single account with a student loan servicer, their credit bureau file may include separate tradelines for each school year.[50] To accurately measure overpayments, we aggregate student loans to the consumer–month level. Appendix Figure B.6 shows that our results are nearly unchanged when mortgage and auto debts are also aggregated at the consumer-month level.

B.2 Costs of Cross-Product Repayment Behaviors

In this appendix, we describe a partial equilibrium "steady-state" counterfactual, following Gathergood *et al.* (2019b), to explore the importance of the cross-product allocations we document in Section 4.1. We also compare the frequency and magnitude of these behaviors to the cross-card allocations documented in Ponce *et al.* (2017) and Gathergood *et al.* (2019b).

Partial Equilibrium Costs. Gathergood *et al.* (2019b) show that consumers do not focus credit card repayments on a single highest-APR card first. To calculate the costs of this behavior, they conduct a counterfactual exercise in which they transfer balances from high- to low-APR credit cards until the low-APR card is maxed out. They then calculate the annual interest savings that would result in this steady state.

We conduct a similar exercise. We take a sample of credit card revolvers at the end of 2019 who have a mortgage, auto, or student loan. We then transfer installment debt overpayments over the prior seven years (the beginning of our data) to credit cards until the credit card is repaid. We do not limit to consumers who overpaid their installment debt: consumers can be included in our sample even without a misallocation. As in Gathergood *et al.* (2019b), our exercise provides an estimate of interest savings if the borrower could optimally transfer installment overpayments in the past seven years to their credit card.

Appendix Table B.3 reports the results of this exercise. Among borrowers with revolving credit card debt and installment debt, revolving debt falls by \$1,817 on average and \$4,926 at the 90th percentile. Savings are the APR differential between the installment and credit card debt multiplied by the reduction in revolving debt. For example, a 10 percentage point APR differential implies annualized average interest savings of \$182, reaching \$493 at the 90th percentile. Because credit card rates are typically variable and installment debt rates are often fixed, larger APR differentials are common during periods of rising interest rates (e.g., in Q1 2024, average outstanding mortgage and credit card rates were 4.1% and 22.6%, respectively).[51] The table shows that a 15 percentage point differential significantly increases

[50] See, e.g., the FAQ on the federal student aid website "I only have one account with Edfinancial Services, but there are multiple loans showing on my credit report. Why?" (`https://tinyurl.com/yc3k86ws`).

[51] See the NMDB Aggregate Statistics Dashboard and FRED series TERMCBCCINTNS.

the cost, with an average of $272 and a 90th percentile of $739.

There are many limitations to this simple analysis. First, because we use a steady-state counterfactual, we fail to account for compounding which leads *marginal* costs to increase over time. Second, because we look at overpayments over seven years, borrowers may have made overpayments in the past before experiencing a recent shock that led to credit card debt (rather than contemporaneous repayments).[52] Third, the seven-year period may underestimate total costs from prior overpayments. Fourth, we fail to account for lenders responding to these behaviors when designing credit card contracts. Our empirical model in Sections 5 and 6 is intended to help overcome these challenges.

Comparison to Cross-Card Allocations. Ponce *et al.* (2017) and Gathergood *et al.* (2019b) show that individuals often do not prioritize credit card payments in excess of the monthly minimums onto a single highest-APR card first. Unlike these prior works, which use data from Mexico and the U.K., we cannot directly observe interest rates.[53] Instead, we look at a "best-case" scenario, in which the card that consumers prioritize most is their highest-APR card, similar to Gathergood *et al.* (2019a).

To begin, we restrict our sample of consumer-months to those in which we observe exactly two cards with actual payments; the consumer did not miss a minimum payment; and total card payments are strictly between the total card balances and the total minimum payments. Appendix Figure B.7 shows that the distribution of payments across the two cards does not concentrate toward the extremes, as would be predicted by the cost-minimizing strategy.[54] Instead, as in Gathergood *et al.* (2019a,b), payments are concentrated toward the middle of the distribution with a large spike at 50% and smaller spikes at 33% and 67%.

Appendix Figure B.8 plots the distribution of *excess* payments across the credit score distribution for these consumer-months. Even under a "best-case" assumption, in which the higher APR card is the one that receives the larger share of payments, borrowers frequently fail to concentrate repayments on the single highest-APR card. Eligible consumers misallocate at least $25 in 48% of months. This is more common than misallocating at least $25 to installment debt while simultaneously revolving on credit cards, which occurs in one-fifth of eligible months. However, conditional on deviating from cost minimization, the average dollar amount misallocated is smaller for cross-card behavior ($101) than for cross-product behavior ($289). Moreover, APR differentials are larger across products than across credit

[52]This concern is mitigated, to an extent, by the persistence of revolving debt: Lee and Maxted (2023) show that 92% of households that revolve debt in one quarter continue to do so a year later.

[53]Gathergood *et al.* (2019a) notes "we are unaware of any US dataset that has interest rates on multiple cards for a broadly representative sample."

[54]Following Gathergood *et al.* (2019a), we randomly chose one of the two cards to display on the x-axis.

cards, implying higher cost per dollar misallocated in the cross-product case.

B.3 Discussion of Other Potential Mechanisms

This appendix discusses other potential mechanisms for the cross-product repayment behaviors documented in Section 4.1.

B.3.1 Optimal Inattention

In optimal inattention models, attention costs (e.g., time, effort) are fixed, and mistakes should decrease in mistake costs (Sims, 2003). We test this theory by comparing the frequency of deviations from cost-minimizing behavior to the economic stakes of this decision, similar to tests in Gathergood *et al.* (2019b), Andersen *et al.* (2020), and Chetty *et al.* (2014).

While the credit bureau data does not directly include interest rates, we use the fact that nearly all credit cards have variable interest rates tied to the prime rate. Changes in the prime rate for borrowers with fixed-rate mortgages, then, substantially change the cost of prepaying mortgages while revolving credit card debt. Appendix Figure B.12 shows that the average mortgage overpayments from borrowers with revolving credit card debt appear to somewhat *increase* as average outstanding credit card interest rates changed through 2017 and 2018, opposite of the prediction of an optimal inattention model. Appendix Table B.4 tests this using regressions with person fixed effects and monthly information on credit card balances and minimums. Even in a sample of consumers with one 30-year mortgage through all of 2017-18, the probability of making an overpayment of $25 or more on a mortgage slightly increases as credit card interest rates increase.

Similar to the findings of Gathergood *et al.* (2019b), optimal inattention does not appear to be a key driver of repayment allocations.

B.3.2 Balance Matching

Gathergood *et al.* (2019b) show across credit cards, borrowers match repayments to the share of balances on each card. Appendix Table B.6 shows that across products, this heuristic would predict that borrowers make substantially larger overpayments to installment loans, suggesting this is not a key driver.

B.3.3 Self-Control

It is theoretically possible that people use mortgage overpayments as a "commitment device," ensuring that they save rather than spend extra liquidity. This mechanism could explain why a borrower might prefer to make an illiquid installment-loan overpayment rather than pay down credit card debt, which would increase available borrowing capacity.

We explore this in our open-ended survey responses. We look for responses that mention concerns related to spending the money, temptation, or a desire to lock funds away. Appendix Figure E.11 shows that only 2% of misallocators mention anything broadly related to self-control. Instead, respondents more often describe rules of thumb, budgeting heuristics, and a desire to repay debts faster relative to the required minimum payment.

Consistent with Liebersohn *et al.* (2024), who study mortgage curtailments unconditionally, our results suggest that self-control is not a key driver of the repayment allocations we document in Section 4.1.

B.3.4 Intra-Household Frictions

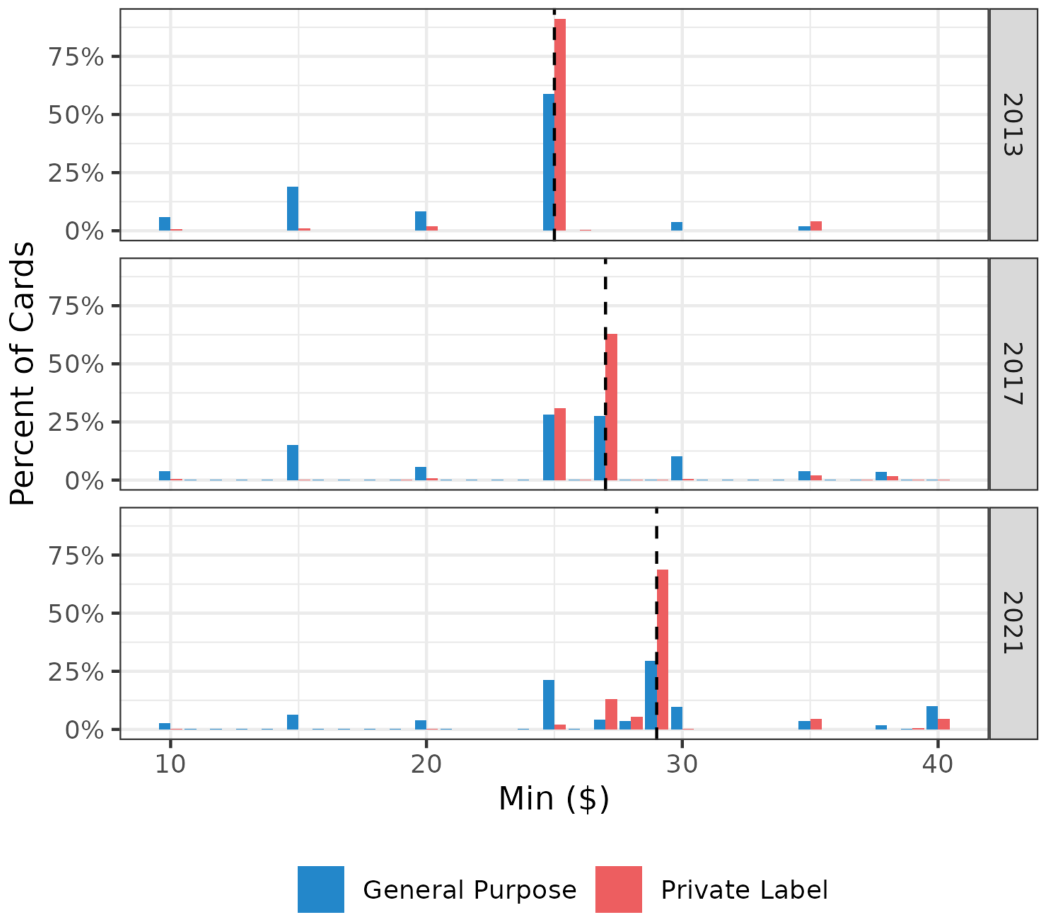
Cross-product repayment allocations may be driven by spouses paying or holding different debts. For example, two spouses may co-hold revolving credit card debt while one also prepays their own student loans.

To explore this, we use a two-way fixed effects design that includes indicators for being married, revolving credit card debt, and their interaction. The interaction term captures how much more or less likely a married individual is to overpay their mortgage while revolving. Column 1 of Appendix Table B.5 shows the interaction is associated with a 1.4 percentage point increase in the propensity to overpay installment debt while revolving, providing evidence that intra-household frictions may play some role in explaining these behaviors. Columns 2-4 show that this effect is strongest for borrowers with student loans—generally taken out when young and not co-held by spouses—and weakest for those with mortgages, which are more likely to be taken out later in life and co-held by spouses.

Similar to Vihriälä (2022), who studies the co-holding of assets and credit card debt, our results suggest intra-household frictions may interact with other consumer biases to play a role in debt repayment.

B.4 Additional Figures

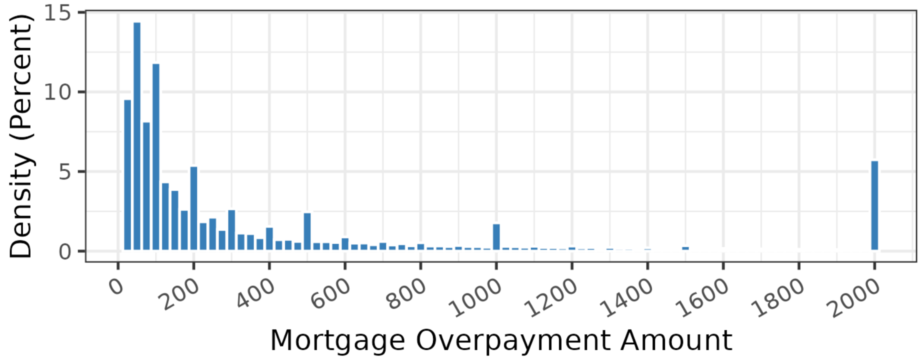
Figure B.1: *Implied Credit Card Minimum μ (Floor) by Card Type*



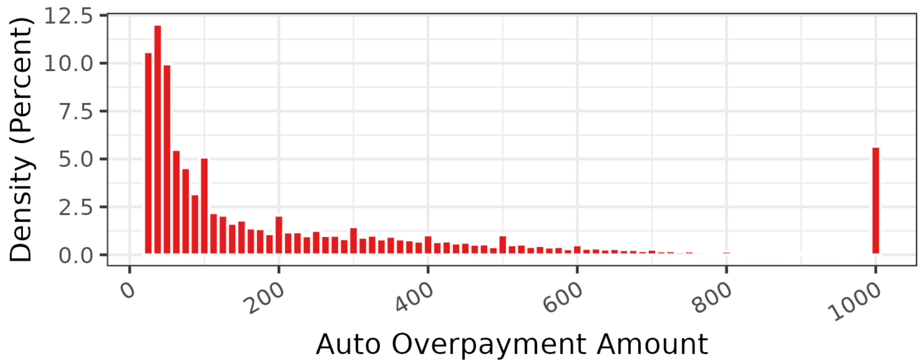
Note: Figure shows estimates of the "floor" of the minimum required payment formula (μ) for general purpose and private label credit cards in the fourth quarter of 2013, 2017, and 2021. Estimates are minimum payments observed in months when individuals did not revolve credit card debt and had an end-of-month balance below $200 but above the minimum. The dashed black line shows the largest late fee a lender could legally charge in that year for a first missed minimum (see amendment history of 12 CFR § 1026.52). Because lenders also cannot charge a late fee larger than the missed minimum, setting the floor to this value allows lenders to more often charge the largest late fee while otherwise keeping minimums low. The figure shows that lenders bunch at this threshold, and that private label cards, whose revenue depends more on late fees (CFPB, 2022), do so more frequently.

Figure B.2: *Distribution of Overpayments ≥ $25 by Debt Type*

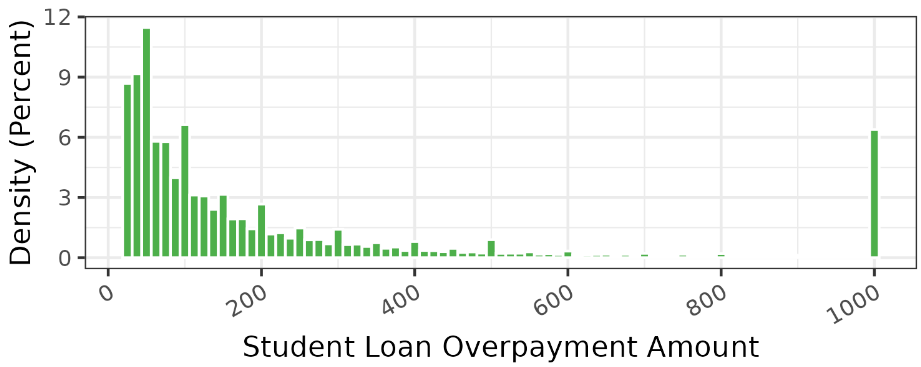
(A) Mortgage



(B) Auto Loan

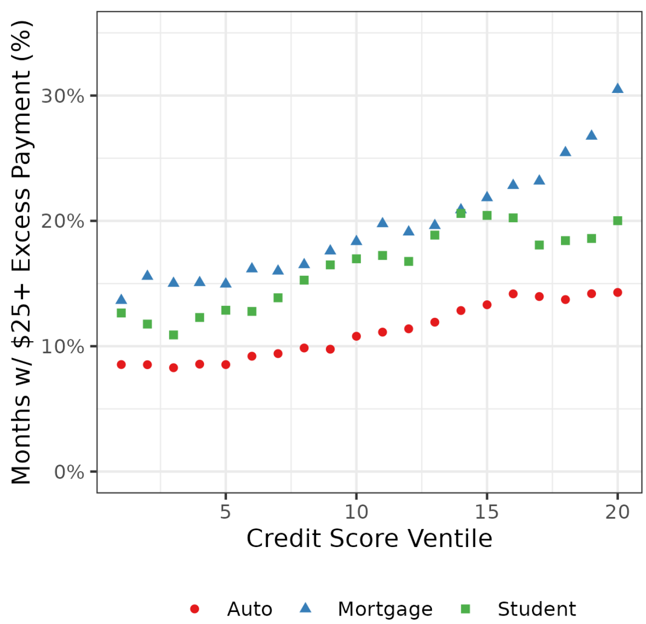


(C) Student Loan



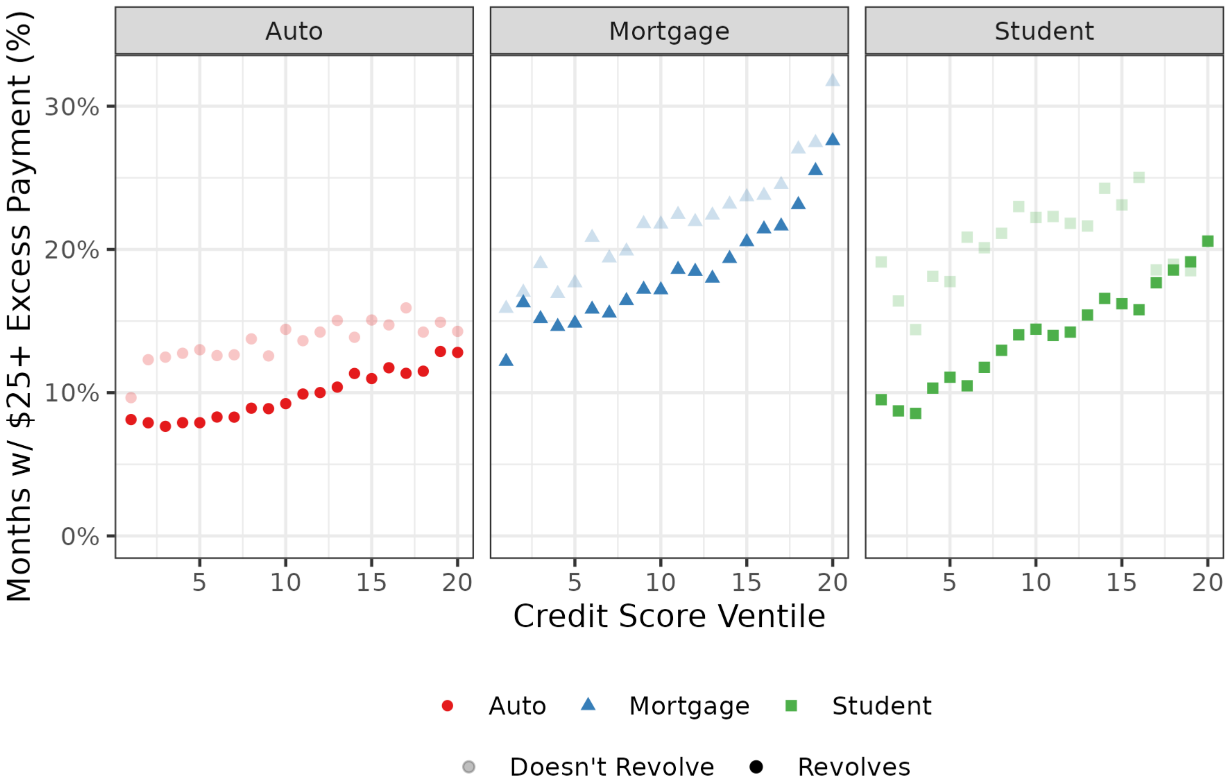
Note: Figure shows the distribution of excess payments for all account-months in 2017-2018 in which there was an excess payment of at least $25. All excess payments larger than $2,000 for mortgages and larger than $1,000 for auto and student loans are grouped into the final bars.

Figure B.3: *Share of Account-Months with Overpayments by Credit Score and Product*



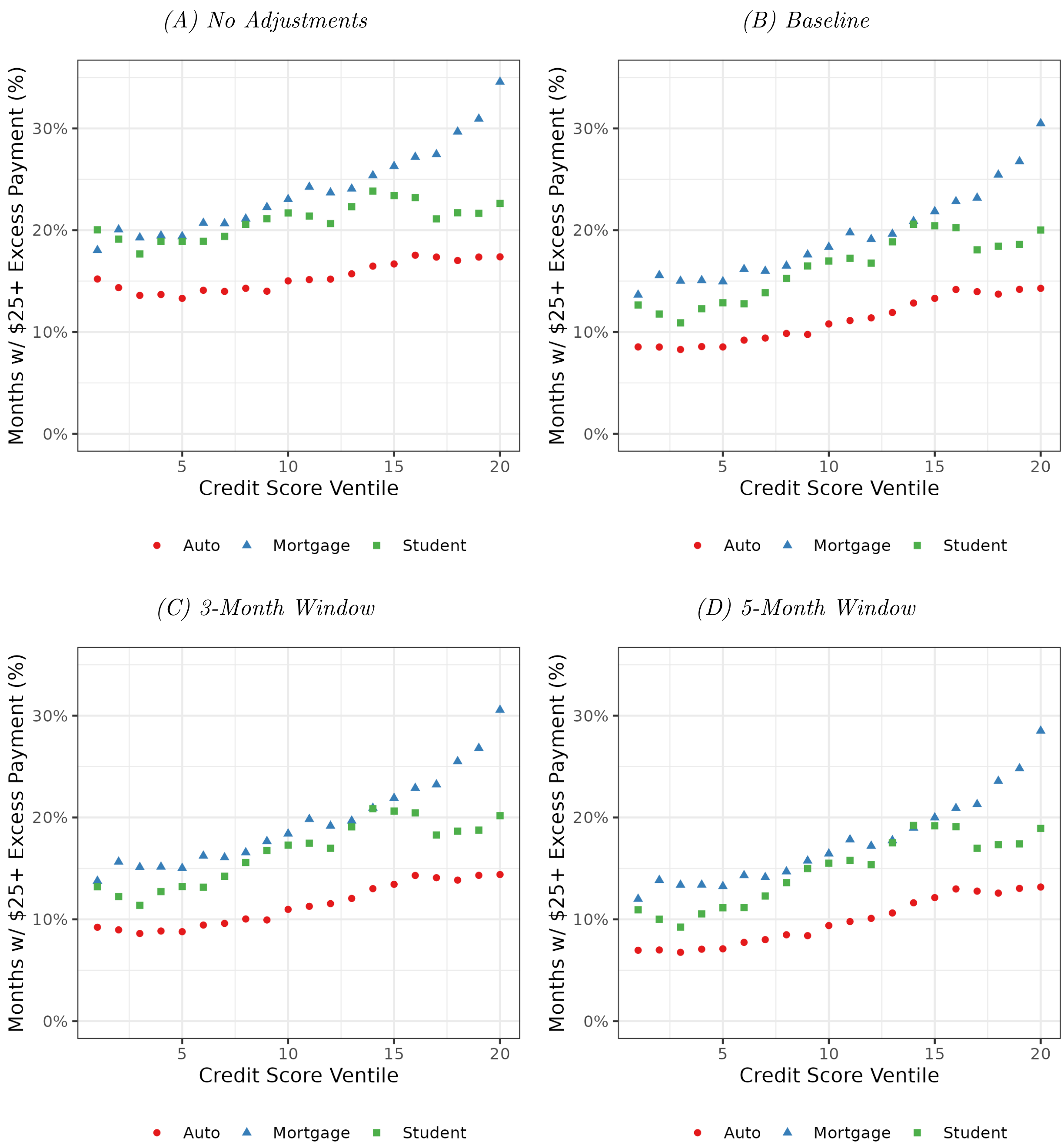
Note: Figure shows, by ventiles of credit score, the share of account-months in 2017-2018 in which there was a payment of at least $25 in excess of the monthly amount due. To account for multiple tradelines within a borrower's account, student loans are aggregated at the borrower–month level (see Appendix B.1). Credit scores are measured as of December 2016.

Figure B.4: *Share of Account-Months with Overpayments by Credit Score, Product, Revolving*



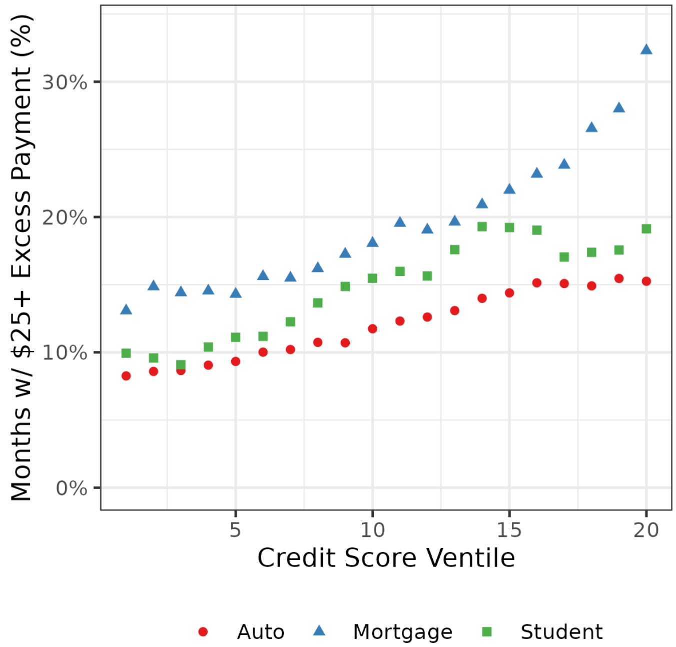
Note: Figure shows, by ventiles of borrower credit score, the share of borrower-months in 2017-2018 in which there was a payment of at least $25 in excess of the monthly amount due. The sample includes only months in which the consumer also had recorded actual payments on a credit card. The transparent and opaque dots display installment debt overpayments for those who did and did not revolve, respectively.

Figure B.5: *Share of Account-Months with Overpayments by Credit Score and Product: Robustness*



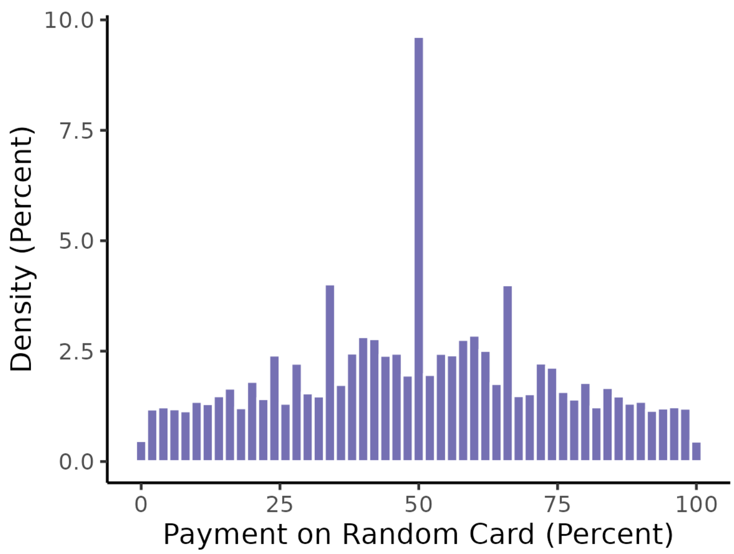
Note: Figure shows alternative versions of Appendix Figure B.3. All panels show, by ventiles of credit score, the share of account-months in 2017-2018 in which there was a payment of at least $25 in excess of the monthly amount due. Panel (a) shows the raw measure computed by comparing actual payments with scheduled monthly payments. Panels (b), (c), and (d) show alternative measures constructed using three approaches described in Appendix B.1.

Figure B.6: *Share of Borrower-Months with Overpayments by Credit Score and Product*



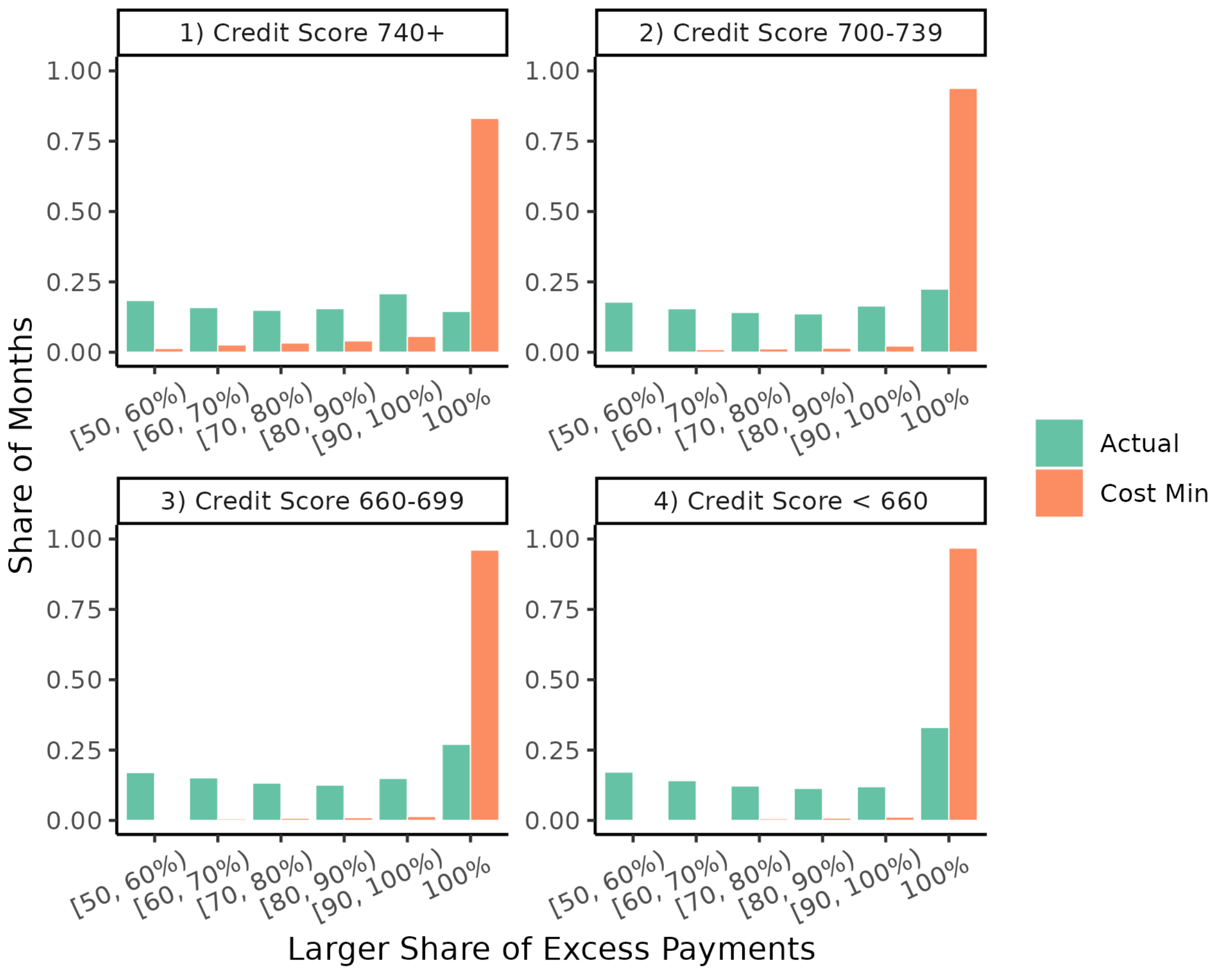
Note: Figure replicates Appendix Figure B.3 with observations aggregated at the consumer–month level rather than the debt–month level.

Figure B.7: *Credit Card Payments, 2-Card Sample*



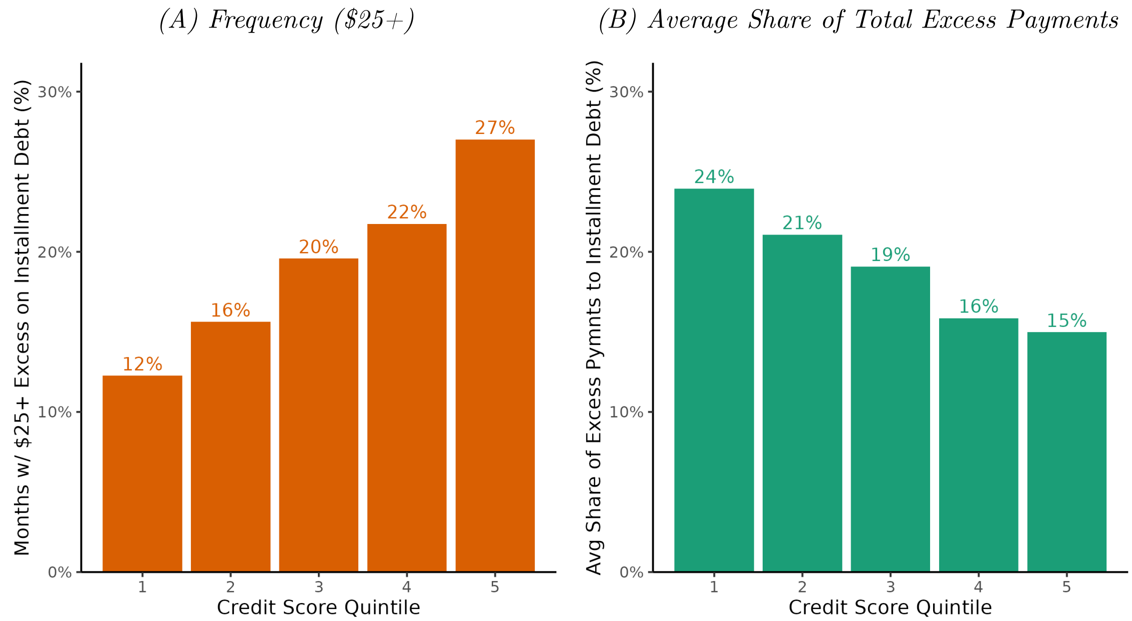
Note: Figure shows the share of credit card payments made on one card. The sample is consumer-months with actual payments for two credit cards and some excess payments, as described in Appendix B.2. The figure is similar to Figure 1 in Gathergood *et al.* (2019b) and Figure 1 in Gathergood *et al.* (2019a).

Figure B.8: *Excess Credit Card Payments, 2-Card Sample: "Best Case" Optimal vs Actual*



Note: Figure shows the share of credit card payments in excess of the minimum going to the card that receives more excess payments. The sample is the same as in Appendix Figure B.7. The green bars display the actual data. The orange bars display the cost-minimizing strategy, as described in Appendix B.2.

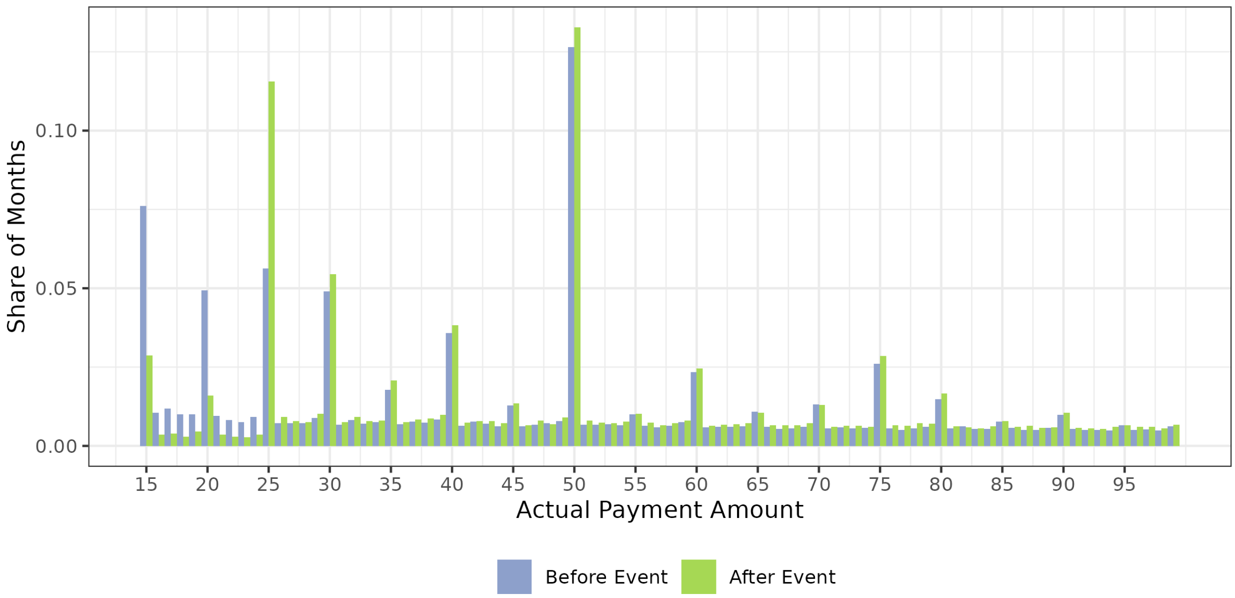
Figure B.9: *Credit Card Revolvers Simultaneously Overpay Installment Debts: Including New Cards*



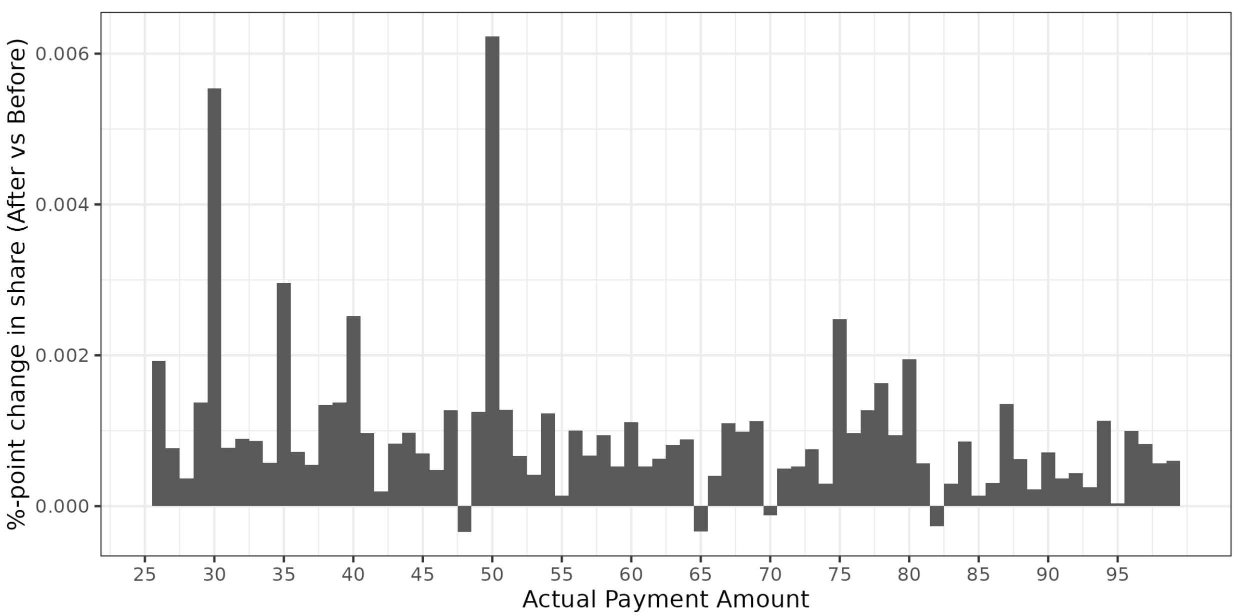
Note: Figure repeats Figure 4, including credit cards that have been open for fewer than 24 months.

Figure B.10: *Distribution of Repayments Around Minimum Formula Change*

(A) Distributions

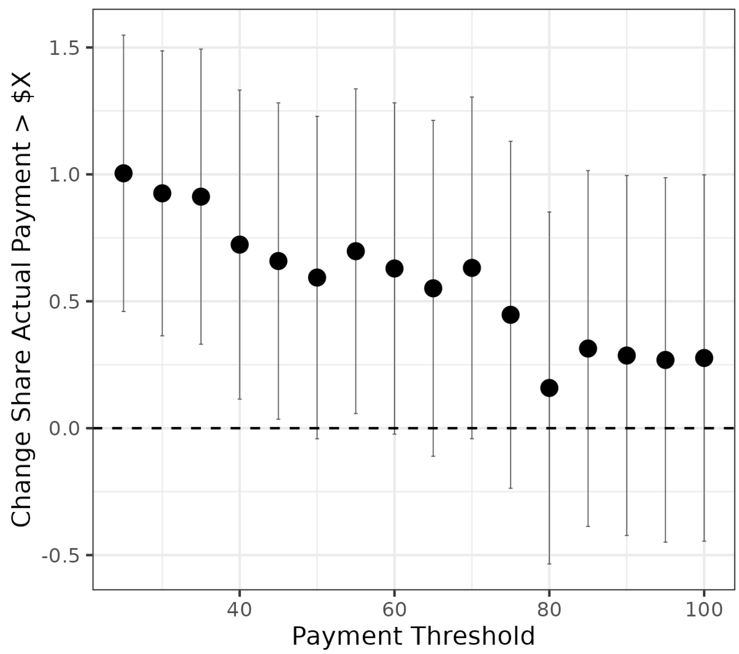


(B) Distribution Change



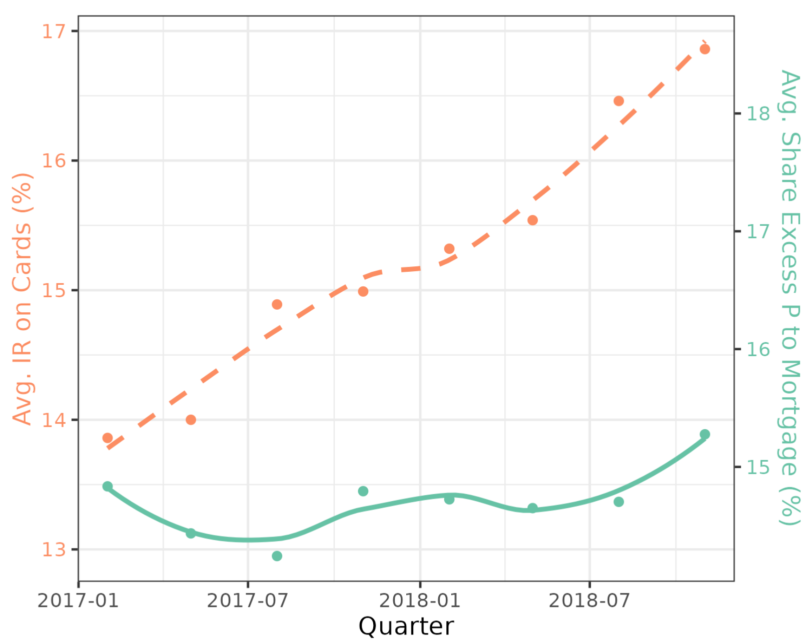
Note: Figure shows the distribution of credit card repayments for the affected lender group in the months before and after the minimum payment change event shown in Figure 5. Panel (a) shows the distributions before and after the event for values less than \$100. Panel (b) shows the change (after minus before) for values between \$25 and \$100.

Figure B.11: *Repayments Around a Formula Change: Alternative Thresholds*



Note: Figure shows results from difference-in-difference designs around the formula change event depicted in Figure 5. The leftmost point displays the results from column 1 of Table 4, where the outcome is an indicator for making a payment above $25. Each subsequent point shifts the payment threshold rightward in $5 increments, defining the outcome as an indicator for actual payment > $X. 95% confidence intervals based on standard errors clustered at the card level.

Figure B.12: *Mortgage Cross-Product Behavior Over Time*



Note: Figure shows the share of excess payments on mortgages and credit cards going to mortgages (solid green) against the average interest rate on credit cards (dashed orange). The sample is consumer-months without a delinquency, a positive mortgage and credit card balance, and with total excess payments on these products that would not cover the credit card balance. The average interest rate comes from FRED series TERMCBCCINTNS.

Figure B.13: *Sensitivity of Parameters to Moments*

< 600

	Cross-product mistake	Share months missed min no def.	Monthly close prob.	Share months no spend	Mean annual income	Mean utilization	Corr log bal. and log total repay.	SD of log total repay. (with FEs)	Mean log spend (intensive)	SD log spend (intensive)	Monthly prob default (percent)	Corr util and default	Corr total repay. and default	Elasticity default wrt min
γ	0.0072	0.0000	0.0000	-0.0000	0.0000	-0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	-0.0000	0.0000	-0.0000
p_{nomin}	0.0000	0.0021	0.0000	-0.0000	0.0000	-0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	-0.0000	0.0000	-0.0000
p_{close}	0.0000	0.0000	0.0002	-0.0000	0.0000	-0.0000	-0.0000	-0.0000	0.0000	0.0000	0.0000	-0.0000	0.0000	0.0000
$p_{nospend}$	-0.0000	-0.0000	-0.0000	0.0027	-0.0000	-0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	-0.0000	-0.0000	-0.0000
$\overline{Y} * 12$ ('000)	0.0000	0.0000	0.0000	-0.0000	0.1706	0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	0.0000	0.0000	0.0000
β_y	0.0007	0.0007	0.0001	-0.0006	-0.0004	-0.0023	-0.0117	-0.0036	0.0038	0.0028	-0.0000	-0.0001	0.0003	0.0000
β_d	0.0007	0.0000	-0.0003	-0.0005	-0.0001	0.0002	0.0121	0.0001	0.0021	0.0008	-0.0000	0.0003	-0.0003	-0.0000
σ_p	-0.0062	-0.0035	0.0013	0.0049	0.0000	0.0102	0.0053	0.0246	-0.0268	-0.0163	0.0000	-0.0002	-0.0010	-0.0000
s_0	-0.0010	-0.0002	0.0014	0.0004	-0.0001	0.0075	-0.0021	0.0018	0.0225	0.0051	0.0000	0.0001	-0.0006	-0.0000
σ_s	-0.0010	-0.0007	0.0008	0.0004	-0.0000	0.0070	-0.0005	0.0016	0.0045	0.0170	0.0000	0.0001	-0.0001	-0.0000
d_0	0.0423	0.3227	0.1056	-0.0344	0.0129	-0.1643	-0.1102	-0.0845	0.2412	0.1582	-0.0002	-0.1620	2.1953	0.0767
d_u	0.0191	-0.2239	-0.1391	-0.0058	-0.0011	-0.1080	-0.0584	-0.1639	-0.0502	-0.0866	-0.0007	-0.1170	-1.7877	-0.0754
d_y	-0.0079	-0.0143	0.0035	0.0054	0.0004	0.0342	0.0222	0.0318	-0.0260	-0.0102	0.0002	0.0359	-0.0630	-0.0025
d_m	0.0000	-0.0000	-0.0000	-0.0000	0.0000	-0.0000	0.0000	-0.0000	0.0000	0.0000	0.0000	-0.0000	-0.0000	0.0001

600-659

	Cross-product mistake	Share months missed min no def.	Monthly close prob.	Share months no spend	Mean annual income	Mean utilization	Corr log bal. and log total repay.	SD of log total repay. (with FEs)	Mean log spend (intensive)	SD log spend (intensive)	Monthly prob default (percent)	Corr util and default	Corr total repay. and default	Elasticity default wrt min
γ	0.0058	-0.0000	-0.0000	0.0000	0.0000	-0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	-0.0000	-0.0000	-0.0000
p_{nomin}	-0.0000	0.0019	0.0000	0.0000	0.0000	-0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	-0.0000	-0.0000	-0.0000
p_{close}	0.0000	0.0000	0.0002	-0.0000	-0.0000	-0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
$p_{nospend}$	0.0000	0.0000	-0.0000	0.0031	-0.0000	0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	0.0000	0.0000	0.0000
$\overline{Y} * 12$ ('000)	0.0000	0.0000	-0.0000	-0.0000	0.1624	0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	0.0000	0.0000	0.0000
β_y	0.0006	0.0006	-0.0000	-0.0009	-0.0002	-0.0026	-0.0111	-0.0035	0.0036	0.0027	0.0000	-0.0001	0.0012	0.0000
β_d	0.0004	-0.0002	-0.0004	-0.0000	-0.0000	0.0011	0.0117	0.0012	0.0007	-0.0001	-0.0000	0.0002	-0.0019	-0.0000
σ_p	-0.0048	-0.0026	0.0029	0.0047	0.0000	0.0084	0.0028	0.0191	-0.0219	-0.0132	0.0000	-0.0001	-0.0003	0.0000
s_0	-0.0006	-0.0001	0.0003	0.0003	-0.0000	0.0042	-0.0021	0.0007	0.0226	0.0034	0.0000	0.0000	-0.0015	-0.0000
σ_s	-0.0005	-0.0004	0.0006	0.0001	-0.0001	0.0042	-0.0027	0.0005	0.0036	0.0146	0.0000	0.0000	-0.0006	-0.0000
d_0	0.0689	1.0354	-0.5772	-0.1957	0.0062	0.0502	-0.3202	-0.0426	0.4324	0.3764	0.0028	0.0669	7.6797	0.1294
d_u	-0.0022	-0.7353	0.1955	0.0484	0.0017	-0.3196	0.0378	-0.2485	-0.0769	-0.2086	-0.0029	-0.5561	-5.6226	-0.1047
d_y	-0.0081	-0.0364	0.0468	0.0185	0.0004	0.0320	0.0353	0.0360	-0.0447	-0.0211	0.0001	0.0597	-0.2462	-0.0051
d_m	0.0000	-0.0000	-0.0000	0.0000	-0.0000	-0.0000	0.0000	-0.0000	0.0000	-0.0000	0.0000	-0.0000	0.0000	0.0001

660-699

	Cross-product mistake	Share months missed min no def.	Monthly close prob.	Share months no spend	Mean annual income	Mean utilization	Corr log bal. and log total repay.	SD of log total repay. (with FEs)	Mean log spend (intensive)	SD log spend (intensive)	Monthly prob default (percent)	Corr util and default	Corr total repay. and default	Elasticity default wrt min
γ	0.0057	-0.0000	-0.0000	-0.0000	0.0000	-0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	-0.0000	-0.0000
p_{nomin}	-0.0000	0.0019	0.0000	-0.0000	0.0000	-0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	-0.0000	-0.0000
p_{close}	0.0000	0.0000	0.0002	0.0000	-0.0000	-0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
$p_{nospend}$	-0.0000	-0.0000	0.0000	0.0041	0.0000	-0.0000	0.0000	-0.0000	0.0000	0.0000	0.0000	0.0000	-0.0000	-0.0000
$\overline{Y}*12$ ('000)	0.0000	0.0000	-0.0000	0.0000	0.2018	0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	0.0000	0.0000
β_y	0.0005	0.0003	-0.0002	-0.0006	-0.0002	-0.0021	-0.0054	-0.0017	0.0024	0.0021	0.0000	0.0001	0.0016	0.0000
β_d	-0.0001	-0.0002	0.0004	0.0001	0.0000	0.0012	0.0056	0.0010	-0.0004	-0.0011	-0.0000	-0.0003	-0.0042	-0.0000
σ_p	-0.0019	-0.0008	0.0012	0.0021	0.0000	0.0038	-0.0002	0.0104	-0.0084	-0.0050	0.0000	0.0001	0.0020	0.0000
s_0	-0.0004	0.0002	0.0007	0.0003	-0.0001	0.0037	-0.0015	0.0000	0.0279	0.0033	-0.0000	-0.0006	-0.0075	-0.0000
σ_s	-0.0001	-0.0003	0.0012	0.0002	-0.0001	0.0038	-0.0013	-0.0001	0.0044	0.0168	-0.0000	-0.0003	-0.0042	-0.0000
d_0	0.2210	0.2641	-1.3837	0.1210	-0.0081	0.4397	-0.5870	-0.0606	0.7594	0.7498	0.0116	2.0594	22.7960	0.1186
d_u	-0.0545	-0.0983	-0.2052	-0.2178	0.0044	-0.5560	0.1012	-0.3214	-0.1448	-0.3250	-0.0019	-2.3488	-6.4351	-0.0308
d_y	-0.0189	-0.0193	0.1874	0.0139	0.0024	0.0178	0.0566	0.0485	-0.0728	-0.0477	-0.0010	0.0560	-1.8551	-0.0121
d_m	0.0000	-0.0000	-0.0000	0.0000	0.0000	-0.0000	0.0000	0.0000	0.0000	-0.0000	0.0000	0.0000	0.0000	0.0001

700-739

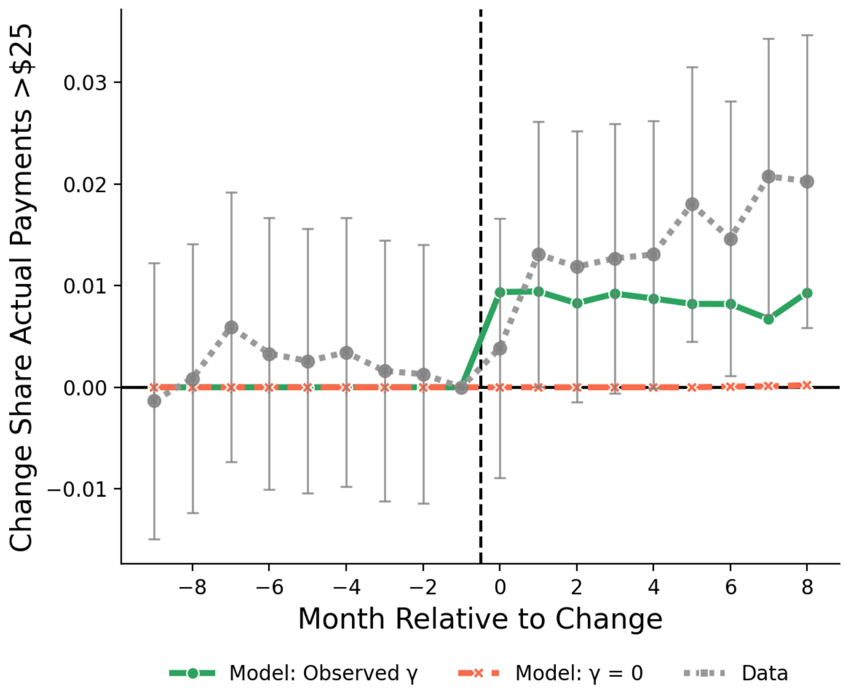
	Cross-product mistake	Share months missed min no def.	Monthly close prob.	Share months no spend	Mean annual income	Mean utilization	Corr log bal. and log total repay.	SD of log total repay. (with FEs)	Mean log spend (intensive)	SD log spend (intensive)	Monthly prob default (percent)	Corr util and default	Corr total repay. and default	Elasticity default wrt min
γ	0.0053	0.0000	0.0000	-0.0000	-0.0000	0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	0.0000	0.0000
p_{nomin}	-0.0000	0.0017	0.0000	-0.0000	-0.0000	-0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	-0.0000	-0.0000
p_{close}	0.0000	0.0000	0.0002	0.0000	0.0000	0.0000	-0.0000	-0.0000	-0.0000	0.0000	0.0000	0.0000	0.0000	-0.0000
$p_{nospend}$	-0.0000	-0.0000	0.0000	0.0044	-0.0000	0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	0.0000
$\overline{Y}*12$ ('000)	-0.0000	-0.0000	0.0000	-0.0000	0.2320	0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	0.0000	0.0000
β_y	0.0004	0.0002	-0.0003	-0.0005	-0.0002	-0.0018	-0.0034	-0.0010	0.0021	0.0021	-0.0000	0.0000	0.0006	0.0000
β_d	-0.0001	-0.0001	0.0002	0.0001	-0.0000	0.0009	0.0034	0.0006	-0.0004	-0.0011	-0.0000	-0.0002	-0.0026	-0.0000
σ_p	-0.0011	-0.0004	0.0004	0.0013	0.0001	0.0025	-0.0014	0.0081	-0.0049	-0.0033	0.0000	0.0003	0.0034	0.0000
s_0	-0.0002	0.0002	0.0009	-0.0001	-0.0001	0.0027	-0.0010	-0.0000	0.0279	0.0024	-0.0000	-0.0007	-0.0066	-0.0000
σ_s	-0.0002	-0.0002	-0.0002	-0.0006	-0.0000	0.0028	-0.0007	-0.0002	0.0034	0.0170	-0.0000	-0.0003	-0.0028	-0.0000
d_0	0.1700	0.2819	-1.0827	0.1827	0.0508	0.4315	-0.1056	0.5642	0.4223	0.4552	0.0065	3.6273	31.8968	0.0906
d_u	-0.0364	0.1150	0.0260	0.0245	0.0048	-0.3001	0.1320	-0.2260	-0.0549	-0.2856	0.0065	-2.8797	2.5979	0.0180
d_y	-0.0151	-0.0490	0.1241	-0.0235	-0.0041	-0.0137	-0.0046	-0.0365	-0.0440	-0.0173	-0.0014	-0.0566	-4.0834	-0.0154
d_m	0.0000	-0.0000	-0.0000	0.0000	0.0000	-0.0000	0.0000	0.0000	0.0000	-0.0000	0.0000	0.0000	0.0000	0.0001

740+

	Cross-product mistake	Share months missed min no def.	Monthly close prob.	Share months no spend	Mean annual income	Mean utilization	Corr log bal. and log total repay.	SD of log total repay. (with FEs)	Mean log spend (intensive)	SD log spend (intensive)	Monthly prob default (percent)	Corr util and default	Corr total repay. and default	Elasticity default wrt min
γ	0.0050	-0.0000	0.0000	-0.0000	0.0000	-0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	-0.0000
p_{nomin}	-0.0000	0.0013	-0.0000	0.0000	-0.0000	-0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	-0.0000	-0.0000
p_{close}	0.0000	-0.0000	0.0002	-0.0000	0.0000	-0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	-0.0000
$p_{nospend}$	-0.0000	0.0000	-0.0000	0.0038	0.0000	-0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	-0.0000	-0.0000
$\overline{Y}*12$ ('000)	0.0000	-0.0000	0.0000	-0.0000	0.2778	-0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	-0.0000	-0.0000
β_y	0.0004	0.0001	-0.0002	-0.0003	-0.0002	-0.0024	-0.0023	-0.0004	0.0026	0.0028	-0.0000	-0.0000	-0.0001	-0.0000
β_d	-0.0000	-0.0001	0.0001	0.0000	-0.0000	0.0007	0.0021	0.0003	-0.0003	-0.0011	-0.0000	0.0004	0.0021	0.0000
σ_p	-0.0004	0.0005	0.0005	0.0005	0.0002	0.0017	-0.0051	0.0079	-0.0021	-0.0022	0.0000	-0.0019	-0.0090	-0.0000
s_0	0.0000	-0.0004	0.0002	0.0004	-0.0000	0.0007	-0.0002	0.0000	0.0238	0.0015	0.0000	0.0007	0.0036	0.0000
σ_s	-0.0000	-0.0002	-0.0001	0.0001	-0.0000	0.0010	-0.0001	-0.0001	0.0018	0.0158	0.0000	0.0004	0.0018	0.0000
d_0	-0.4839	3.6598	-0.4634	1.0634	0.0180	1.6928	1.0203	-0.1587	-1.6851	-2.0056	-0.0350	-8.7793	-55.4838	-0.1274
d_u	-0.5535	1.7218	-0.2734	0.3415	-0.0191	2.0198	0.5564	-0.6212	-2.3142	-2.5741	0.0058	-13.5512	26.1619	-0.0198
d_y	0.1253	-0.6321	0.0852	-0.1624	0.0026	-0.4508	-0.1864	0.0970	0.4842	0.5540	0.0036	2.7038	9.5884	0.0128
d_m	-0.0000	0.0000	-0.0000	0.0000	-0.0000	-0.0000	0.0000	-0.0000	0.0000	0.0000	0.0000	-0.0000	-0.0000	0.0001

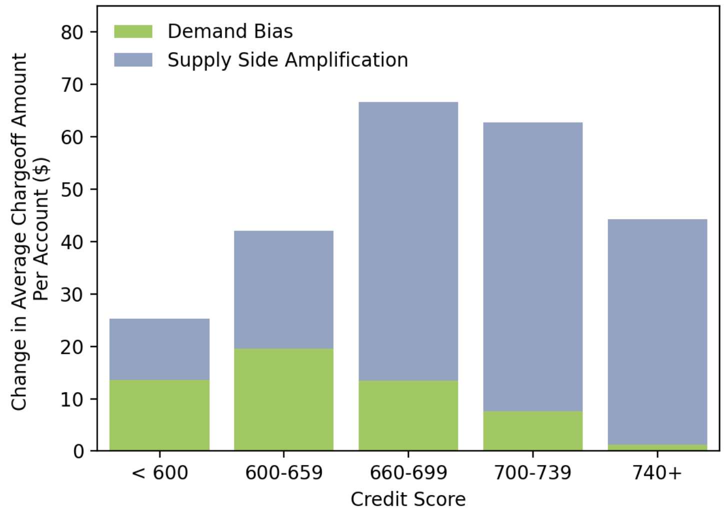
Note: Figure shows sensitivity analysis of parameters to moments following Andrews *et al.* (2017). For each credit score bin we report $\Lambda \cdot \sqrt{(1 + D/S)\Omega_g}$, where $\Lambda = (G'WG)^{-1}G'W$ (same notation as in Appendix C.2) as recommended by Andrews *et al.* (2017) for classical minimum distance estimators. Each element (p, m) should be interpreted as the impact of a one standard-deviation change in the moment m on the corresponding parameter p. Colors are assigned relative to the absolute value, normalized within row.

Figure B.14: *Repayments Around a Formula Change in the Model vs. Data*



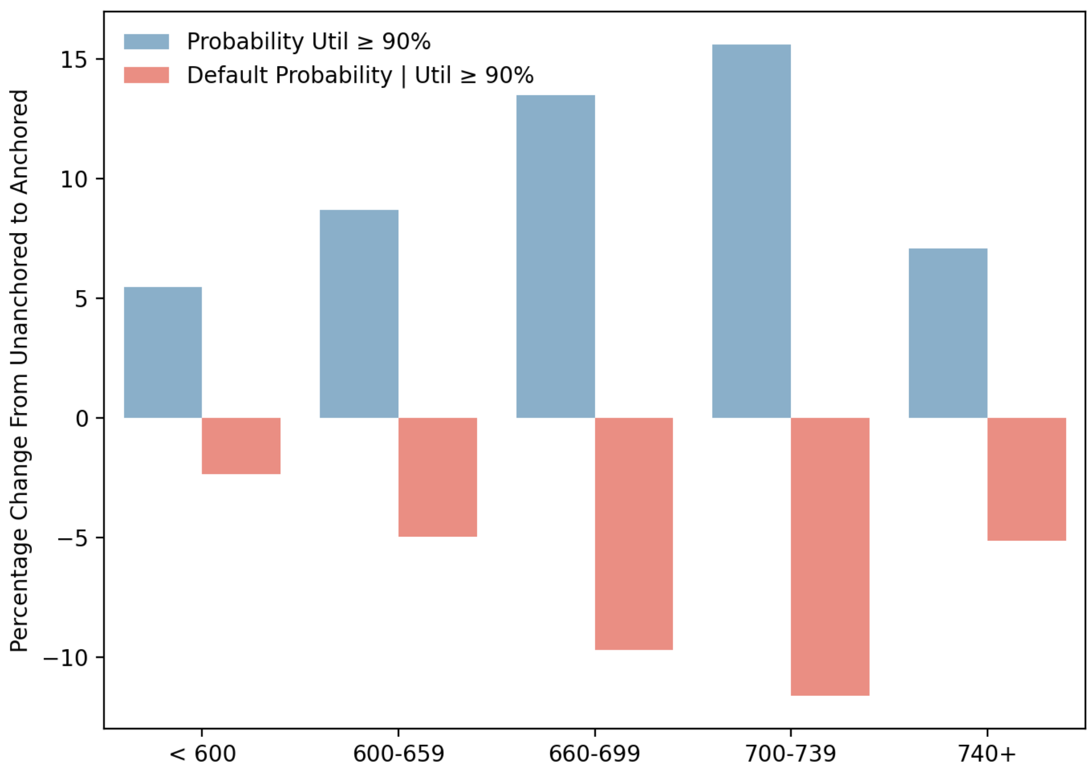
Note: Figure shows changes in actual credit card repayments > \$25 around a minimum formula change in the model and the data. The dotted gray line is from panel (d) in Figure 5. The green and orange lines are constructed from simulations in which the minimum floor increases from \$15 to \$25, 18 months after consumers open their cards. As in Figure 5, we restrict to consumer-months where the minimum is \$25 or less. We directly compare each consumer's repayments in a simulation with the floor change to those in a simulation where minimums remain at \$15. The solid green line shows the change in the model when γ matches its observed distribution in the data (the "heterogeneous anchoring" model described in Appendix C.3). The dashed orange line shows the change when $\gamma = 0$.

Figure B.15: *Increase in Default Costs Due to Anchoring*



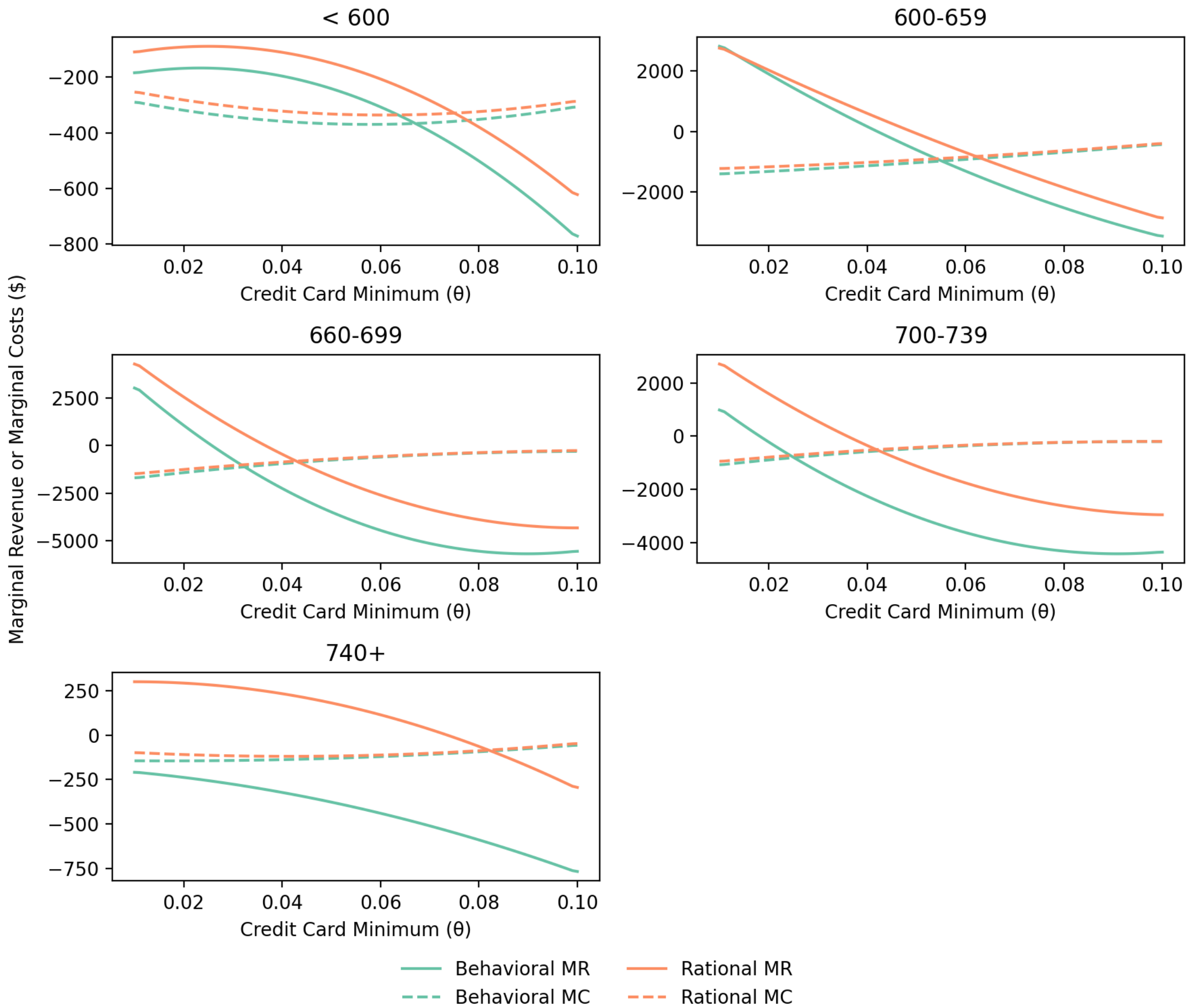
Note: Figure shows the change in default costs in a counterfactual exercise in which consumers change from unanchored to anchored. The bars show the average dollar change in default per account by credit score bin. The green and purple portions show the effect of "Demand Bias" and "Supply Side Amplification", respectively (see Section 6).

Figure B.16: *Percentage Change in High Utilization & Default Due to Anchoring*



Note: Figure shows, by credit score group, the probability of having a utilization greater than 90% (blue bars); and conditional on having utilization greater than 90%, the probability of default (red bars). The percentage change is going from unanchored to anchored borrowers, holding minimum payments constant at the optimal minimum for unanchored borrowers ("Demand Bias" only).

Figure B.17: *Marginal Revenue and Marginal Cost Curves By Credit Score Group*



Note: Figure shows marginal revenue and marginal cost curves by credit score bin, with and without anchoring ("behavioral" versus "rational" respectively). Revenue is given by discounted repayments and chargeoffs, less spending (i.e., interest revenue). Costs are given by discounted chargeoffs. To smooth simulation error, lines show the numerical derivative of a spline fitted to the marginal cost and revenue curves.

B.5 Additional Tables

Table B.1: *Summary of "All Accounts" Sample*

	Mean	SD	p10	p25	p50	p75	p90
Credit Card							
N Open	3.13	2.39	1	1	2	4	6
N Non-Zero Bal.	2.21	1.66	1	1	2	3	4
Total Credit Limit	$28,276	$31,590	$1,500	$6,000	$18,500	$39,500	$67,551
Total Balance	$6,209	$10,251	$255	$801	$2,617	$7,161	$16,035
Total Monthly Amt Due	$159	$258	$25	$40	$85	$185	$374
Mortgage							
Has 1+ Open	0.33	0.47	0	0	0	1	1
Total Balance	$71,592	$161,450	$0	$0	$0	$94,961	$240,522
Total Monthly Amt Due	$573	$1,735	$0	$0	$0	$917	$1,890
Total Bal. Cond. on > 0	$214,550	$217,817	$52,274	$94,752	$162,370	$267,792	$406,293
Auto Loan							
Has 1+ Open	0.35	0.48	0	0	0	1	1
Total Balance	$7,098	$13,882	$0	$0	$0	$10,368	$24,337
Total Monthly Amt Due	$179	$317	$0	$0	$0	$328	$574
Total Bal. Cond. on > 0	$20,001	$16,882	$4,592	$9,118	$16,087	$26,000	$39,298
Student Loan							
Has 1+ Open	0.18	0.38	0	0	0	0	1
Total Balance	$6,699	$25,744	$0	$0	$0	$0	$17,252
Total Monthly Amt Due	$41	$228	$0	$0	$0	$0	$106
Total Bal. Cond. on > 0	$37,340	$50,496	$3,564	$8,529	$20,796	$45,929	$86,341
All Four Types							
N Open	4.65	3.47	1	2	4	6	9
N Unique Types	1.88	0.84	1	1	2	2	3
Total Bal	$91,598	$168,422	$536	$2,825	$21,187	$121,930	$272,804
Total Monthly Amt Due	$952	$1,863	$27	$80	$451	$1,396	$2,537

Note: Table presents summary statistics on 2017-18 consumer-months in the credit bureau data, as described in Section 3.2. The sample includes only consumer-months with at least one card with a positive statement balance. The rows "Total Bal. Cond. on > 0" limit to consumers that have a positive balance for that debt. $N = 13{,}350{,}723$.

Table B.2: *Summary of Cards With and Without Actual Payments*

	Mean	SD	p10	p25	p50	p75	p90
Has Actual Payments							
Monthly Balance Amount	\$1,864	\$3,162	\$39	\$185	\$644	\$2,097	\$5,107
Credit Score	717.38	101.97	589	653	732	800	824
No Actual Payments							
Monthly Balance Amount	\$2,182	\$3,854	\$28	\$197	\$822	\$2,573	\$5,701
Credit Score	726.55	104.79	596	668	752	805	829

Note: Table shows summaries of credit cards that do and do not have any actual payments data reported in 2017-18. Both groups only include cards with non-zero balances in some month over the sample period. "Monthly Balance Amount" shows summaries of the within-card average (across months) of the monthly balance amount.

Table B.3: *Partial Equilibrium Costs of Cross-Product Behaviors*

	Mean	SD	p50	p75	p90
Total Installment Excess Paid (2013-19)	\$6,201	\$21,789	\$1,692	\$5,251	\$12,724
Credit Card Debt Reduction	\$1,817	\$2,993	\$700	\$2,237	\$4,926
Share of Credit Card Debt Reduction	52.6%	42.8%	47.2%	100%	100%
Annualized Interest Savings: 10pp APR-Δ	\$182	\$299	\$70	\$224	\$493
Annualized Interest Savings: 15pp APR-Δ	\$272	\$449	\$105	\$336	\$739

Note: Table provides estimates of the costs of cross-product debt repayment behaviors. Estimates come from the counterfactual analysis described in Section 4.1. The sample is individuals who revolved credit card debt at the end of 2019, were not delinquent between 2013 and 2019, and made at least two years of payments (including only the required payment) on any mortgage, auto, or student loan debt between 2013 and 2019. We transfer installment loan excess payments from this period to the revolving credit card balance at the end of 2019. When excess payments exceed the revolving balance, the revolving balance is set to zero.

Table B.4: *Optimal Inattention and Cross-Product Behavior*

Dependent Var: 100 × Overpays Mortgage ≥ \$25			
	(1)	(2)	(3)
Avg. IR on Cards	0.32***	0.33***	0.32***
	(0.04)	(0.04)	(0.06)
Log(Balance Amt Card)		0.01	−0.01
		(0.07)	(0.10)
Log(Monthly Amt Due Card)		−0.14	−0.16
		(0.10)	(0.15)
Sample	Baseline	Baseline	One 30-Year
Person FE	✓	✓	✓
Observations	1,354,684	1,349,806	598,485
R^2 Adj.	0.527	0.527	0.517

$^+$ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Note: Table shows results from regressions described in Appendix B.3.1. The sample is consumer-months with a positive mortgage and credit card balance, and with total excess payments on these products that would not cover the credit card balance. The outcome in all columns is the share of months with a mortgage overpayment of \$25 or larger. The sample in the final column is borrowers who had one 30-year mortgage through all of 2017 and 2018. The average interest rate comes from FRED series TERMCBCCINTNS.

Table B.5: *Intra-Household Frictions and Cross-Product Behavior*

Dependent Var: 100 × Overpays Installment Debt ≥ $25				
	(1)	(2)	(3)	(4)
Is Married	−1.40***	−1.22***	−1.49***	−0.55**
	(0.08)	(0.16)	(0.21)	(0.15)
Is Revolving	−5.28***	−4.65***	−7.21***	−4.18***
	(0.11)	(0.19)	(0.28)	(0.21)
Is Married X Is Revolving	1.40***	0.90***	2.51***	0.38^{+}
	(0.10)	(0.17)	(0.29)	(0.21)
Log(Bal Amt Card)	0.07***	0.01	0.10	0.12***
	(0.02)	(0.03)	(0.07)	(0.03)
Log(Month Amt Due Card)	−0.41***	−0.51***	−0.76***	−0.44***
	(0.03)	(0.04)	(0.10)	(0.03)
Log(Bal Amt Install)	−1.23***	−1.42***	−1.70***	−6.33***
	(0.07)	(0.08)	(0.07)	(0.19)
Log(Month Amt Due Install)	7.31***	10.65***	7.30***	11.50***
	(0.11)	(0.17)	(0.11)	(0.26)
Credit Score	0.04***	0.04***	0.04***	0.04***
	(0.00)	(0.00)	(0.00)	(0.00)
Sample	All	Has Auto	Has Edu	Has Mort
Month FEs	✓	✓	✓	✓
Observations	2,544,562	1,553,180	482,931	1,555,756
R2 Adj.	0.037	0.054	0.051	0.022

$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Table shows results from regressions described in Appendix B.3.4. The baseline sample is all consumer-months with a positive installment debt and credit card balance. The outcome in all columns is the share of months with an installment debt overpayment of $25 or larger. The sample in columns 2-4 filters to those who are overpaying auto, student, and mortgage loans, respectively.

Table B.6: *Share of Balance and Actual Payments on Cards vs Installment Loans*

	Mean	SD	p10	p25	p50	p75	p90
Share Balance on Credit Card	8.8%	14.8%	0.1%	0.7%	2.8%	9.4%	25.9%
Share Actual Pymnt on Credit Card	33.5%	25.9%	5%	11.4%	26.5%	52%	74.3%

Note: Table shows summaries of the share of payments that were on credit cards versus installment loans. Sample is all consumer-months in which the consumer had a non-zero balance on one or more installment loans and one or more credit cards and did not miss the minimum required payment on either.

Table B.7: *Missed Payments Credit Bureau Data vs Late Fees CFPB using Y-14 Data*

Group	Share Missed Min	CFPB: Share Late Fee
1) Superprime	23%	15%
2) Prime	38%	32%
3) Near-prime	45%	43%
4) Subprime	54%	53%
5) Deep Subprime	65%	70%

Note: Table compares, by credit score group, the card-level likelihood of any missed payment over a year in our credit bureau data to the likelihood of any late fee over a year in Y-14 data. Column 1 presents, of cards open at the end of 2017 and for which we observe any actual payments in 2018, the share that had a "missed" minimum payment. Column 2 shows comparable data on late fees in 2019 from Figure 4 in CFPB, 2022. Credit score categories are: ≥ 720 is superprime; 660-719 is prime; 620-659 is near-prime; 580-619 is subprime; ≤ 580 is deep subprime.

Table B.8: *Outcomes Around a Minimum Change for Robustness Models*

	Has Balance x 100	Misses Min x 100	Log(Total Pymnt)
After Change X Treated	0.00	0.16	0.01
	(0.25)	(0.16)	(0.01)
Sample	Any Mo	Any Mo w/ Balance	Any Mo w/ CC Pymnt
Month FE	✓	✓	✓
Treated FE	✓	✓	✓
Observations	1,553,412	1,310,261	1,193,469
R^2 Adj.	0.000	0.000	0.005

$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Table shows changes in three outcomes around the formula change event depicted in Figure 5. "Has Balance" is an indicator for whether the borrower has a non-zero statement balance. "Misses Min" is an indicator for whether a borrower pays below the minimum required payment. "Log(Total Pymnt)" is the log of payments across all debts. Standard errors are clustered at the card level.

Table B.9: *First Stage Parameters (Values)*

Description	Parameter	Value
Fixed Parameters		
APR	$(R-1)*12$	[0.24, 0.22, 0.23, 0.21, 0.17]
Credit limit ($)	$\overline{L}$	[1693, 3355, 5436, 7026, 10009]
Minimum floor ($)	μ	25
Minimum slope	θ	[0.05, 0.035, 0.025, 0.02, 0.02]
Max late fee ($)	$F_{\max}$	25
Monthly installment min ($)	m_{other}	[476, 569, 762, 944, 1254]
Annual discount rate	$1-\delta^{12}$	0.05
Chargeoff recovery rate	Λ	0.25
Income		
Average annual income ($'000)	$\overline{Y}*12$	[29, 53, 69, 82, 111]
Persistence	ρ	0.989
Standard deviation	σ_y	0.078
Spending		
No spending probability	$p_{nospend}$	[0.1, 0.14, 0.21, 0.21, 0.15]
Card Closure		
Card closing probability	p_{close}	[0.008, 0.009, 0.011, 0.011, 0.014]
Repayments		
Missed min probability	p_{nomin}	[0.12, 0.11, 0.09, 0.08, 0.05]
Anchoring	γ	[0.26, 0.26, 0.24, 0.23, 0.18]

Note: Table presents values of first stage parameters. Values enclosed inside brackets correspond to the five credit score bins (in increasing order). See Table 5 for a description of how these values were calculated.

Table B.10: *Expected Profits and Minimum Floors*

Floor (μ)	< 600	600-659	660-699	700-739	740+
0	550	1151	1990	1790	617
25	557	1157	2001	1807	639
50	551	1149	1996	1804	638

Note: Table shows how expected profits per card change with different minimum floors μ by credit score bin. Note that this table is produced holding anchoring and minimums fixed at the values observed in the data (no counterfactuals).

Table B.11: *Model Fit*

	< 600	600-659	660-699	700-739	740+
Real (Data)					
Mean utilization	0.724	0.662	0.574	0.466	0.241
Corr log bal. and log total repay.	0.159	0.223	0.233	0.242	0.276
SD of log total repay. (with FEs)	0.338	0.343	0.349	0.357	0.331
Mean log spend (intensive)	3.946	4.106	4.53	4.875	5.494
SD log spend (intensive)	1.792	1.971	2.127	2.101	1.936
Monthly prob default (percent)	0.673	0.361	0.165	0.082	0.017
Corr util and default	0.123	0.098	0.075	0.068	0.054
Corr total repay. and default	-0.034	-0.025	-0.019	-0.014	-0.008
Elasticity default wrt min	0.13	0.097	0.076	0.06	0.025
Fit (Model)					
Mean utilization	0.724	0.662	0.574	0.466	0.241
Corr log bal. and log total repay.	0.159	0.223	0.233	0.242	0.276
SD of log total repay. (with FEs)	0.338	0.343	0.349	0.357	0.331
Mean log spend (intensive)	3.946	4.106	4.53	4.875	5.494
SD log spend (intensive)	1.792	1.971	2.127	2.101	1.936
Monthly prob default (percent)	0.673	0.361	0.165	0.082	0.017
Corr util and default	0.123	0.098	0.075	0.068	0.054
Corr total repay. and default	-0.034	-0.025	-0.019	-0.014	-0.008
Elasticity default wrt min	0.13	0.097	0.076	0.06	0.025

Note: Table shows the value of simulated moments using the optimal parameters in Table 7, comparing real vs. model moments.

Table B.12: *Lender-Optimal θ in Alternative Models*

	< 600	600-659	660-699	700-739	740+
Panel A: Optimal Min					
Baseline	0.067	0.056	0.032	0.025	0.01
Interchange	0.114	0.067	0.038	0.033	0.038
No Recovery	0.093	0.064	0.037	0.033	0.038
Hetero Anchoring	0.074	0.058	0.033	0.026	0.01
Time-Varying Anchoring	0.074	0.058	0.032	0.024	0.01
High Closure Elast to Min	0.056	0.049	0.025	0.016	0.01
High Late Fee Elast to Min	0.122	0.072	0.043	0.046	0.091
Total Repayment Elast to Min	0.01	0.042	0.01	0.01	0.01
Homogeneous Default Elast to Min	0.099	0.058	0.032	0.024	0.01
Transitory Income Shocks	0.075	0.062	0.043	0.038	0.01
Panel B: Counterfactual Min Change					
Baseline	1.1x	1.09x	1.34x	1.64x	7.8x
Interchange	1.04x	1.09x	1.32x	1.55x	2.37x
No Recovery	1.06x	1.09x	1.35x	1.55x	2.37x
Hetero Anchoring	1.0x	1.05x	1.3x	1.58x	7.8x
Time-Varying Anchoring	1.0x	1.05x	1.34x	1.71x	7.8x
High Closure Elast to Min	1.21x	1.14x	1.4x	2.0x	1.3x
High Late Fee Elast to Min	1.08x	1.1x	1.26x	1.13x	1.01x
Total Repayment Elast to Min	7.4x	1.45x	4.3x	4.1x	7.8x
Homogeneous Default Elast to Min	1.08x	1.09x	1.34x	1.67x	7.7x
Transitory Income Shocks	1.08x	1.06x	1.28x	1.39x	9.2x

Note: Table shows the results of alternative simulations described in Appendix C.3. Panel A shows the lender-optimal credit card minimum contract term, θ, in a model with anchoring. Panel B shows the change in this lender-optimal θ in the counterfactual where borrowers are unanchored ($\gamma = 0$).

C Empirical Model Appendix

In this Appendix, we provide details about the estimation of our empirical model described in Section 5.

C.1 First Stage Calibration and Estimation

Sample. Our estimation uses a sample of cards opened in 2015. This allows us to track outcomes for four years before the start of the COVID-19 pandemic. We limit to the 75% of cards associated with borrowers who have an installment debt, allowing us to use our results in Section 4.1 to quantify anchoring. In total, our sample includes 63,587 cards.

Fixed Parameters. For a given set of borrower parameters, the model simulates $N = 10,000$ borrowers over $T = 240$ months. To reduce simulation error from the low frequency of defaults, we model each simulated borrower as representing a unit mass of identical borrowers and track the corresponding share of this mass that has defaulted over time.

Income. To convert Guerrieri and Lorenzoni (2017)'s quarterly income process to monthly, we follow the same procedure these authors used to convert Floden and Lindé (2001)'s annual income process to quarterly. In particular, for an AR(1), given annual σ_a and ρ_a, solving for monthly σ_m and ρ_m requires solving the following system of equations (equating variances and autocovariances):

$$m_1 = \left(\frac{1}{12}\right)^2 \left(12 + 2\sum_{i=1}^{11}(12-i)(\rho_m)^i\right)\left(\frac{\sigma_m^2}{1-\rho_m^2}\right) \tag{C.1}$$

$$m_2 = \left(\frac{1}{12}\right)^2 \left(\sum_{i=1}^{12} i(\rho_m)^i + \sum_{j=13}^{23}(24-j)(\rho_m)^j\right)\left(\frac{\sigma_m^2}{1-\rho_m^2}\right) \tag{C.2}$$

$$m_1 = \frac{\sigma_a^2}{1-\rho_a^2} \tag{C.3}$$

$$m_2/m_1 = \rho_a \tag{C.4}$$

We simulate all income processes starting off at mean income, but have a $10 \times T$ month burn-in period (so in the model all simulated individuals have a different starting income).

Card Closure. To calibrate card closures, we match the average share of cards that transition into being unused for a full year or more. Specifically, let s_x be the share of cards unused after x years for at least one year. Then,

$$p_{close} = \left(s_1 + \frac{s_2 - s_1}{1 - s_1} + \frac{s_3 - s_2}{1 - s_2} \right) /36$$

This incorporates soft card closures, in which the borrower stops using the card without formally closing it.

C.2 Second Stage Estimation and Standard Errors

Elasticity of Default to Minimums from d'Astous and Shore (2017). We calibrate the elasticity of default to minimums using estimates from d'Astous and Shore (2017), who study short-run responses to higher credit card minimums using proprietary bank data. In columns 3–4 of Table 4, Panel B, a fully exposed borrower's probability of write-off six months after the change rises by 0.08 pp. Dividing by the 1.7% baseline write-off rate gives a 4.7% increase; dividing again by the 66% change in minimums yields an elasticity of 0.071.

To allow heterogeneity by credit score, we use Appendix Table IA-4, where the probability of becoming late falls by 4.11 pp for a 1000-point decrease in the bank's credit score. To map this to write-off probabilities, we multiply by 10%, the share curing before being late for six months (implied by the 0.017 monthly cure rate in Table 2). Using the 141-point standard deviation of bank credit scores (Table 1), we multiply by $141/1000$ to obtain a 0.058 pp increase in the sensitivity of write-off to the change per SD of credit score. To apply this to our credit score buckets, we compute average z-scores of credit scores in each bucket, $[-1.14, -0.496, -0.0935, 0.225, 0.895]$. We multiply by the slope and add the 0.08 pp intercept. Again dividing by 1.7% and 0.66 gives elasticities $[0.130, 0.0969, 0.0761, 0.0597, 0.0250]$.

In Appendix Table B.12, we also report results using a homogeneous parameter d_m. Lender-optimal minimums do not substantially change for most borrowers, but rise slightly in the lowest credit score bucket where the heterogeneous estimates imply the default response to minimums is strongest. Our main qualitative result—that lenders significantly increase minimums when borrowers become unanchored—remains unchanged.

Optimization Algorithm. To ensure that a global optimum is found, we do several rounds of global and local optimization. The global optimizer we use is Python's Differential Evolution (DE) algorithm, giving the optimizer the following set of bounds for $\Theta_2 = (\beta_y, \beta_b, \sigma_p, s_0, \sigma_s, d_0, d_u, d_y, d_m)$:

$$\text{Bounds} = [(0, 1), (0, 1), (0, 1.5), (-10, 10), (0, 5), (-100, 100), (0, 200), (-15, 0), (0, 1)]$$

We first run DE, and then refine the solution with five Nelder-Mead runs with no bounds on any parameter. Note that since our system is just-identified, if the optimizer finds a (precise) zero we can be fairly confident that a solution has been found. Lender-optimal minimums (given borrower parameter values) are found by searching for the optimal model-implied θ. Since this is only 1-D, we simply search over a θ grid, $[0.01, 0.011, 0.012, \ldots, 0.15]$.

Standard Errors. We adapt the standard errors expression (and notation) in de Silva (2023) and Laibson *et al.* (2024) to compute standard errors. To account for correlation between the first and second stage errors, we calculate the standard errors by collapsing the first and second stage parameters and moments even though we estimate the model in two steps. Let there be N_{Θ_1} first stage parameters, N_{Θ_2} second stage parameters, M_{Θ_1} first stage moments (used to set the first-stage parameters), and M_{Θ_2} second stage moments. Note that from how we constructed the first stage, $N_{\Theta_1} = M_{\Theta_1} = |\Theta_1|$. In our just identified case, $N_{\Theta_2} = M_{\Theta_2}$ as well.

Define $g(\Theta_1, \Theta_2) = [m_{all}(\Theta_1, \Theta_2) - \hat{m}_{all}]$ where m_{all} are stacked first and second stage moments (Tables 5 and 6) and $\hat{m}_{all}$ is the empirical moment. Let $G' = \partial g(\Theta_1, \Theta_2)/\partial\Theta$, so G' is a $(M_{\Theta_1} + M_{\Theta_2}) \times (N_{\Theta_1} + N_{\Theta_2})$ matrix. Let $\Omega_g = \mathbb{E}[g(\Theta_1, \Theta_2)g(\Theta_1, \Theta_2)']$ and W is a weighting matrix. Then:

$$\Theta^* = \arg\min_{\Theta} g(\Theta)' W g(\Theta)$$

If Θ_0 is the true value, under regularity conditions, $\sqrt{N}(\Theta^* - \Theta_0)$ converges in distribution to a normal with mean zero and asymptotic variance V. Since our model is just identified, G' is invertible which implies that W does not affect the standard errors, but we include it in the general expression below. To account for simulation error, let S be the number of simulations and D the number of observations in the data. The asymptotic variance, V, is:

$$V = (G'WG)^{-1}G'W \cdot [(1 + D/S)\Omega_g] \cdot WG(G'WG)^{-1}$$

Since we do not observe any population quantities in the expression for V, we instead estimate sample analogs (which can be justified using the continuous mapping theorem). Ω_g is estimated using 10,000 bootstrap samples (separately for each credit score bin, sampled at the borrower level) and is the variance covariance matrix of the empirical first and second stage moments.

The Jacobian G' can be split into three components. The top left has dimension $M_{\Theta_1} \times N_{\Theta_1}$ and is the derivative of the first stage moments on the first stage parameters. Since first stage parameters are directly assigned, the top left is just an identity matrix of size $|\Theta_1|$. The top right, of size $M_{\Theta_1} \times N_{\Theta_2}$, is how the second stage parameters affect the first stage moments. This is zero since the first stage parameters are assigned independently from any second stage parameters. Finally, the bottom half of G' has dimension $M_{\Theta_2} \times (N_{\Theta_1} + N_{\Theta_2})$ and is how the first and second stage parameters affect the second stage moments. We compute these derivatives numerically, to find how the distance function changes when the first or second stage parameters change from $\hat{\Theta}^*$ (optimal Θ from our simulations). Following de Silva (2023) we use a step size equal to 1% of the optimal $\hat{\Theta}^*$, and implement this using Python's `approx_fprime` function.

C.3 Description of Alternative Models

Appendix Table B.12 shows the baseline and counterfactual lender-optimal contract θ in a number of alternative simulations (holding other parameters fixed). Each set of simulations is constructed as follows:

- *Interchange:* The lender receives 1.75% of every dollar spent on the card in interchange fees, following Wang (2025). We view this as relatively conservative, as a large share of interchange fees are often assumed to be passed back to consumers in rewards.
- *No Recovery:* When borrowers default, the lender does not recover anything ($\Lambda = 0$).
- *Heterogeneous Anchoring:* In each credit score bin, we compute the empirical percentiles of the distribution of γ across all consumer-month observations. For each of the 10,000 simulated consumers, we draw from this empirical distribution.
- *Time-Varying Anchoring:* In each credit score bin, we model γ as a Markov process. We estimate an empirical transition matrix across seven bins of γ: 0, $(0, 0.2]$, $(0.2, 0.4]$, $(0.4, 0.6]$, $(0.6, 0.8]$, $(0.8, 1)$, and 1. This captures the fact that in any given month, many borrowers either fully prioritize their credit card debt ($\gamma = 0$) or their installment debt ($\gamma = 1$). Borrowers are initialized at the stationary distribution implied by the transition matrix and simulated forward according to the transition probabilities.
- *High Closure Elasticity to the Minimum:* Borrowers with high minimums may transfer balances to lower-minimum cards. While we view this as unlikely (see discussion in Section 5.1.1), we allow for this possibility using estimates from the minimum-formula change described in Section 4.2. Appendix Table B.8 shows no significant increase in zero statement balances after the change (the point estimate implies the opposite). To test the implications of a high elasticity, we use the upper bound of the 95% confidence interval. We convert this to an elasticity by dividing by the average probability of a closure and by the change in log minimums, yielding an elasticity of -0.012. In the

model, we translate this into a slope for each credit score bin and compute an intercept that keeps the overall probability of a closure (p_{close}) unchanged.

- *High Late Fee Elasticity to the Minimum:* Borrowers with high minimums may be more likely to miss the minimum (e.g., due to short-term illiquidity shocks). Appendix Table B.8 shows that the point estimate of this response is insignificant and negative. To test the implications of a high elasticity, we again use the upper bound of the 95% confidence interval. Following the same procedure as above yields an elasticity estimate of 0.137. We again convert this to a slope and intercept by credit score bin that leave the overall probability of a missed minimum (p_{nomin}) unchanged.

- *Total Repayment Elasticity to the Minimum:* Anchoring may also cause borrowers to reduce their total repayments across all debts. We parameterize total repayment as $\tilde{p}(B_t, Y_t; m_t) = \beta_y y_t + \beta_b b_t + \beta_m \log(m_t) + \epsilon_t^p$. Appendix Table B.8 shows an insignificant increase in total payments following a minimum increase. We convert this point estimate to an elasticity using the same procedure as above and use it directly for β_m. In the counterfactual, we set both $\gamma = 0$ and $\beta_m = 0$.

- *Homogeneous Default Elasticity to the Minimum:* In every credit score bin, we use our estimated d_m parameter from the middle (660-699) credit score bin.

- *Transitory Income Shocks*: In each credit score bin, we introduce a transitory income shock such that income can be 50% higher or lower than implied by the income process in Guerrieri and Lorenzoni (2017). Transitory shocks occur i.i.d with probability 2.5% for positive shocks and 2.5% for negative shocks. These parameters allow the distribution of monthly income growth to better match Figure 1(b) in Ganong *et al.* (2025). Smaller transitory shocks are not captured by this income process; however, the effect of these on repayments would be captured in σ_p, which our data are better suited to directly estimate.

C.4 Simulating Quebec Policy Change

We simulate a policy change implemented in Quebec in our model. As studied by Allen *et al.* (2026), Quebec required minimums on (existing) credit cards to be at least $\max\{2\% \times \text{outstanding balance}, \$10\}$ by August 2019, with stricter requirements each year such that by August 2025, minimums were at least $\max\{5\% \times \text{outstanding balance}, \$10\}$. Prior to the policy change, many lenders had lower minimums, including \$10 + interest + fees; see Table 1 in Allen *et al.* (2026).

To simulate this, we change minimums from $\max\{1.5\% \times \text{outstanding balance}, \$10\}$ to $\max\{2.5\% \times \text{outstanding balance}, \$10\}$ 18 months after consumers open their cards. We then measure revolving balances 24 months after the simulated policy change. Average revolving balances fall by 1.44%. For comparison, Table 4 in Allen *et al.* (2026) reports a 5.2% decrease in revolving balances at 24 months, with a 95% confidence interval of 0.0%–10.7%. Our baseline model is somewhat different than the setting pre-change in Quebec: in particular, balances are lower and minimums are higher, which may help explain why our simulations yield a smaller change. In addition, the weaker response is consistent with γ being a conservative estimate of anchoring, identified only from intra-temporal allocations (we discuss this in Section 5.1.2). Nevertheless, consistent with the model, the policy change shows that an increase in minimum payments can meaningfully reduce revolving debt.

D CFPB Credit Card Agreement Database

In this appendix, we describe our analyses using the CFPB Credit Card Agreement Database. The 2009 CARD Act requires that issuers with over 10,000 accounts submit agreements quarterly. The agreements have general terms and conditions, pricing, and fee information which are not specific to individual accounts.

We use agreements in the fourth quarter of 2022 from 25 of the largest credit card issuers in the US. Specifically, we look at the largest Mastercard and Visa credit card issuers by outstanding receivables according to Nilson Reports. To these issuers, we add Discover and American Express. Three issuers—Credit One, Navy Federal Credit Union, and USAA Federal Savings Bank—are not in the Q4 2022 data. For each we use their Q4 2021 agreements. We exclude Capital One, who does not report how minimum payments are calculated in their sample generic consumer cards agreement.

Some issuers only list a single generic agreement. For issuers with multiple agreements, when possible, we first filter to general purpose cards that are not store branded. We then filter to unsecured cards. Finally, we randomly sample from any remaining cards. We manually read the selected agreements. Appendix Figure D.1 shows examples of two agreements' information on minimum payment calculations. Appendix Table D.1 shows information about the minimum formulas for all selected agreements.

Figure D.1: *Example Agreements from CFPB Credit Card Agreement Database*

(A) Citizens Bank

HOW WE CALCULATE THE MINIMUM PAYMENT
If your new balance is $30 or less, your minimum payment will be the new balance. Otherwise, it will be the greater of (i) $30; or (ii) equal to the total billed Interest charges (excluding transaction fees for balance transfers, cash advances, foreign transactions, and cash equivalents), and any billed late payment fees and 1% of the new balance.

(B) Synchrony Financial

Minimum Payment Calculation
Your total minimum payment is calculated as follows.
The greater of:

1. $30, or $41 (which includes any past due amounts) if you have failed to pay the total minimum payment due by the due date in any one or more of the prior six billing cycles.
   OR
2. The sum of:
   a. Any past due amounts; PLUS
   b. 1% of your new balance (excluding any balance in connection with a special promotional purchase with a unique payment calculation) shown on your billing statement; PLUS
   c. Any late payment fees charged in the current billing cycle; PLUS
   d. All interest charged in the current billing cycle; PLUS
   e. Any payment due in connection with a special promotional purchase with a unique payment calculation.

We round up to the next highest whole dollar in figuring your total minimum payment. Your total minimum payment will never be more than your new balance. Payments required in connection with a special promotional purchase with a unique payment calculation will not be increased to, but may be included in the $30 or $41 minimum amount otherwise due on your account.

Note: Figure shows example minimum payment formulas in the CFPB Credit Card Agreement Database.

Table D.1: *Minimum Payments in CFPB Credit Card Agreement Database*

Institution Name	**Sampled Agreement**	**Listed θ (μ)**	**Details**
American Express	Blue Cash Everyday	0.02 (40)	Higher of 2% or 1% + interest
Bank of America	World Elite Mastercard	0.01 (35)	1% + interest
Barclays Bank Delaware	Generic Agreement	0.01 (25-29)	1% + interest
Citibank	Simplicity Card	0.01 (20)	1% + interest
Citizens Bank	Cash Back Plus Card	0.01 (30)	1% + interest
Commerce Bank	Miles Credit Card	0.01 (30)	1% + interest
Credit One Bank	Generic Agreement	0.05 (30)	5%, no interest added
Discover Bank	Near Prime Agreement	0.03 (20)	Higher of 3% or $15 + interest
Fifth Third Bank	1% Cash Back Card	0.01 (35)	1% + interest
First National Bank	Legacy Visa Card	0.04 (30)	Higher of 4% or 1% + interest
First Premier Bank	Agreement CRKK75	0.07 (30)	7%, no interest added
Goldman Sachs Bank	Apple Card	0.01 (25)	1% + interest
JPMorgan Chase Bank	Agreement 271320	0.01 (40)	1% + interest
KeyBank	Cashback Credit Card	0.01 (30)	1% + interest
M&T Bank	Generic Agreement	0.025 (15)	2.5%, no interest added
Navy Fed Credit Union	Generic Agreement	0.02 (20)	2%, no interest added
Pentagon Fed Credit Union	Generic Agreement	0.02 (15)	2%, no interest added
PNC Bank	Agreement 302913	0.01 (27)	1% + interest
Regions Bank	Generic Agreement	0.01 (25)	1% + interest
Synchrony Financial	Premier World Mastercard	0.01 (30/41)	1% + interest; μ=41 w/ miss
TD Bank	TD Cash	0.01 (35)	1% + interest
Truist Bank	Enjoy Cash Credit Card	0.01 (27)	1% + interest
US Bank	Classic Accounts	0.01 (40)	1% + interest
USAA Fed Savings Bank	Generic Agreement	0.01 (15)	1% + interest
Wells Fargo Bank	Active Cash Card	0.01 (25)	1% + interest

Note: Table shows information on the minimum payment formulas reported in the CFPB Credit Card Agreement Database. The process for selecting institutions and agreements is described in Appendix D. The listed θ and μ describe features of the minimum formula, as defined in Equation 5. The contract database provides general terms and conditions, and features may differ between individual accounts. The final column includes information on whether interest is added to the minimum formula.

E Survey of Households

In this Appendix, we provide additional details and results from a survey on debt repayment. The survey included both an experiment and open-ended questions about how individuals repay debt. It was conducted on Prolific in July 2025. We screened for respondents who were 18 or older, live in the U.S., and have at least one open credit card and mortgage. A pre-registration of our experimental design—including the full survey instrument—is available at: `https://www.socialscienceregistry.org/trials/16321/`.

We collected 1,800 total responses. As pre-registered, we excluded respondents who (1) failed an attention check instructing them to select specific days of the week as their favorite regardless of their actual preferences, or (2) reported using ChatGPT or another online resource to answer questions (asked at the end, with assurance that it would not affect payment). After using these two filters, we had 1,598 valid responses. Appendix Table E.4 summarizes the demographics of respondents.

Survey Experiment Setup

The survey presented consumers with hypothetical bill repayment scenarios involving a credit card and a mortgage. There were three treatment arms. In the baseline, respondents saw bills modeled on real statements, along with a typical credit card repayment interface with buttons to pay the minimum, pay in full, or enter a custom amount. In our primary *de-anchor treatment*, the minimum payment still appeared on the bill and could be entered manually, but the dedicated button to pay the minimum was removed.[55] We also included a *box treatment*, which added the CARD Act–mandated disclosure highlighting the costs of making minimum payments, to explore information disclosure effects. Appendix Figures E.12 and E.13 show images of each scenario and treatment arm.

Borrowers made choices in two scenarios: one based on their own finances and one with a fixed budget. We primarily focus on the former in our description of results, but results were similar across scenarios. Appendix Table E.1 reports results for all pre-registered outcomes across treatment arms and scenarios. Appendix Table E.2 shows results in regressions that control for demographics, an analysis we pre-registered.

[55] Similar interventions were used in Stewart (2009); Guttman-Kenney *et al.* (2018). Our intervention differed from Guttman-Kenney *et al.* (2023), who shrouded the *autopay* option, as we focus on manual payments. Only 20% of U.S. cards made an autopay payment in 2022 (CFPB, 2023a), and autopay-enrolled borrowers could make additional payments. Guttman-Kenney (2025) found relatively small effects from a field intervention, but the sample mostly consisted of subprime borrowers who were likely to be constrained.

Survey Experiment Results

Appendix Figure E.1 shows that overall credit card repayments increased in both treatment arms.[56] The green bars indicate that repayment behavior in the control group resembles patterns in administrative data, suggesting the setting is realistic. The orange bars show a substantial increase in repayments under the de-anchor treatment: the share of those paying exactly the minimum declined from 23.4% to 10.2%, while the share paying exactly the full balance rose from 42.3% to 55.9%.[57] The CARD Act box treatment produced a much smaller increase in repayments.

Appendix Figure E.3 shows that the increase in credit card repayments under the treatment reduced the incidence of failures to cost-minimize across debts. The share of respondents failing to cost minimize decreased by nearly one-third, from 7.7% to 5.2%. Many borrowers paid off their full card balance in this scenario, limiting the scope for misallocation. In the fixed budget scenario—where borrowers could not fully pay off the credit card and all respondents had to actively allocate payments across debts—the percentage decline was similar: a 28% reduction, from 44.9% to 33.0%. Overall, these results suggest that de-anchoring interventions may increase the cost effectiveness of debt repayment allocations.

Respondents were also asked how long it would take to repay and the total cost if they made only minimum payments each month. Appendix Figures E.4 and E.5 show the distribution of responses compared to the correct answers.[58] Respondents in the baseline and de-anchoring treatments consistently underestimated both the total cost and time to repay. Appendix Table E.1 shows median estimates of around $2,100 and 7 years in these groups, well below the correct values of $4,082 and 14 years. In contrast, most respondents in the box treatment—where the disclosure box states the correct answer—reported accurate estimates.

Questions About Own Repayments

The survey also asked respondents about their own financial decisions. We summarize our results in three figures.

First, Appendix Figure E.6 shows the features respondents consider most important when applying for a new credit card. They could select up to three features. Over 60% selected annual fees, rewards, and interest rates. Only 5.2% mentioned the minimum payment amount, consistent with our baseline model assumption that lenders do not compete on this attribute.

[56] Appendix Figure E.2 shows responses in the budget scenario.

[57] The lowest bar in Appendix Figure E.1 includes both minimum payers and near-minimum payers.

[58] The correct answer assumes the minimum payment remains constant at the amount displayed on the bill, $25 (as if the borrower is already at the payment floor, μ). If the minimum declined with the balance, repayment would take longer and cost more.

Second, Appendix Figure E.7 shows how often respondents report reading the minimum payment cost disclosure box mandated by the 2009 CARD Act (see Section 4.2). Panel (a) shows the box is more often used by those who typically revolve. However, even among these respondents, nearly half report never looking at the box or doing so less than once per year. To benchmark our results, some respondents were shown a placebo box (Appendix Figure E.8) not found on actual credit card statements. Panel (b) shows fewer respondents report using this placebo box, though about a quarter of those who revolve still claim to use it at least a few times per year—consistent with some confusion or misremembering. This suggests that reported usage of the real box in panel (a) may be overstated, and, in turn, that borrowers not seeing the box on their statements (e.g., because they use online bill pay only) may partly explain the limited effectiveness of the CARD Act disclosure.

Third, Appendix Figure E.9 shows responses to the question: "Suppose your lender increased the minimum payment on your most used credit card. At what point (if any) would you consider missing a payment?" The maximum response option was \$500. 56% of respondents said any increase under \$500 would be manageable, while only 16% said some increase under \$100 would be unmanageable. These responses suggest that many borrowers could find liquidity to meet higher minimum payments.

Open-Ended Rationales for Cross-Product Behaviors

The survey asked respondents whether they had ever paid more than the required monthly payment on a mortgage, student loan, or auto loan in a month when they paid less than the full statement balance on their credit card, and then asked them to explain their answer. We analyze these open-ended responses for the subsample of respondents who report that they typically revolve credit card debt.

We classify the responses using an LLM-assisted coding procedure. We define a set of labels intended to capture the most common themes in the qualitative responses and potential mechanisms underlying cross-product repayment behavior (Appendix Table E.3). We provide the LLM with the labels and a set of hand-coded example responses.

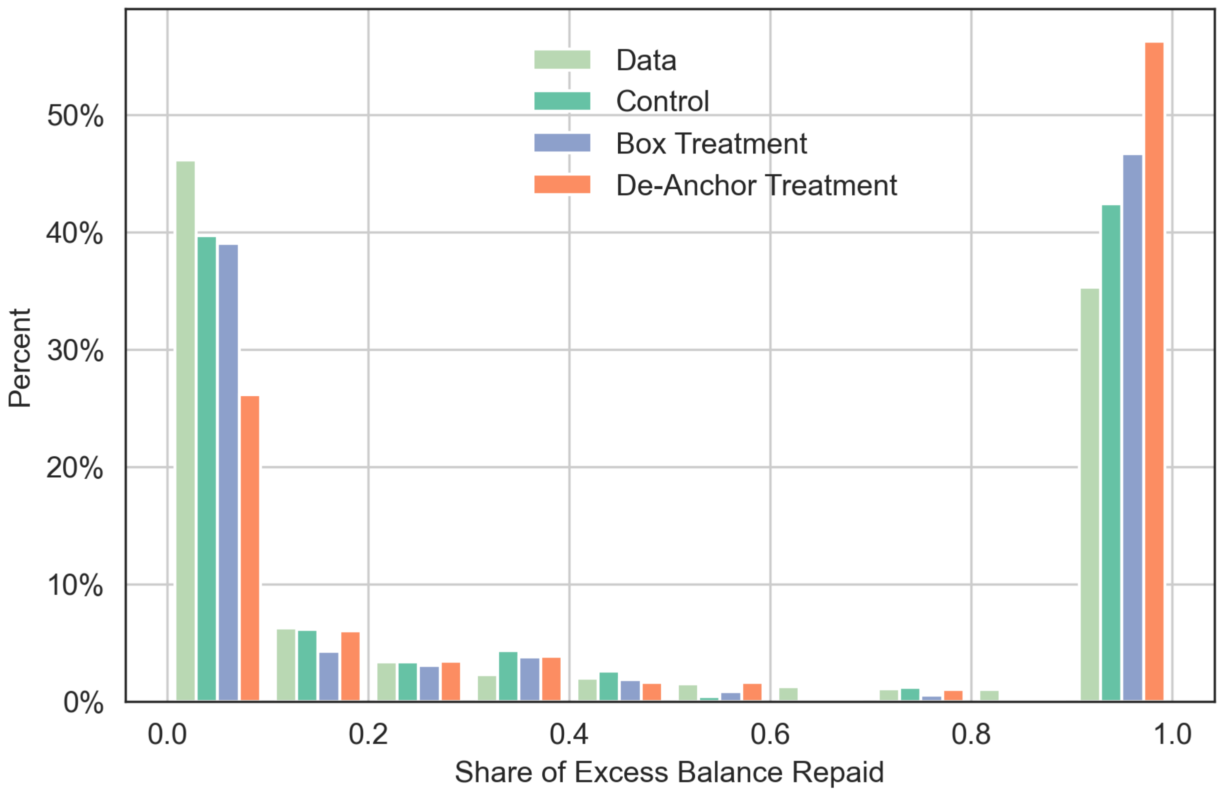
We code responses in two stages. First, we prompt the LLM to classify responses according to our labels and examples. To do so, we use the prompts and procedures in the `classify` method of the GABRIEL package (Asirvatham *et al.*, 2026) with additional instructions that supply the labeled examples. In the second stage, we refine the preliminary labels using a separate OpenAI API call that supervises the initial labels and removes incorrect assignments. In particular, responses coded as "description only" or "not enough money to pay above the minimum" are not assigned any additional labels, and multiple labels are retained only when a response clearly provides multiple distinct rationales. Appendix Figure

E.10 shows the prompt used in this refinement step. In both stages we use gpt-5.4-mini.

Appendix Figure E.11 reports the share of responses assigned to each label, separately for revolvers who report having overpaid installment debt at the same time ("misallocators") and revolvers who report not having done so ("non-misallocators"). Misallocators are more likely to describe explicit rules of thumb, budgeting heuristics, and a desire to repay debt faster relative to the required minimum. By contrast, references to default risk, asset ownership, and self-control are relatively infrequent in both groups. Mentions of interest costs are similarly common across the two groups overall, but non-misallocators are more likely to compare interest rates across debt products. Non-misallocators are also more likely either to report that they lacked funds to pay above the minimum on any debt or to describe their behavior without providing a rationale.

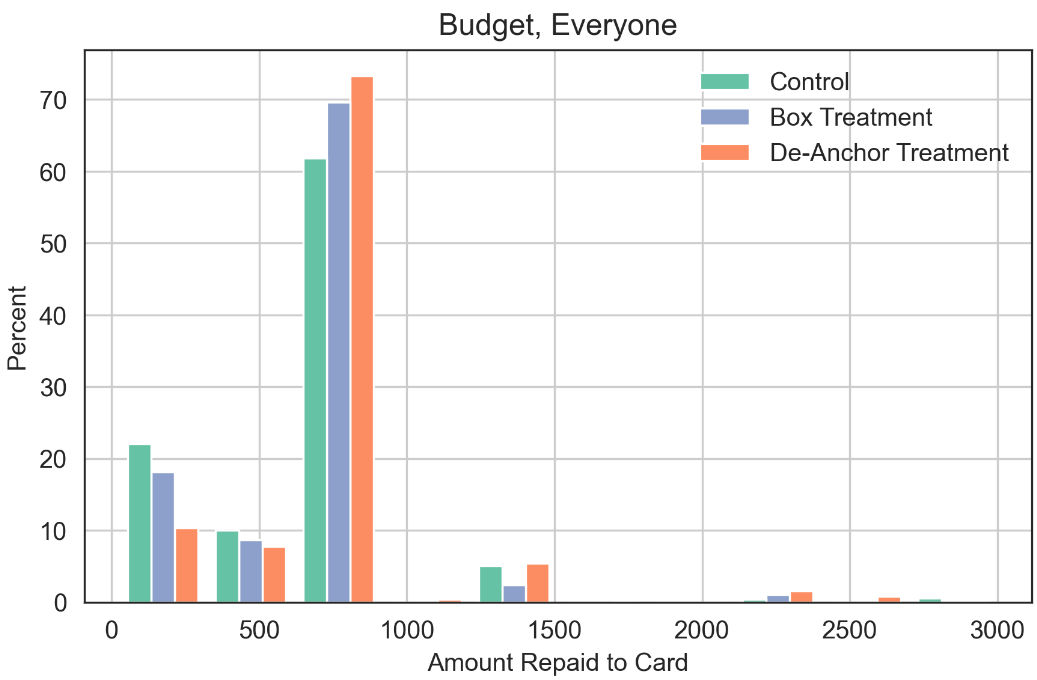
E.1 Survey Figures

Figure E.1: *Response to Survey Experiment Interventions, No Budget Scenario*



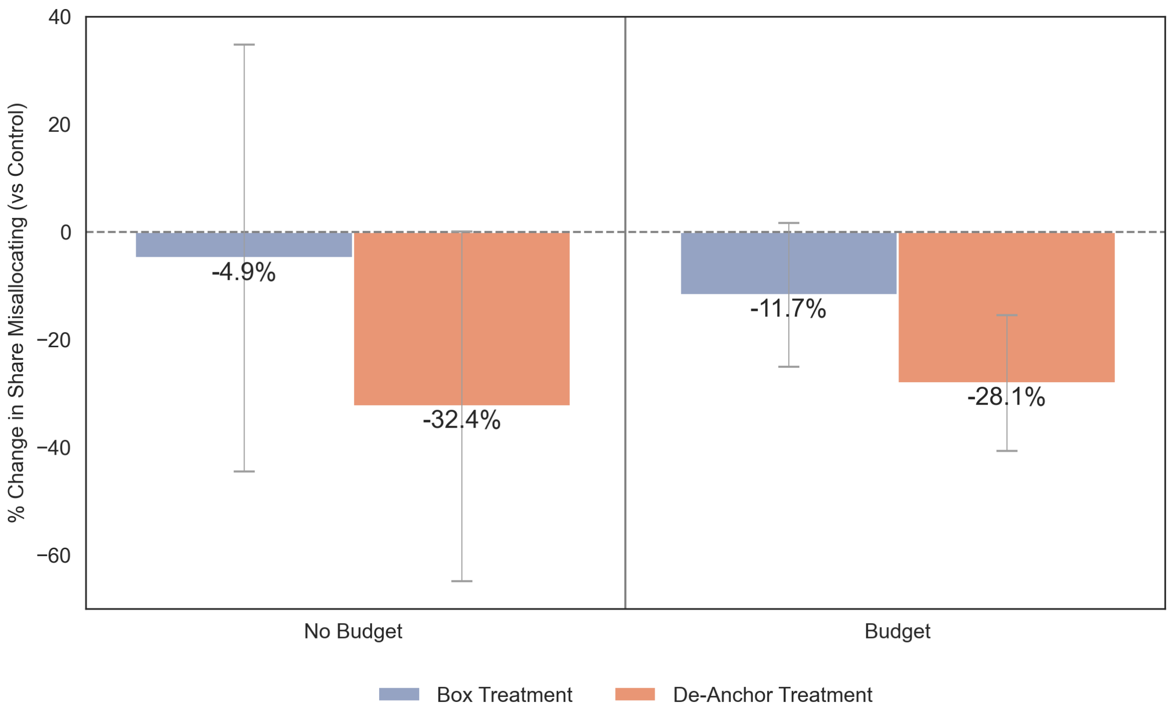
Note: Figure shows the distribution of credit card payments chosen in the survey experiment described in Section 4.2. Appendix Figure E.12 shows the question and treatment arms. The light green bars show repayments for borrowers in our credit bureau data who hold a mortgage (analogous to the survey sample).

Figure E.2: *Response to Survey Experiment Interventions, Budget Scenario*



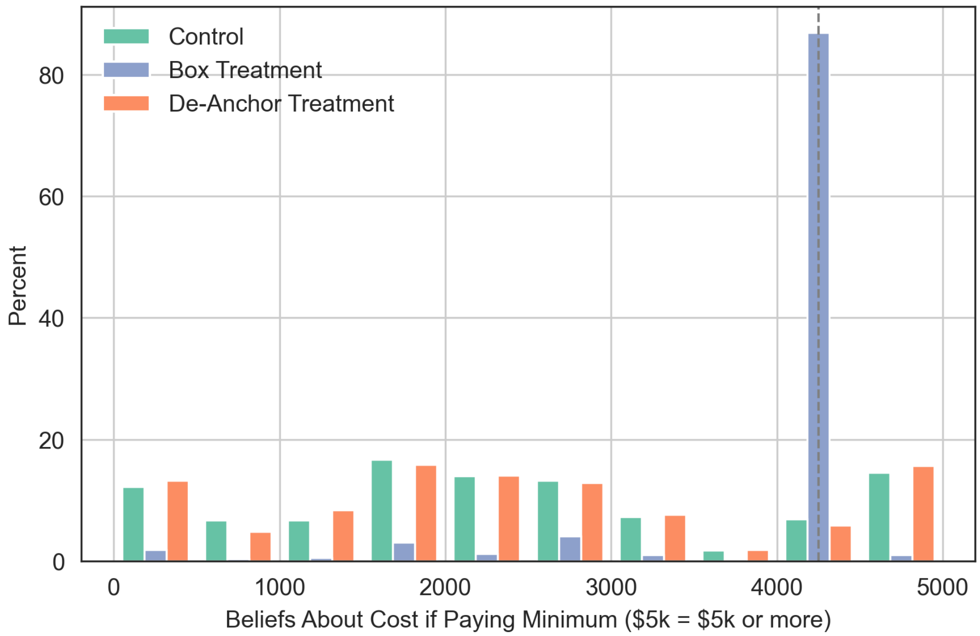
Note: Figure shows the distribution of credit card payments chosen in the survey experiment described in Appendix E, in which respondents were given a fixed budget. Appendix Figure E.13 shows the question and treatment arms. The cost-minimizing payment is \$815. Respondents who chose amounts above \$815 would have incurred a late fee on their mortgage.

Figure E.3: *Experiment Change in Share Misallocating (vs Control)*



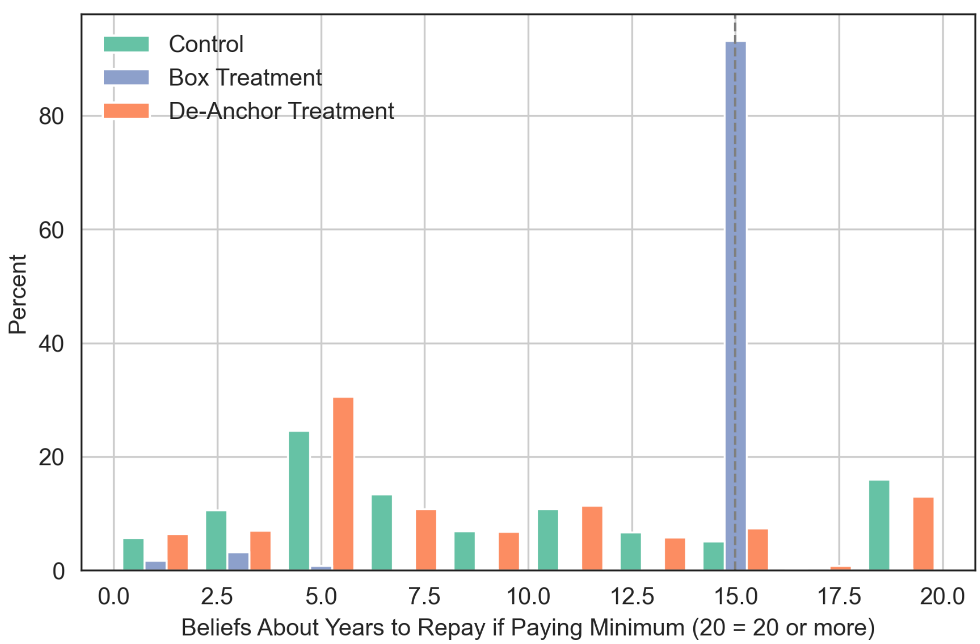
Note: Figure shows responses to the survey experiment in Section 4.2. Bars show percentage changes in misallocation rates, (treatment − control)/control, where a misallocation is overpaying the mortgage without fully paying the credit card. Left and right panels correspond to scenarios in Appendix Figures E.12 and E.13. Error bars show 95% confidence intervals, constructed using the delta method.

Figure E.4: *Estimated Costs of Repaying if Paying Minimum by Treatment Arm*



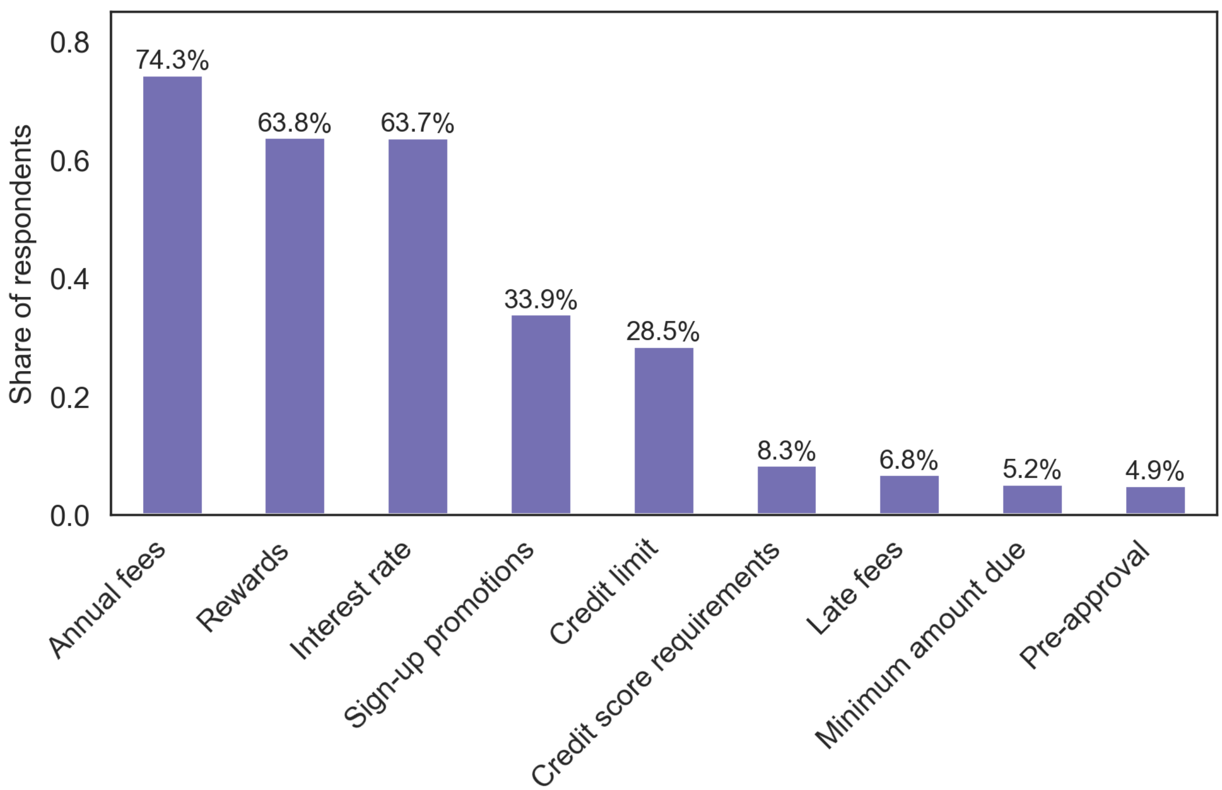
Note: Figure shows the distribution of responses to the survey question "If you paid only the minimum each month and made no additional purchases, how much would you pay in total?" The dashed gray line indicates the correct answer when the minimum payment remains constant at the bill amount ($25). Responses are winsorized at $5,000.

Figure E.5: *Estimated Time to Repay if Paying Minimum by Treatment Arm*



Note: Figure shows the distribution of responses to the survey question "If you paid only the minimum each month and made no additional purchases, how long would it take to fully repay the $1,399 balance?" The dashed gray line indicates the correct answer when the minimum payment remains constant at the bill amount ($25). Responses are winsorized at 20 years.

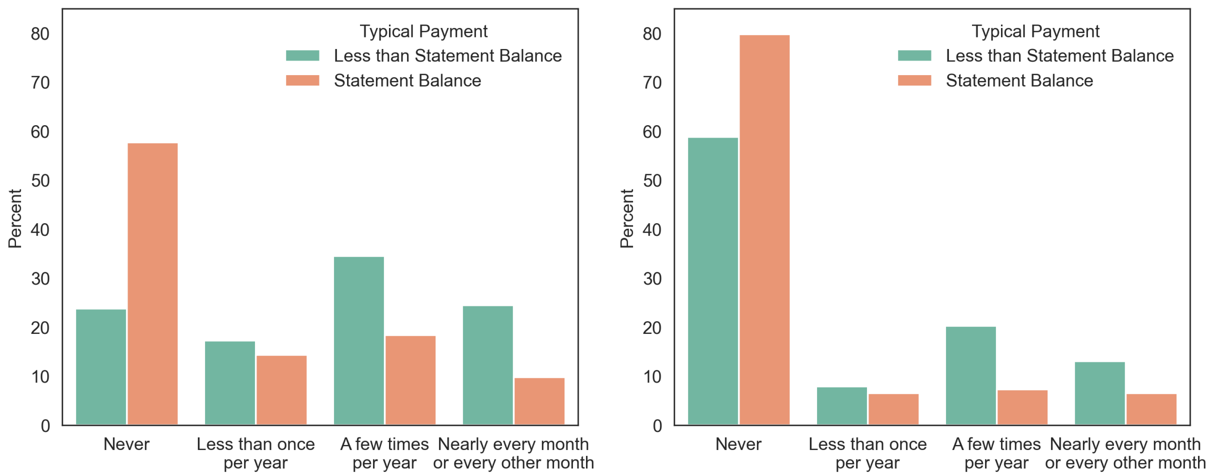
Figure E.6: *Credit Card Features Considered When Applying*



Note: Figure shows responses to the question "When applying for a new credit card, what features of the card do you look at before applying?" Respondents could select up to three most important features.

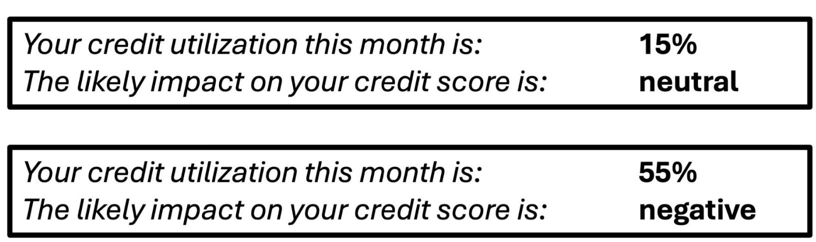
Figure E.7: *Reported Frequency of Using Disclosure Box*

(A) Real Costs of Paying Min Box *(B) Placebo Box*



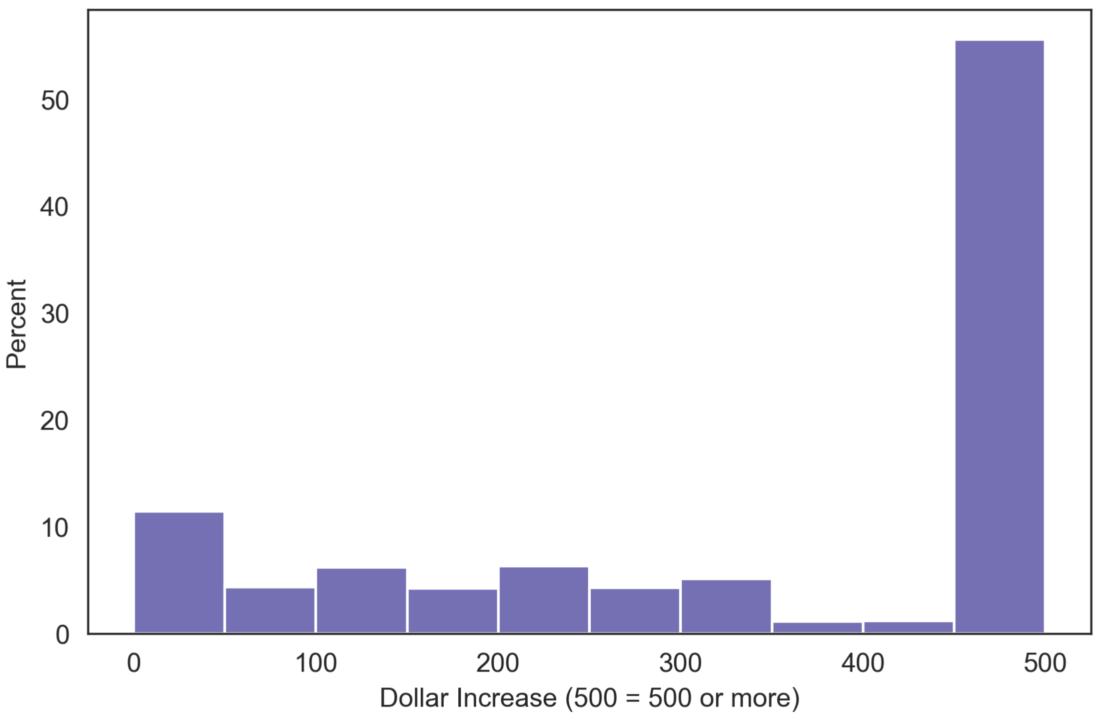
Note: Figure shows responses to the questions "Have you ever seen a box that contains information like this on your own credit card statement before?" and "How often do you read this box before making your credit card repayment?" Respondents who answered "no" to the first question are coded as "Never." Panel (a) shows responses for a disclosure box mandated by the 2009 CARD Act, and panel (b) shows responses for a placebo box. Green and orange bars correspond to respondents who report that they do and do not typically pay less than the statement balance, respectively.

Figure E.8: *Placebo Box*



Note: Figure shows the placebo box used in the analysis whose results are displayed in Figure E.7.

Figure E.9: *Minimum Payment Increase that is Manageable*

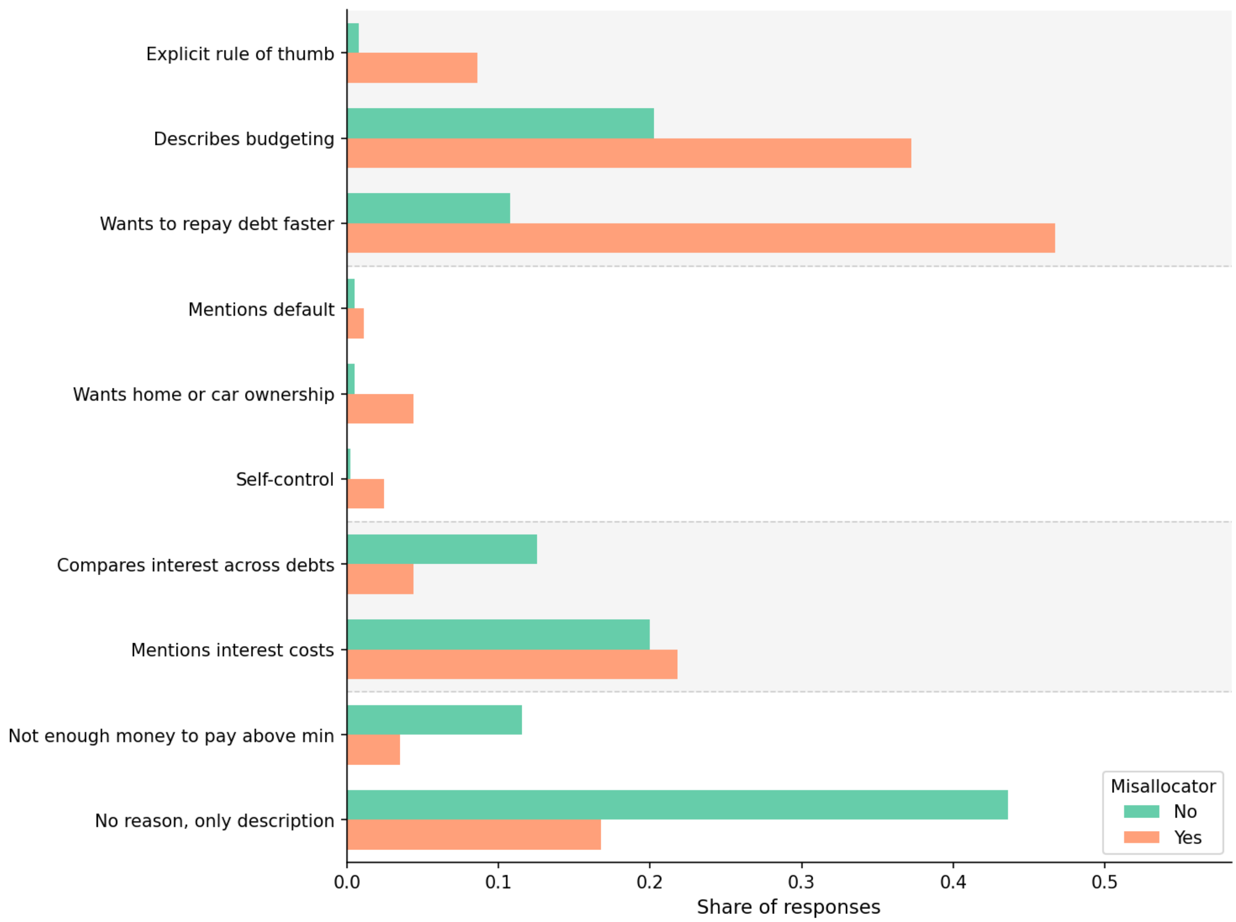


Note: Figure shows responses to the question "Suppose your lender increased the minimum payment on your most used credit card. At what point (if any) would you consider missing a payment?" Respondents could select the option "Any increase under $500 is manageable."

Figure E.10: *Prompt for Open-Ended Survey Response Refinement*

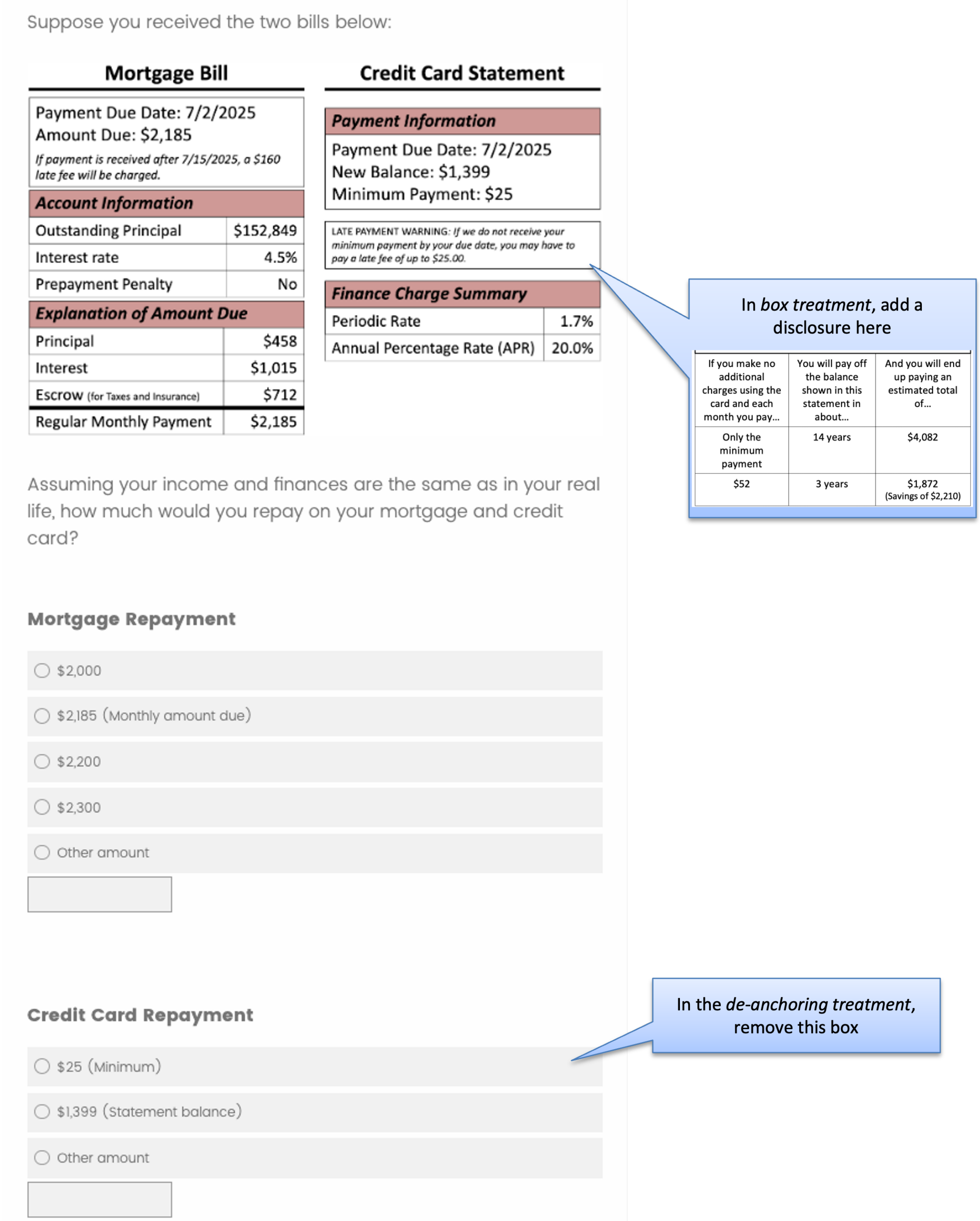
```
You are a research assistant tasked with categorizing survey responses.
You want maximally accurate and parsimonious classifications.

You will receive a batch of survey responses with preliminary labels
(True/False).
The survey question was:
"<question text>"

The label definitions are:
<label definitions; see Table E.3>

For each label currently marked True, determine whether it is applied
correctly; if not, flip it to False.

Rules:
1. If you keep "description_only" True, then ALL other labels MUST be False.
2. If you keep "not_enough_money_to_pay_above_min" True, then ALL other labels
MUST be False.
3. Only keep multiple labels True if the response genuinely gives multiple
distinct reasons.  If it gives one discrete reason, keep only the single best
label.

Respond with ONLY a JSON array of objects (one per row, in order), each
mapping every label name to true or false.  No explanation, no markdown
fences.
```

Figure E.11: *Characteristics of Revolver Responses (Misallocators vs Non-Misallocators)*



Note: Figure shows the share of open-ended survey responses assigned to each label using the LLM-assisted coding procedure, separately for respondents who report overpaying installment debt while revolving credit card debt ("misallocators") and those who do not ("non-misallocators"). The sample is restricted to respondents who report typically revolving credit card debt. Labels are defined in Appendix Table E.3, and responses may be assigned multiple labels.

Figure E.12: *Survey Screenshot: Own Finances Scenario*



Suppose you received the two bills below:

Mortgage Bill

Payment Due Date: 7/2/2025
Amount Due: $2,185
If payment is received after 7/15/2025, a $160 late fee will be charged.

Account Information	
Outstanding Principal	$152,849
Interest rate	4.5%
Prepayment Penalty	No

Explanation of Amount Due	
Principal	$458
Interest	$1,015
Escrow (for Taxes and Insurance)	$712
Regular Monthly Payment	$2,185

Credit Card Statement

Payment Information

Payment Due Date: 7/2/2025
New Balance: $1,399
Minimum Payment: $25

LATE PAYMENT WARNING: *If we do not receive your minimum payment by your due date, you may have to pay a late fee of up to $25.00.*

Finance Charge Summary	
Periodic Rate	1.7%
Annual Percentage Rate (APR)	20.0%

In *box treatment*, add a disclosure here

If you make no additional charges using the card and each month you pay…	You will pay off the balance shown in this statement in about…	And you will end up paying an estimated total of…
Only the minimum payment	14 years	$4,082
$52	3 years	$1,872 (Savings of $2,210)

Assuming your income and finances are the same as in your real life, how much would you repay on your mortgage and credit card?

Mortgage Repayment

- $2,000
- $2,185 (Monthly amount due)
- $2,200
- $2,300
- Other amount

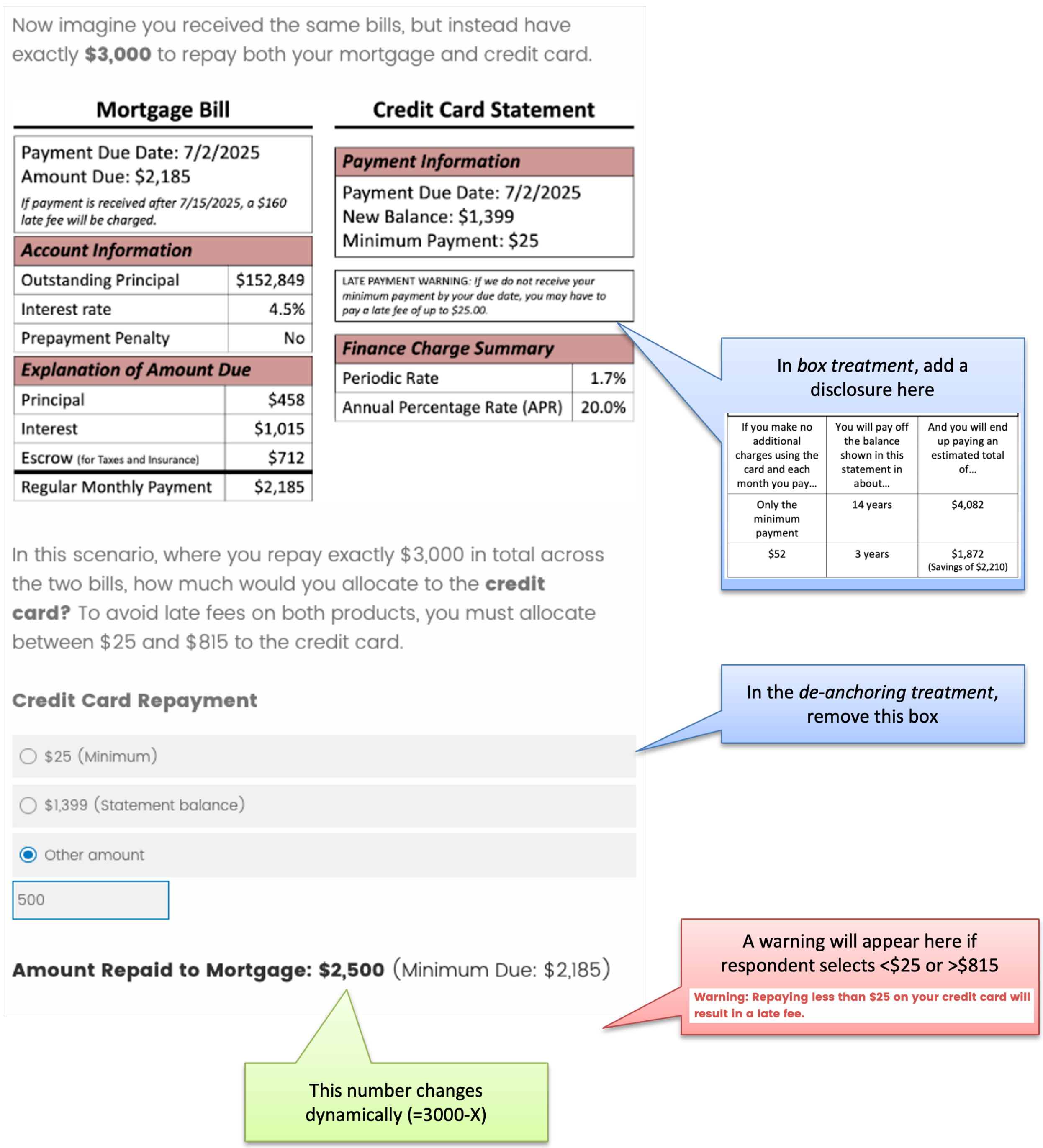
Credit Card Repayment

In the *de-anchoring treatment*, remove this box

- $25 (Minimum)
- $1,399 (Statement balance)
- Other amount

Note: Figure shows screenshot from the "own finances scenario" of the survey experiment described in Section 4.2. Results from this scenario are shown in Figure E.1. Bill amounts are calibrated to roughly match the median mortgage- and credit card–holder in our credit bureau sample.

Figure E.13: *Survey Screenshot: Budget Scenario*



Note: Figure shows screenshot from the "budget scenario" of the survey experiment described in Appendix E. Results from this scenario are shown in Appendix Figure E.2. Bill amounts are calibrated to roughly match the median mortgage- and credit card–holder in our credit bureau sample.

E.2 Survey Tables

Table E.1: *Survey Experiment: All Results*

Question	Control	Box	De-Anchor
No Budget			
Share Paying CC Min (%)	23.43	19.02	10.18
Share Paying CC Full Bal (%)	42.32	46.52	55.89
Share Paying > Mortgage Min (%)	18.90	15.79	17.56
Share Making Any Excess Pymnt (%)	77.95	81.66	89.62
Share w/ Misallocation (%)	7.68	7.30	5.19
Share w/ Misallocation >$25 (%)	1.97	2.38	2.00
Share of Excess Repayers w/ Misallocation (%)	9.85	8.94	5.79
Share of Excess Repayers w/ Misallocation >$25 (%)	2.53	2.91	2.23
Avg Misallocation Size, Cond Misallocation ($)	51.00	56.49	53.46
Budget			
Share Paying CC Min (%)	14.56	11.52	4.16
Share w/ Misallocation (%)	44.94	38.65	33.04
Share w/ Misallocation >$25 (%)	36.92	31.38	24.73
Avg Misallocation Size, Cond Misallocation ($)	476.55	446.52	345.55
Costs			
Share Underestimate Time to Repay by >10%	0.76	0.06	0.75
Share Underestimate Cost to Repay by >10%	0.78	0.12	0.77
Median Est Time to Repay (Yrs)	7.00	14.00	6.92
Median Est Cost to Repay ($)	2100.00	4082.00	2060.00

Note: Table shows all outcomes from the survey experiment described in Section 4.2 and Appendix E. In the budget scenario, responses are limited to those who paid at least the minimum on both their credit card and mortgage and would therefore have avoided late fees. Including these responses does not substantially change our results (see Appendix Figure E.2).

Table E.2: *Survey Experiment: All Results in Regression*

Question	Box	De-Anchor
No Budget		
Share Paying CC Min (%)	-0.027 (0.022)	-0.115*** (0.021)
Share Paying CC Full Bal (%)	0.031 (0.026)	0.120*** (0.027)
Share Paying > Mortgage Min (%)	-0.032 (0.023)	-0.012 (0.024)
Share Making Any Excess Pymnt (%)	0.021 (0.022)	0.099*** (0.021)
Share w/ Misallocation (%)	-0.004 (0.016)	-0.023 (0.015)
Share w/ Misallocation >$25 (%)	0.003 (0.011)	-0.003 (0.011)
Share of Excess Repayers w/ Misallocation (%)	-0.009 (0.020)	-0.038* (0.019)
Share of Excess Repayers w/ Misallocation >$25 (%)	0.003 (0.011)	-0.003 (0.011)
Avg Misallocation Size, Cond Misallocation ($)	-3.996 (17.338)	0.244 (21.355)
Budget		
Share Paying CC Min (%)	-0.017 (0.020)	-0.091*** (0.018)
Share w/ Misallocation (%)	-0.044 (0.029)	-0.100** (0.030)
Share w/ Misallocation >$25 (%)	-0.041 (0.028)	-0.106*** (0.029)
Avg Misallocation Size, Cond Misallocation ($)	-29.457 (29.829)	-122.516*** (31.621)
Costs		
Share Underestimate Time to Repay by >10%	-0.687*** (0.022)	-0.005 (0.027)
Share Underestimate Cost to Repay by >10%	-0.654*** (0.023)	0.000 (0.026)
Est Time to Repay (Yrs)	3.464*** (0.376)	-0.415 (0.494)
Est Cost to Repay ($)	1264.325*** (89.945)	-1.494 (116.726)

Note: Table shows regression coefficients corresponding to the rows in Table E.1. The "Box" and "De-Anchor" columns show coefficients for those treatment arms relative to the control group. Standard errors are in parentheses. Estimated time and cost of repaying the minimum are winsorized at the 95th percentile. All regressions include fixed effects for the categories of income, education, age, and credit score in Table E.4. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table E.3: *Labels for Open-Ended Survey Responses*

Label	Description
`explicit_rules_of_thumb`	The response mentions rules of thumb such as rounding up payments, doubling the payment, adding a fixed extra dollar amount each month, or making a round payment (e.g., "I round up to the nearest $100," "I always add $50 extra," "I pay bi-monthly," "I pay $100," "I make two extra payments per year," "I paid $20 more," "I triple my payment").

Continued on next page

Table E.3 continued from previous page

Label	Description
`budgeting`	The response includes evidence of strategies for managing debt payments, including the allocation of money across competing categories or obligations. This includes mentioning cash flow constraints, directing extra cash strategically across categories, or statements about heuristics or budget rules. Examples: "when I have extra cash I put it toward X" or "it depends on my other bills that month."
`repay_faster`	The response indicates the borrower is motivated by reducing balances by a greater amount, getting balances to zero more quickly, or paying down debt faster. This includes statements about paying off debt or loans "quicker," "earlier," "asap," "sooner," or with other references to the speed of repayment.
`mentions_default`	The response mentions default, being worried about defaulting on a debt, fear of foreclosure, homelessness, repossession, or losing an asset due to non-payment.
`mentions_ownership`	The response expresses a desire for home or car ownership, wanting to own an asset outright, or be free of the associated loan. This includes *implicit* references to ownership such as "having a roof over our heads," "I want my house paid for," "trying to pay off the house," or "I wanted to own my car." The key is that the respondent frames the debt in terms of the asset they want to possess or keep, not just the debt itself.
`self_control`	The response suggests the respondent overpays their installment debts (e.g., mortgage) because if they didn't, they would spend the money on other things—i.e., using debt payments as a self-control or commitment device.

Continued on next page

Table E.3 continued from previous page

Label	Description
`compares_interest_across_debts`	The response compares interest rates across *different* types of debts (e.g., credit card interest vs. mortgage interest, credit card rates vs. auto loan rates). Simply mentioning interest costs generally does not count, but statements such as "credit interest is higher" or "paying more on the house is dumb because the interest rate is lower" do count. Other examples: "I want to pay off the credit card first because of the high interest" or "we pay the mortgage slowly because of the lower interest rate."
`mentions_interest_costs`	The response mentions interest (interest rates, interest payments, interest costs, APR, etc.) or minimizing borrowing costs in any way (e.g., "I want to reduce interest").
`not_enough_money_to_pay_above_min`	The response indicates the respondent does not have enough money to pay more than the required monthly payment on any of their debts. Examples: "We can't afford to pay more on any of our debts"; "I have not had extra money to put towards paying more than the required monthly payment"; "Like I said earlier, we live paycheck to paycheck, so huge bills barely get covered, let alone extra." Responses in this category are *not* coded into any of the categories above.
`description_only`	The response describes what the respondent did but gives no reason or explanation for why—it simply restates the behavior without any rationale. Short answers are often description-only, but longer restatements of the behavior also count. Examples: "I just have done that"; "i have not"; "I have never paid over my mortgage"; "I occasionally pay less on the credit card and carry a balance"; "I usually pay the minimum on my loans"; "If I make an extra payment, it's only my credit cards"; "I always pay the required payments, not more." Responses in this category are *not* coded into any of the categories above.

Table E.4: *Survey Respondent Demographics*

Category	Proportion
Age Bucket	
18–29	0.08
30–39	0.29
40–49	0.28
50–59	0.22
60+	0.13
Sex	
Female	0.59
Male	0.41
Ethnicity	
Asian	0.05
Black	0.08
Mixed	0.05
White	0.80
Other	0.02
Credit Score	
< 600	0.05
600 - 659	0.08
660 - 699	0.11
700 - 739	0.20
740+	0.55
Unsure	0.01
Education	
No high school degree	0.00
High school degree/GED	0.05
Some college	0.13
2-year college degree	0.10
4-year college degree	0.43
Master's degree, MBA	0.23
PhD, JD, MD	0.06
Income	
\$0 - \$24,999	0.02
\$25,000 - \$49,999	0.08
\$50,000 - \$74,999	0.17
\$75,000 - \$99,999	0.19
\$100,000 - \$149,999	0.30
\$150,000+	0.24

Note: Table shows the demographics of respondents in the survey described in Appendix E. N=1,598.

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