The Supply Side of Consumer Debt Repayment*

Justin Katz† Dominic Russel‡ Claire Shi§

November 7, 2024

Abstract

Minimum payments on credit card debt allow consumers to repay slowly: despite being unsecured, the average $7,000 balance generally amortizes in over 20 years. We study how lenders choose these minimum payments and the impacts of these choices on equilibrium consumer debt outcomes. When short-term illiquidity makes many borrowers unable to make higher payments, lenders set low minimums to limit default costs. Alternatively, if many borrowers make near-minimum payments for reasons besides illiquidity (e.g., due to anchoring), lenders set low minimums to generate interest revenue. To separate these two forces, we use payment-level data from a credit bureau to document a new fact about intra-temporal debt repayment. Consumers often revolve high-interest credit card debt while making excess payments on low-interest installment debt, providing evidence that low payments aren't solely liquidity-driven. We use this fact to estimate an empirical model that predicts realistically low lender minimums. The model suggests that without anchoring, minimums would be over twice as high for most borrowers. Lenders amplify consumer biases, accounting for 20% of the total increase in credit card debt and 85% of defaults from anchoring in our model.

*We are especially grateful to John Campbell, Raj Chetty, Mark Egan, Toren Fronsdal, Xavier Gabaix, Ed Glaeser, Sam Hanson, Nathan Hendren, Larry Katz, David Laibson, Pascal Noel, Joshua Schwartzstein, Jesse Shapiro, Andrei Shleifer, Emil Siriwardane, Jeremy Stein, Adi Sunderam, and Joseph Vavra for helpful comments and feedback. Human subjects approval was given by Harvard IRB (Protocol 23-1538).

†Harvard University: jkatz@g.harvard.edu

‡Harvard University: drussel@g.harvard.edu

§Harvard University: cshi@g.harvard.edu

1 Introduction

Roughly half of American households carry high-interest credit card debt from month to month (FRB, 2024). Although credit cards are unsecured, lenders generally allow borrowers to make small monthly payments on these debts. Under a typical contract, the average revolving balance of \$7,000[1] would amortize in 20 years if the borrower makes only the minimum payment. While low minimums may provide short-term financial flexibility, critics argue that they are primarily intended to slow repayments and generate interest revenue, increasing debt balances and household risk (see, e.g., Tescher and Stone, 2022).

In this paper, we study the incentives driving lenders' choice of monthly minimum credit card payments and analyze how these incentives affect consumer debt outcomes. This supply-side focus allows us to understand a mechanism through which optimizing lenders *amplify* consumer biases, helping explain why even behavioral models with demand-side biases struggle to fully explain US credit card debt levels.[2]

We begin with a motivating framework that illustrates the forces that shape lenders' decisions. Optimal required payments are low when many borrowers are illiquid and unable to make higher payments today, or when many borrowers make minimum or near-minimum payments independent of liquidity (e.g., due to anchoring). Intuitively, low minimums may reduce lender costs by preventing illiquidity-driven defaults or increase interest revenue by slowing repayments from liquid, behavioral borrowers. However, low minimums may also increase losses from borrowers who become insolvent and default on larger debts, potentially leading lenders to set higher minimums in equilibrium.

We next provide evidence that illiquidity or anchoring-like behaviors drive lenders to set low minimums for much of the credit score distribution. Minimums are set by formulas that increase in balances, leading to a convex amortization different from other US consumer debts. Using a monthly, tradeline-level panel from a major credit bureau with actual payments for one million US consumers, we document four key facts: (1) many borrowers pay close to the minimum, with two-thirds of those revolving debt paying within \$100 of the minimum; (2) lenders often set minimums near the lowest regulatory allowable, with minimum-paying borrowers repaying only 1% of their balance plus interest and fees; (3) for the lowest credit score borrowers, minimums are higher, with requirements to pay back as much as 5% to 7% of balances each month; and (4) minimum payment formula "floors" appear to be a response to regulations that cap late fees at the minimum.

[1]The average balance for households carrying credit card debt in the 2019 Survey of Consumer Finances (SCF) is \$7,270. The SCF has been shown to underreport revolving credit card debt levels (see Zinman, 2009), and larger balances would imply even longer durations.

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

Our rich data allows us to show that illiquidity cannot fully explain equilibrium minimum outcomes. We do so by documenting how consumers repay debts *intra*-temporally—across debts in a given month. First, we show that borrowers frequently "curtail" installment debts with small overpayments, reducing their loan duration and total interest paid. For example, 23% of mortgage months include a payment of $25 or more than their required payment. We then show that *even borrowers who carry high-APR credit card debts* frequently have the liquidity to make overpayments on lower-APR installment debts. In months when mortgage borrowers also revolve high-APR credit card debt, they make mortgage overpayments of $25 or more 21% of the time. These repayment patterns fail to minimize debt repayment costs, suggesting borrowers often have the liquidity to make larger credit card repayments.[3]

While the fact that borrowers fail to focus liquidity on high-APR credit cards is enough to separate rationales for lenders' choice of low minimum payments, we also briefly explore the mechanisms for these behaviors. We show that even while overpaying installment debts, borrowers make payments near the minimum at round dollar amounts. In a pilot survey, borrowers also frequently report repayment strategies relative to minimums.[4] Consistent with several existing studies (e.g., Stewart, 2009; Keys and Wang, 2019; Medina and Negrin, 2022), our results suggest anchoring may play a substantial role in debt repayment.

How do these borrower behaviors shape equilibrium debt outcomes? Following Gathergood *et al.* (2019b), we first provide back-of-the-envelope estimates from a simple partial equilibrium "steady-state" counterfactual. Among all borrowers with revolving credit card debt and any installment debt, revolving debt in the counterfactual would fall by $1,765 on average and $4,726 at the 90th percentile. For a ten percentage point APR differential between debts, this implies annualized interest savings of $177 and $473, respectively. There are many limitations to this analysis, including the absence of a reoptimizing supply side.

To better understand the implications of anchoring-like repayment behaviors on both the demand and supply side of consumer debt markets, we use our credit bureau data to estimate an empirical model of credit card borrowers and lenders. In the model, low credit card payments may be either due to borrower income or anchoring, where borrowers are behaviorally influenced by minimums regardless of income. We identify anchoring with the frequency and magnitude of intra-temporal mistakes. Crucially, because our identification strategy relies on failures to cost-minimize, we avoid taking a normative stance on whether behavioral frictions affect consumers' allocation between consumption and debt repayment.[5]

[3]The findings we document are stronger than the co-holding puzzle (Gathergood and Weber, 2014) in the sense that we are not looking at allocation across savings versus debt, but rather within debt accounts.

[4]For example, "I usually try to pay a little more than the minimum". Appendix E provides more examples.

[5]We view this as an important advantage of our approach, since it is challenging to take a normative stance on how consumers trade dollars and utils. If this tradeoff is made sub-optimally, e.g. due to present

Our model closely fits untargeted moments such as the distribution of credit card excess payments, spending, and utilization. Model-implied optimal minimums are also close to those we observe empirically, suggesting the model captures lenders' primary incentives.

Our empirical model allows us to conduct counterfactuals that answer two important questions. First, how different would minimum payments be without anchoring? Second, how does anchoring, combined with lenders' incentives to generate interest revenue, shape revolving debt levels and defaults?

Our first set of counterfactuals shows that anchoring helps generate realistically low credit card minimums. When borrowers are unanchored, changes in minimums only impact payments for consumers paying close to the minimum. These borrowers are at a high risk of default and are unlikely to generate significant future interest revenue. When borrowers become anchored, changes in minimums impact payments for anchored consumers as well, who are not close to default. This increases marginal revenue from lowering minimums since it increases balances, and hence interest revenue, for consumers who are not close to default. Lenders therefore decrease minimums in response to borrower anchoring, causing borrowers to revolve higher balances. For borrowers in the middle to top of the credit score distribution, our model suggests that conditional on balance, minimums would be at least three times higher without anchoring. In the top credit score bin, a borrower at the credit limit would have a minimum of \$330 instead of \$100. Paying only the minimum would fully amortize their debt in 9 years instead of 23 years. For lower credit score borrowers, where existing minimums are already higher, the increase is smaller.

In our second set of counterfactuals, we estimate how much anchoring increases total debt and default. We first estimate the "demand-side" effect of anchoring on credit card debt, holding minimums fixed. We then estimate the "supply-side" response to anchoring by allowing the lender to re-optimize the minimum payment formula. Anchoring increases revolving debt levels by 24%. Of this increase, 80% is demand-driven and 20% is driven by the supply-side response. Anchoring increases defaults by 5%, with over 85% of this effect coming from supply-side response rather than demand-side behaviors. Default effects are larger for higher credit score bins where baseline defaults are lower: for borrowers with credit scores between 700-739 defaults increase by 15%, almost entirely driven by supply-side amplification. Our results show the importance of incorporating an optimizing supply side into models that seek to explain demand-side consumer debt outcomes.

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

focus misaligned with long-run preferences, our estimates may provide a lower bound on the effect of biases.

on cross-debt repayment behaviors and documents new debt repayment mistakes. Section 5 introduces the empirical model and Section 6 contains counterfactuals. Section 7 concludes.

Relevant Literature Our work relates to several papers which document some form of behavioral debt repayment; for example, anchoring or targeting minimums (e.g., Argyle *et al.*, 2020; Bartels *et al.*, 2023; Guttman-Kenney *et al.*, 2023; Keys and Wang, 2019; Medina and Negrin, 2022; Stewart, 2009), not prioritizing or over-borrowing on the higher APR product (e.g., Avery and Turner, 2012; Gathergood *et al.*, 2019b; Katz, 2023; Ponce *et al.*, 2017), and borrowers being inattentive to fees, impatient, or having biased beliefs about repayment (for one overview, see Zinman, 2014). Even with behavioral biases, models consistently underestimate the amount of credit card debt Zinman (2015). A key innovation of our paper is that an optimizing supply side, when faced with behavioral borrowers, can amplify the total amount of debt in equilibrium.

We also extend the behavioral contract design literature by studying anchoring and its impact on minimums. Heidhues and Kőszegi (2010) show that when borrowers are present-focused, optimal credit card contracts are front-loaded (meant to be repaid quickly) but have high fees when overly optimistic borrowers fall behind. Importantly, we bring our model to the data, corroborating empirical work that uses natural experiments to analyze the impact of one-off changes to required minimum payments in other contexts (Allen *et al.*, 2024; Castellanos *et al.*, 2018). To estimate anchoring, we build off work on the amortization of debt and borrowers choosing to make (small) mortgage curtailments (Amromin *et al.*, 2007; Bernstein and Koudijs, 2024; Liebersohn *et al.*, 2024; Xu, 2023). Similar to Einav *et al.* (2012), we study contracting in a consumer credit market by solving for the optimal response to a set of linear policy functions on the demand side.

Finally, less attention has been focused on the lenders' choice of optimal minimum payments relative to other contract features such as APRs (e.g., Nelson, 2017), credit limits (e.g., Agarwal *et al.*, 2018), and fees (e.g., Agarwal *et al.*, 2015). Our notion that the supply side can amplify the total amount of debt in equilibrium relates to others who study how lenders influence borrowing decisions, either through targeting behavioral borrowers (Ru and Schoar, 2023) or non-price channels such as advice (Foà *et al.*, 2019).

2 Motivating Framework

This section presents a framework to illustrate the forces that shape lenders' choice of required minimum payments on revolving debt. The framework shows low minimums are optimal when many borrowers are illiquid, unable to make higher payments today, or when many borrowers' repayments are sensitive to the minimum and uncorrelated with default. We use the framework to structure our analysis.

Setup. Consider a lender that offers a revolving debt contract that allows borrowing at gross interest rate R. In period $t = 0$, the lender sets a minimum payment schedule as a function of balances B_t outstanding at the start of period t: $m_t = m(B_t)$. In each period, the consumer defaults with probability χ_t. Conditional on no default, balances evolve based on new borrower spending s_t and repayments p_t:

$$B_{t+1} = RB_t - p_t + s_t$$

Current balances affect new spending $s_t = s(B_t)$. Current balances and minimum payments affect debt repayment, $p_t = p(B_t, m_t)$, and default, $\chi_t = \chi(B_t, m_t)$. Default probability depends on minimums because some borrowers may lack the liquid resources necessary to make minimum payments. We refer minimum-driven defaults as "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. We refer to balance-driven defaults as "insolvency defaults." After default, $p_t, s_t = 0$.

Lender's Problem. The lender discounts at their cost of capital $\delta \equiv \frac{1}{R_l}$, and sets a schedule of minimum payments as a function of balances, $m(B)$, to maximize the present value of profits:

$$\Pi(B_0) \equiv \max_m \; E_0 \sum_{t=0}^{\infty} \delta^t (p_t - s_t)$$

The optimal schedule for minimum payments satisfies the Bellman equation:

$$\Pi(B_t) = \max_m \,(1 - \chi_t)\,(p_t - s_t + \delta\,[\Pi(B_{t+1})]) \quad \text{s.t.} \quad B_{t+1} = RB_t + s_t - p_t$$

In Appendix A.1 we show an interior solution satisfies the following (we omit time subscripts):

$$\underbrace{(1-\chi)\frac{\partial p}{\partial m}}_{\uparrow \text{ Curr Payment}} - \underbrace{\frac{\partial \chi}{\partial m}\tilde{\Pi}(B)}_{\uparrow \text{ Illiquid Default}} = \delta(1-\chi)\frac{\partial p}{\partial m}\left[\underbrace{\frac{\partial \tilde{\Pi}(B_{+1})}{\partial B_{+1}}(1-\chi_{+1})}_{\downarrow \text{ Net Interest Revenue}} - \underbrace{\frac{\partial \chi_{+1}}{\partial B_{+1}}\tilde{\Pi}(B_{+1})}_{\downarrow \text{ Insolvency Default}}\right] \tag{1}$$

where $\tilde{\Pi}(B_t) \equiv p_t - s_t + \delta\Pi(B_{t+1})$ is lender profit conditional on no default in t.

Equation 1 is an Euler equation, equating marginal effects on current and future profits. The left-hand side shows how changes in the minimums affect profits today. The first term, $\frac{\partial p}{\partial m} \geq 0$, shows the effect on current payment. It is positive, capturing that borrowers who would have liked to pay less than the new minimum increase their payments to avoid default, or that borrowers are behaviorally anchored to the minimum. The second term, $\frac{\partial \chi}{\partial m} \geq 0$, captures the direct effect of higher minimums on illiquidity defaults by consumers with insufficient short-run liquid resources to meet minimum payments.

The right-hand side shows how changes in the minimums affect future profits. The first term captures that higher minimums increase repayment, reducing balances and the net interest revenue that balances generate in the future. The second term captures that higher minimums reduce balances, reducing future costs due to insolvency defaults.

Framework Implications. The framework highlights a central tradeoff for the lender: increasing minimums increases revenue from payments today and decreases costs from defaults in the future, but also decreases potential future interest revenue and increases costs from illiquidity-driven defaults. An optimizing lender will set low minimums when the latter two forces—the second and third terms in equation 1—dominate.

This tradeoff shows two explanations consistent with low required minimums on the supply side and large debt balances on the demand side. First, consumers might borrow because they are liquidity-constrained, making small payments today in response to short- and medium-term shocks. Lenders would set low minimums to allow them to borrow, avoiding higher minimums to prevent illiquidity defaults. Second, consumers might borrow because of behavioral frictions that lead them to make small repayments responsive to minimums and not strongly correlated with default risk. Lenders would set low minimums to amplify these behaviors and generate interest revenue.

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. Additionally, under US regulations minimum payments limit the size of the fee a lender can charge. Both forces theoretically push minimums higher for low balances.

The remainder of the paper explores the forces in our framework. In Section 3, we provide evidence on the determinants of minimum credit card payments, showing the equilibrium outcomes of the framework's forces. In Section 4, we document new facts on households' intra-temporal debt repayments to understand how borrower behaviors and liquidity shape these outcomes. Behaviors that make borrowers responsive to minimum (e.g., anchoring) have the potential to not only affect $\frac{\partial p}{\partial m}$, but also $\frac{\partial \tilde{\pi}(B)}{\partial B}$ and $\frac{\partial \chi}{\partial B}$, because, for example, anchoring leads high-liquidity borrowers to have higher balances in the long-run. To understand these dynamic forces, in Sections 5 and 6 of the paper we estimate an empirical model and simulate counterfactuals. We show how credit card minimums would adjust without anchoring behaviors, and use our estimates to understand how lender responses to borrower behaviors affect debt levels and defaults.

3 Background and Evidence on Minimum Payments

3.1 Overview of Credit Card Minimum Payments and Regulations

Credit card minimum payments determine the minimum amount a borrower is required to pay in a particular month to avoid late fees. Additionally, if the borrower misses a minimum and does not repay in 30 days, a delinquency is reported on their credit report, potentially limiting their access to credit, housing, and employment. Borrowers who pay any amount less than the total balance on their credit card—generally substantially larger than the minimum—generate interest on their unpaid balances that must be paid in later months.

Law & Regulations. US law and regulatory guidance affect minimum payments in two direct ways.[6] First, financial regulators have provided guidance that credit card minimums should not cause negative amortization and, in general, should lead to amortization over a "reasonable period of time."[7] Regardless of their supervisor, lenders have set minimums to avoid negative amortization in response.[8] Second, the late fees lenders charge for missing a minimum can be no larger than the minimum itself.[9]

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). In principle, lenders can set any schedule that they choose, subject to the regulations above. In practice, in the contracts database, we find that all of 25 large credit card issuers 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-

[6] In addition to direct regulations, the 2009 CARD Act required monthly credit card statements to display the cost of making minimum payments compared to the cost of paying off the balance within 36 months to nudge consumers away from the minimum. Agarwal *et al.* (2015) find evidence this led to a small increase in borrowers making the 36-month payment value, but no evidence it led to a change in overall repayment.

[7] See FRB (2003), OCC (2003), and OCC (2005) as well as the OCC and FDIC handbooks for examiners.

[8] See, for example, discussion in Guttman-Kenney and Shahidinejad (2023).

[9] See the OCC discussion of 12 CFR § 1026 (Regulation Z), here

implied minimum is less than the floor.[10] The most common formula is:

$$\text{Minimum}_t = \max\{\mu, \theta \cdot \text{Balance}_t + \text{Interest}_t + \text{Fees}_t\} \tag{2}$$

where Balance_t is the statement balance at the end of month t, Interest_t is the one-month interest on that balance, and Fees_t are the fees the borrower owes (e.g., from missing a prior payment).[11] Because the formula explicitly includes any interest and fees generated, it prevents negative amortization.[12] Generally, minimum payment formulas do not change over time within account or with borrower behavior.

The prevailing minimum payment formula slows the path of required payments as balances decrease. Figure 1 provides an illustrative example using a debt of $10,000 and an APR of 20%. The red line in the figure shows the amortization schedule a loan with fixed payments over seven years, typical of the longest personal loans in the US. The concave amortization schedule contrasts with the credit card in blue and green, in which required payments drop causing convex amortization.

3.2 Data and Summary Statistics

Our primary data source is monthly tradeline-level information on a panel of US consumers from a major credit bureau. Importantly, the data includes information on actual payments, which allows us to measure revolving credit card balances, unlike traditional credit bureau data. The data also enables us to link an individual's repayment behavior across all their debts, unlike bank supervision data or data from a single financial institution. These two features help us to disentangle the forces in the motivating framework.

Our data covers a random sample of one million individuals from 2013 to 2022 and includes monthly tradeline-level information on balances, minimum payments, and actual payments made. We focus on general purpose credit cards and the three other largest sources of US household debt: mortgage, student, and auto loans (NY Fed, 2023).[13]

We build a sample of consumers who had a positive statement balance on at least one open credit card in 2017 or 2018.[14] Table 1 summarizes all such consumer-months over this

[10] Our notation follows Guttman-Kenney and Shahidinejad (2023) who use the minimum payment formula to estimate financing charges.

[11] If balances are so low as to fall below the floor, the minimum payment is set to the balance. For ease of exposition, we ignore these small balance months in our notation.

[12] Some lenders use the max of μ and $\theta \cdot \text{Balance}_t$, with θ high enough to also avoid negative amortization.

[13] We generally exclude private label cards which are only able to be used at one merchant. These cards make up around 6% of total credit card purchase volume (CFPB, 2023a).

[14] We focus on these years to avoid the effects of COVID-related stimulus. In 2022, 82% of US adults had at least one credit card (GAO, 2023).

period. Appendix B.1 provides more detail on our outcome measures. The table shows that the median credit card holder has four open tradelines across two different debt types and nearly $20,000 in total debts.

Much of our analysis involves studying credit card debt that is carried, or "revolved", between months. Calculating revolving credit card debt requires observing actual payment information, reported by only a subset of credit card providers (CFPB, 2020; CFPB, 2023b). We observe actual payments for 35% 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.[15] Our baseline sample, summarized in Table 2, restricts to tradeline-months for which we can observe payments and consumer-months for which there is at least one such credit card. This reduces the sample of consumer-months from 13 million to 6.3 million.[16]

In our baseline sample, we construct a measure of revolving balances by subtracting actual payments made in a month from the credit card statement balance in the prior month.[17] Consumers revolve balances in 65% of our sample months.[18] The median monthly minimum and actual credit card payments are $51 and $250, respectively.

3.3 Empirical Evidence on Minimum Payments

We analyze US credit card repayments and required minimums using our credit bureau data. We summarize our findings in four key facts.

Fact 1: Many borrowers pay close to the minimum. Figure 2 plots the distribution of credit card repayments. The distribution is U-shaped, with one group of borrowers 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 52% are within $50 of the minimum. Such a pattern is consistent with borrowers being liquidity-constrained or borrowers behaviorally using the minimum in their repayment choice (i.e., "anchoring").

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 payments increase with balances,

[15]These estimates are similar to CFPB (2020) and Guttman-Kenney and Shahidinejad (2023).

[16]In Appendix Table B.1 we compare the credit card tradelines for which we can and cannot see actual payments. Those with actual payments have slightly higher credit scores and monthly statement balances on average; however, each group includes cardholders across the full credit score distribution.

[17]As described in Appendix B.1 We do this because credit cards typically allow a grace-period for borrowers to repay their statement balance from the end of the billing period.

[18]This magnitude is similar to Grodzicki and Koulayev (2019) who find that, at the card level, two-thirds of actively used credit cards carry a revolving balance.

in the credit bureau data by credit score bin.[19] The most common value of θ is 1%, the lowest whole number that avoids negative amortization.[20] Two-thirds of accounts have θ of 2.5% or lower. Figure 1 illustrates how seemingly small changes in the minimum payment formula can have large impacts on the path of debt repayment. For a borrower paying the minimum, going from θ equal to 1% to 3% decreases the duration of the credit card debt from 22 years to under 10 years and the total interest paid from \$15,447 to \$5,357.

Fact 3: Minimums are higher for low credit score borrowers. While lower minimums are common among higher credit score borrowers, Figure 3 also shows that much higher θ (e.g., 5% and 7%) are common for lower credit score borrowers. Our framework suggests this is driven by lenders' incentive to set high minimums to avoid insolvency defaults for low credit score borrowers.

Fact 4: Minimum floors appear shaped by late fee regulations. Figure 4 plots a measure of μ, the contract floor, by year and credit card type. We include both private label cards, which can only be used at specific merchants, and general purpose cards. The black lines in each figure show the largest late fee lenders were legally allowed to charge, which automatically adjusted upward for inflation over this period.[21] In each year, the most common floor is at that limit. 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 private label cards, whose revenue is more dependent on late fees (CFPB, 2022), are more often at this threshold.

4 Debt Repayment Allocation

To understand the causes and effects of low required credit card minimum payments, we explore how consumers allocate repayments across different debts *intra*-temporally, within a period of time. We show consumers often revolve high-interest credit card debt while

[19] We plot, for each individual, the lowest minimum divided by the balance among months in which (a) the individual did not revolve debt and (to avoid noise from interest charges) and (b) had a minimum larger than \$40 (to avoid noise from the floor, μ).

[20] FDIC guidance states: "Minimum payment requirements that would not confirm a cardholder's ability to amortize the debt in less than 10 years or that are so small as to draw into question whether the borrower has the proper financial capacity likely warrant close review..." A borrower who makes payments equal to interest plus 1% of their balance *today* (not 1% of the balance as it decreases), and does not continue to spend on their card, will pay off their balance in 8 years and 4 months.

[21] See 12 CFR § 1026.52 (Regulation Z). The rule also allows larger late fees for borrowers who have already missed a minimum in the prior six months. Panel (B) of Appendix Figure D.1 shows that some providers adjust their minimums to this limit after a miss, ensuring the larger fee can be charged.

making excess payments on lower-interest installment debt. This new fact suggests low credit card repayments (and therefore minimums) are not only driven by borrower illiquidity. We explore potential mechanisms, presenting evidence that anchoring plays an important role. Regardless of the specific mechanism, this behavior suggests some notion of behavioral "minimum sensitivity", whereby borrowers' repayments are affected by the minimum even conditional on liquidity, shapes debt repayment decisions.

4.1 Consumers Frequently Overpay Installment Debts

US borrowers frequently make small overpayments on their auto, mortgage, and student debts. These prepayments are generally applied to the principal of one's debt, curtailing the outstanding balance and duration of the loan. Relatively little work exists on the topic despite — as this section shows — it being both a prevalent and economically important household financial behavior. Two recent exceptions are Xu (2023) and Liebersohn *et al.* (2024), who focus on mortgages using Fannie Mae data. Each of their results is quantitatively very close to our results for mortgage borrowers.[22]

Panel (A) of Figure 5 shows the probability that a mortgage, auto, or student loan trade-month includes an overpayment of $25 or more across credit scores.[23] Overpayments increase in credit score, but are frequent across the distribution: 23% of mortgage-months, 14% of auto loan-months, and 9% of student loan-months have such overpayments. The distribution of overpayments larger than $25 has a long right tail: as a percentage of the required payments, the median (75th-percentile) overpayment represents 15% (76%) for mortgages, 50% (100%) for auto loans, and 101% (200%) for student loans.[24]

To further understand these payments, Table 3 decomposes mortgage overpayment consumer-months into categories. Of these consumer-months, nearly half appear to be consumers "rounding-up" (24%) or "doubling" (15%) their mortgage payments in a month. Each of these strategies is commonly discussed by financial advice personalities as strategies for paying off debt sooner.[25] Consumers also frequently make overpayments in other round numbers (e.g., adding $200 to their required amount due). While following these heuristics may reduce direct interest costs, they may not minimize costs if fixed-rate debt falls below the risk-free rate due to rising interest rates (Liebersohn *et al.*, 2024) or, as we explore next, if

[22] In particular, Xu (2023) finds that 22% of Fannie Mae-owned mortgages originated between 2009 and 2018 were curtailed by $30 or more in a given quarter; Liebersohn *et al.* (2024) similarly finds 21% by $20 or more for quarters between January 2022-Feruary 2023.

[23] Appendix B.1 describes our procedure for accounting for "catch up" payments. As noted in the appendix, this procedure does not substantially change our results.

[24] Appendix Figure B.1 shows the full distribution of overpayments for each debt.

[25] See, e.g., Dave Ramsey's advice to "round up your payments so you're paying at least a few extra dollars each month" and David Bach's advice to make an extra mortgage payment when you receive a windfall.

consumers apply them while also carrying high-interest credit card debt.

4.2 Consumers Overpay Installment Debts amid Credit Card Debt

Given the frequency at which households both make installment debt curtailments and revolve high-APR credit card debt, this section explores the extent to which the same households do both at the same time. Because credit cards have substantially higher interest rates than installment debts, these repayments represent failures to cost minimize.[26]

We first restrict our sample to the 65% of months in which individuals revolve credit card debt. To avoid "teaser" 0-APR introductory interest rates, we then filter to cards that have been open for at least 24 months. Finally, we limit to consumer-months in which we observe both a card and another form of debt with actual payments; the consumer did not miss a minimum payment; and total payments are strictly between the total debt balance across debt and the total minimum payments due.[27] Figure 6 shows that excess payments in these consumer-months are often not concentrated on credit card debt. Among these consumers who revolve credit card debt and also have a mortgage, student loan, or auto loan, 46% do not cost-minimize in given month, making prepayments on their installment debt.

While many of these overpayments are small, a substantial share of consumers make large overpayments while revolving credit card debt: panel B of Figure 5 shows that, among revolvers, overpayments of $25 or more are nearly as common as in the general population. These patterns suggest borrowers' credit card repayments are not solely driven by liquidity constraints, as they could reallocate these other excess payments.

Partial Equilibrium Costs of Cross-Product Behaviors. To better understand the costs of these repayment behaviors, we follow Gathergood *et al.* (2019b), who measure the costs of repayment prioritization across credit cards with a simple "steady-state" counterfactual. In their counterfactual, they transfer balances from high-APR to low-APR credit cards until an individual maxes out their lower APR card. We similarly transfer installment debt overpayments to credit cards until the credit card debt is repaid. We conservatively use only excess payments the borrower made in the prior five years. The exercise provides an estimate of interest savings if the borrower could optimally transfer installment overpayments in the past five years to their credit card debt.

[26] 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).

[27] Put differently, the final filter requires that borrowers make *some* payment in excess of the minimum monthly due, whether that be on a credit or another debt product.

Table 4 shows the results of this exercise. Among all borrowers with revolving credit card debt and any installment debt, revolving debt falls by $1,765 on average and $4,726 at the 90th percentile. Savings depends on the APR differential between the installment and credit card debt. For a 10 percentage point APR-differential, annualized interest savings average $177, reaching $473 at the 90th percentile. Since 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).[28] The table shows that a 15 percentage point differential significantly increases the cost, with an average of $265 and a 90th percentile of $709.

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 five years, borrowers may have made overpayments in the past before experiencing a recent shock that led to credit card debt (rather than contemporaneous repayments).[29] Third, the five year period may underestimate total costs from prior overpayments. Fourth, we fail to account for the ways lenders themselves respond to these behaviors when designing credit card contracts. Our empirical model in the final section of this paper is intended to overcome these challenges by simulating forward card-level behaviors and lenders' response.

Comparison to Cross-Card Behaviors. To benchmark the frequency and magnitude of these behaviors, Appendix B.2 compares them to the cross-card behaviors documented in Gathergood *et al.* (2019a,b). While these failures to cost-minimize are somewhat less frequent, they are larger on average. The sizeable cross-product rate differentials also make these behaviors substantially more costly per occurrence.[30]

4.3 Potential Mechanisms for Cross-Product Behaviors

In this section, we discuss a number of mechanisms that may drive cross-product repayment behaviors. While the patterns in Section 4.2, regardless of the underlying mechanisms, will allow us help us to separate between rationales for low credit card minimum payments, their determinants may provide insights into the cognitive drivers of credit card debt. Many leading behavioral models of credit card choice (e.g., present bias) are generally intended to

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

[29]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.

[30]In a sample of credit card offers in a single month, Stango and Zinman (2016) find the median within-person highest versus lowest 24-month APR difference net of teaser rates was 7.5%. In a sample of UK consumers with two cards, Gathergood *et al.* (2019a) show a mean 6.3% within-person difference in APRs.

target *inter*-, rather than *intra*-temporal moments, so do not directly apply in this context.

Anchoring & Minimum-Based Targets. A number of existing studies provide evidence that borrowers anchor on minimum payments or otherwise set minimum-related repayment targets (e.g., Stewart, 2009; Keys and Wang, 2019; Medina and Negrin, 2022). In Appendix B.5 we show that, even while overpaying installment debts, borrowers frequently make payments near the minimum at round dollar amounts. These results provide evidence that borrowers target repayments relative to minimum amounts due and that this anchoring may play a substantial role in the observed cross-product repayment behaviors.

Intra-Household Frictions. Recent studies explore within-household interactions in financial choice (e.g., Kim, 2021; Vihriälä, 2022). In this context, cross-product behaviors 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. Appendix B.4 presents evidence from a two-way fixed effects design to explore this. Similar to Vihriälä (2022), who studies the co-holding of assets and credit card debt, our results suggest intra-household frictions and anchoring may interact to shape cross-product repayment behaviors.

Optimal Inattention. In optimal inattention models, attention costs (e.g., time, effort) are fixed, and mistakes should generally decrease in mistake costs (Sims, 2003). In Appendix B.3, we show that as interest rates increase and the gap between average outstanding credit card and mortgage interest rates widens, the frequency of mortgage prepayments while revolving debt does not decrease. Similar to the findings of Gathergood *et al.* (2019b) across credit cards, optimal inattention does not appear to be a key driver across products.

Balance Matching. Gathergood *et al.* (2019b) show borrowers match the share of balances across credit cards in repayments, following a balance matching heuristic. Appendix Table B.4 shows that across products, this heuristic would predict that borrowers make substantially larger overpayments to installment loans, suggesting this is not a key driver.

Default Consequences. When borrowers face financial hardship and choose debts to make *minimum* payments on, they generally prioritize mortgages and auto loans over credit card debts (Conway and Plosser, 2017). The prioritization of collateralized debts, which directly shape the security of one's house or car, may also affect *excess* payments. However, two pieces of prior evidence suggest such a mechanism, if it exists, is not a complete explanation.

First, similar patterns of overpayment exist for student loans, which are uncollaterized.[31] Second, Figure 6 shows that the frequency of installment debt overpayments while revolving credit card debt increases in credit score and, therefore, decreases in default risk. While general notions of security may affect excess repayments, high rates of costly overpayment among high credit score borrowers suggest this behavior is challenging to rationalize.

To further understand potential mechanisms, we conducted a short pilot survey of borrowers on Prolific. Appendix E provides more information on the survey and our results. We find that borrowers frequently report repayment strategies relative to minimum amounts (e.g., "I usually try to pay a little more than the minimum"), consistent with anchoring. A smaller set of borrowers mentions housing security in payment prioritization. Either mechanism is consistent with borrowers having additional liquidity to repay credit card debts.

5 Empirical Model

The analysis in Section 4 provides evidence that repayments are, in part, driven by behavioral minimum sensitivity (hereafter borrowers "anchoring" to the minimum). Yet two important questions remain unanswered. First, how different would minimum payments be without these behaviors? Second, how does anchoring, combined with lenders' incentives to generate interest revenue, shape revolving debt levels and defaults? In this section, we use our results from Section 4.2 to estimate an empirical model that will allow us to answer these questions.

5.1 Model Description

In our model, borrowers make spending, debt repayment, and default choices, while lenders set minimums to maximize the present-value of expected profits. We adopt a reduced-form approach to modeling borrower behavior to capture observed patterns relevant for lender profits, similar to Einav *et al.* (2012). We parameterize anchoring as a deviation from cost-minimizing debt repayment behavior, which is agnostic to other standard or behavioral forces determining repayment, and quantify its importance using estimates from Section 4.2.

5.1.1 Borrower Behavior

When setting minimums, the lender considers the relationship between borrowing, which determines interest revenue, and default, which determines costs. We introduce this rela-

[31] It is possible that borrowers understand that student loans are generally difficult discharge in bankruptcy and, due to that, prioritize excess payments on student loans. Qualitatively, we do not find evidence for this in our survey of borrowers, described below.

tionship through borrower income, which is unobserved to the lender, but jointly determines spending, repayments, and defaults. The borrower-side is parameterized as follows.

Timing. Time is discrete, with each period t representing a month. At $t = 0$ each borrower, i, opens a card with zero balance (in the text we omit i subscripts for brevity). The card allows borrowing up to a credit limit $\overline{L}$ at interest rate R, with required monthly payments as a function of μ and θ, as in Equation (2).

In each month $t < T$, the borrower receives income Y_t and chooses spending s_t. Afterwards, they receive a statement balance with the amount due, d_t, and the minimum required payment, m_t.[32] They then choose whether to default, close their card, or repay some amount, p_t. Card closing and default are absorbing states. Revolving balances carried forward are $b_t = d_t - p_t$. Missing the minimum results in a late fee f_t. Borrowers also have fixed, non-time varying minimums on installment debts, m_{other}. After period $t = T$, any non-defaulting borrowers close their card by repaying balances in full.[33]

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):

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

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

Spending. Consumers decide to use their card for spending with probability $1 - p_{nospend}$.[34] If they use the card, spending follows a lognormal distribution constrained by the remaining credit available, $L_t = \max(\overline{L} - Rb_{t-1} - f_t, 0)$.

$$s_t = \begin{cases} 0 & \text{with probability } p_{nospend} \\ \min(\exp(s_0 + \epsilon_t^s), L_t) & \text{with probability } 1 - p_{nospend} \end{cases}$$

Default & Repayment. Borrowers receive a statement balance with an amount due, $d_t = Rb_{t-1} + f_t + s_t$, and minimum m_t, and may then default. *Illiquidity* defaults occur if minimums are too high relative to current income and other financial obligations: $y_t < m_t + m_{other}$.[35] *Insolvency* defaults occur if their expected present-value of future income is

[32]Minimums follow Equation (2), and if d_t is less than the floor μ, $m_t = d_t$.

[33]In the simulation we set $T = 240$ and only only 3-5% of cards are still open after these 20 years.

[34]This captures the fact that many borrowers hold multiple cards (as shown in Table 2) and may change which card they spend on in a given month.

[35]This implicitly assumes that cardholders will default on their credit card rather than other debts. We

less than the current amount due: $\psi \text{NPV}(y_t) < d_t$.[36] If the borrower defaults in t, $p_{t'} = 0$ for all $t' \geq t$ and $s_{t'} = 0$ for all $t' > t$ (borrower is cut off from borrowing in future periods).

Conditional on no default, borrowers either keep their credit card or permanently close their account. Closure occurs with iid probability p_{close} in each period. If the borrower closes their card in t, they are cutoff from future spending, $p_t = d_t$ and $p_{t'} = s_{t'} = 0$ for all $t' > t$.[37]

If the borrower does not default or close their account, with iid probability p_{nomin}, the borrower misses their minimum payment and incurs a fee to be paid in the next period. In this case, $p_t = 0$ and $f_{t+1} = \min(f_{max}, m_t)$ (following Figure 4). Otherwise, we assume that borrowers repay based on a combination of *total repayment demand* and *anchoring*. Total repayment demand is the borrower's ability to repay debt in month t, and is thus increasing in income, parameterized as:

$$\log(\tilde{p}_t) = \beta_y \log(Y_t) + \epsilon_t^p \tag{3}$$

We assume that ϵ_t^p and ϵ_t^s are distributed jointly normal, with variances σ_s^2, σ_p^2 and correlation $\rho_{s,p}$. The correlation between spending and repayments captures the empirical fact that consumers appear to switch cards that are "top of wallet."[38]

If borrowers minimized interest costs, they would repay $\tilde{p}_t^r = \tilde{p}_t - m_{other}$. However, Section 4.2 shows that many borrowers do not cost-minimize, and instead make repayments in ways consistent with *anchoring* on the minimum m_t. We parameterize this deviation as:

$$p_t = \min(d_t, \max(m_t, (1-\gamma)\tilde{p}_t^r + \gamma m_t)) \tag{4}$$

The parameter γ controls the degree of anchoring: when $\gamma = 1$, borrowers just pay the minimum, regardless of their income; when $\gamma = 0$, borrowers cost-minimize.

view this assumption as reasonable, since credit card debts are uncollateralized and therefore have lower default costs relative to auto loans or mortgages. It is also consistent with Conway and Plosser (2017).

[36] The present-value of income only depends on current income as it is assumed to be AR(1), with a the discount rate equal to the credit card APR (marginal source of borrowing). We scale the present value by parameter ψ to capture average ad valorem non-financial default costs.

[37] The possibility that borrowers may payoff and close accounts with relatively large balances is consistent with the existence of balance transfer products that allow borrowers to move debt to a new card.

[38] It also could be viewed as capturing that the marginal utility shocks implicitly parameterized in ϵ_t^s also potentially impact debt repayment.

5.1.2 Lender Problem

As in our framework in Section 2, the lender chooses a minimum payment contract, parameterized by μ and θ, to maximize expected discounted profits, given discount rate R_l:

$$\max_{\mu,\theta} \mathbb{E}_0 \sum_{t=0}^{T} \left(\frac{1}{R_l}\right)^t [p_t(m(\theta,\mu,d_t)) - s_t(m(\theta,\mu,d_t))]$$

In our setup, lenders solve a monopoly problem over minimum payments. In practice, minimum payments are not revealed to borrowers shopping for credit cards, meaning that unlike interest rates or credit limits, they are largely shrouded attributes from the consumer perspective. Consistent with our setup, models of shrouded attributes have producers set the shrouded price to the monopoly price, even if that profit is competed away in salient prices (Gabaix and Laibson, 2006). It is theoretically possible that, ex-post, borrowers who experience 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 structure. Indeed, Castellanos *et al.* (2018) shows that one lender's doubling of minimum payments in Mexico led to zero crowd-out of borrowing. Additionally, this ex-post force would drive actual minimums to be lower than model-implied minimums, which will not be the case in our estimation.[39]

In Section 6, we conduct counterfactuals in which borrowers no longer anchor. While lenders could re-optimize over different contract terms in such a scenario (e.g., APRs 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. This follows the approach of Agarwal *et al.* (2014) and Agarwal *et al.* (2018), which uses 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. 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.[40]

[39]That lenders bunch minimum floors at the max late fee (Figure 4) also provides evidence that competitive pressures do not drive down minimums.

[40]For example, if we wanted to study the impact of a floor on minimum payments, we might need to consider how lenders would adjust other features of their contracts to offset lost revenue relative to the current equilibrium.

5.2 Parametrization & Estimation

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

There are 20 parameters associated with the borrower's problem: calibrated fixed parameters of the credit card contract $(R, \overline{L}, \mu, \theta, f_{max}, m_{other}, R_l)$, calibrated parameters of the income process $(\overline{Y}, \rho, \sigma_y)$, and estimated parameters relating to spending $(p_{nospend}, s_0, \sigma_s)$, default (ψ), card closure (p_{close}), and repayments $(p_{nomin}, \beta_y, \sigma_p, \gamma, \rho_{s,p})$. We calibrate and estimate 14 parameters Θ_1 in the first stage, and 6 parameters $\Theta_2 = (\psi, \beta_y, \sigma_p, s_0, \sigma_s, \rho_{s,p})$ jointly in the second stage.

Our estimation uses a sample of credit cards that were opened in 2015. This allows us track card-level outcomes for four years before the start of the COVID-19 pandemic. We limit to the 75% of credit cards associated with borrowers who have some installment debt, which will allow us to use our results in Section 4.2 to estimate the importance of anchoring. In total, our sample includes 63,072 cards.

5.2.1 First Stage Parameters

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

Fixed Parameters. We calibrate parameters of the credit card contract as follows. We use APRs by credit score from CFPB (2021) (Section 3, Figure 3). We estimated the average credit limit and median installment minimum within credit score group in our credit bureau data. We use the median slope on credit card minimums and set the floor and maximum late fee to be fixed at $25, the regulatory maximum at the time of our sample. We set the lender's annual discount rate at 6% based on banks' cost of equity.[41]

Calibrated Income Process. We follow Guerrieri and Lorenzoni (2017) in parametrizing the income process, converting their quarterly AR(1) income process into a monthly one, which yields a monthly persistence of 0.989 and variance of 0.078. To set the average income by credit score, we use an imputed measure provided by the credit bureau based on

[41] At the start of our sample in 2015, the cost of equity was 6.81% for money center banks and 5.2% for regional banks according to estimates from https://pages.stern.nyu.edu/adamodar/.

information including the location of the borrower.[42]

Estimated Spending & Repayment Parameters. We directly match the estimated probability of nonzero spending, card closure, and missed minimums from our data. For closures, we incorporate soft card closures, in which the borrower stops using the card without formally closing it, by matching the average share of cards that transition into being unused for a full year or more.[43] For missed minimums, we match the probability of missing a minimum with the proportion of borrower-months where the borrower misses a minimum but makes some payment in the future.[44]

Anchoring. The key behavioral parameter in the model and counterfactuals is γ, which governs anchoring. Since γ is linear in Equation 4 if payments are interior ($p_t < d_t$ and $\tilde{p}_t > m_{other} + m_t$), and

$$p_t = (1-\gamma)(\tilde{p}_t - m_{other}) + \gamma m_t \Rightarrow \gamma = \frac{\tilde{p}_t - m_{other} - p_t}{\tilde{p}_t - m_{other} - m_t} = \frac{p_{other} - m_{other}}{\tilde{p}_t - m_{other} - m_t}$$

the moment identifying γ is:

$$\gamma = \mathbb{E}\left[\frac{p_{other} - m_{other}}{\tilde{p}_t - m_{other} - m_t}\middle|\tilde{p}_t > m_t + m_{other} \text{ and } p_t < d_t\right] \tag{5}$$

The parameter γ is the share of total excess payments allocated toward paying down installment debt rather than credit card debt, our main result in Section 4.2. If borrowers minimize costs by focusing all excess payments on their credit cards, then $\gamma = 0$. Conversely, if borrowers are fully anchored and only pay the credit card minimum, regardless of liquidity, then $\gamma = 1$.

Our estimate of γ comes from cross-product repayment behaviors, conditional on the chosen total amount of debt repayment. This is a lower bound of the overall impact of anchoring, which may also cause borrowers to reduce repayments across all debts. Our conservative approach allows us to avoid taking a normative stance on whether borrowers optimally trade off consumption and repayment, a challenge in prior work.

[42]Specifically, we use an individual-level measure from the credit bureau, scaling by two for married individuals to convert to household income. We average across households in each credit score bin.

[43]More precisely, let s_x be the share of cards unused after x years for at least one year. Then,

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

[44]In Appendix Table B.5 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). The Y-14 data only cover bank holding companies with total consolidated assets of $100 billion or more.

5.2.2 Second Stage Simulated Minimum Distance

We estimate the 6 remaining parameters $\Theta_2 = (\psi, \beta_y, \sigma_p, s_0, \sigma_s, \rho_{s,p})$ using just-identified simulated minimum distance, minimizing the sum of squared deviations between sample moments $\hat{m}$ and modeled moments $m(\Theta_1, \Theta_2)$:

$$\Theta_2^* = \arg\min_{\Theta_2} (\hat{m} - m(\Theta_1^*, \Theta_2))'(\hat{m} - m(\Theta_1^*, \Theta_2)) \tag{6}$$

where Θ_1^* are the first stage parameters from in Section 5.2.1. We calculate standard errors that account for simulation error and uncertainty in first stage estimated parameters using the Delta method. See Appendix C for details.[45]

Table 6 shows the empirical moments we select, $\hat{m}$, and how these are intended to provide variation to identify each parameter in the joint estimation. We present formal sensitivity analysis, following Andrews *et al.* (2017), in Appendix B.6. Most of the targeted moments are intuitive (e.g., ψ governs defaults and helps match empirical default probabilities). To estimate total repayment shocks, we use the standard deviation of the residuals from a regression of log total repayments on individual-level fixed effects.[46]

5.3 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.[47] Our estimates are overall precise. The coefficient on log income, β_y, determines the share of income being paid towards debt repayment. Our estimates of β_y between 0.7-0.9 empirically translate into on average, approximately 20-30% of income being paid towards total debt repayment for the bottom three credit score groups, and about 35-60% for the top two groups. This compares favorably to the debt-to-income ratio of 30-40% common for auto-loans and mortgages.[48]

[45] Overall we run each simulation with $N = 10,000$ borrowers. We bootstrap $10,000$ times.

[46] Our just-identified model matches targeted moments exactly, as shown in Table B.8.

[47] Because the credit limit, installment minimum, and some contract features (see Table 5) are calibrated model inputs, our standard errors do not consider uncertainty in these estimates.

[48] For example, Fannie Mae writes "For manually underwritten loans, Fannie Mae's maximum total DTI ratio is 36% of the borrower's stable monthly income. The maximum can be exceeded up to 45% if the borrower meets the credit score and reserve requirements...for loan casefiles underwritten through DU, the

The variance of log total debt repayment, σ_p, decreases with credit score, consistent with low-score borrowers facing more volatile marginal utility of consumption. Spending and $\rho_{s,p}$ both increase with credit score, consistent with the higher prevalence of high-income credit card transactors in high-score groups.

5.3.2 Untargeted Moments & Optimal Minimums for Lenders

To verify that the model captures meaningful relationships between variables that influence repayment decisions, we next analyze the full distributions of utilization, spending, and excess repayments, as well as the profit-maximizing minimums implied by the model.[49]

Figure 7 plots the distribution of utilization, spending, and excess repayments in the model versus data by credit score group. As in the data, high credit score borrowers have much lower utilization rates than low credit score borrowers, and overall, the share of borrowers in each utilization bin aligns well with the data. The distribution of spending also aligns with the data, suggesting our log-normal approximation for spending is reasonable. Finally, the model replicates the U-shaped distribution of excess repayments documented in Fact 1 of Section 3.3, with many borrowers paying close to the minimum.

We next compare real and model-implied lender minimums.[50] If our model of borrower behavior implies profit-maximizing minimums that match the current equilibrium, it provides strong support that we have captured the important forces that matter for lenders' choice. Furthermore, if we can predict empirically-realistic minimums in the current equilibrium, we have more confidence we can predict realistic minimums in counterfactual equilibria.

Panel A of Table 8 shows that the model reproduces the key features of equilibrium minimums described in Section 3.3. First, consistent with Fact 2, the optimal θ is near the lowest regulatory allowed for the top three credit score groups, at 0.012 or below. For example, lenders' optimal θ for the 740+ group is 0.01, matching the modal θ in the data, and implying the long 20+ year amortization schedules for a \$10,000 debt shown in Figure 1. Second, consistent with Fact 3, the optimal θ is higher for lower credit score borrowers, reaching 0.036 for the lowest credit score group, though somewhat below the actual mode of 0.05. Like real-world minimums, this pattern is driven by a combination of low credit score borrowers being more susceptible to insolvency defaults and less profitable revolvers.[51]

maximum allowable DTI ratio is 50%." We view our estimates as reasonable, since DTI ratios are based on minimums, and many of our payments are above the minimum (especially for high credit score borrowers).

[49] While we match some utilization and spending moments, we do not match their full distribution.

[50] To find the optimal model-implied θ, we search over a θ grid of size $[0.01, 0.011, 0.012, \ldots, 0.01]$

[51] It is not ex-ante obvious that minimums should always be increasing in credit score. For example, if low credit score borrowers are more likely to be liquidity-constrained, this force would push toward setting lower minimums for these groups.

Appendix Table B.7 shows how expected profits vary with the floor, μ. Without a floor, lenders cannot charge the maximum late fee to borrowers with low balances. 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, consistent with Fact 4.[52]

Our estimated borrower primitives also allow us to compare a model-implied change in defaults from a change in minimums with external estimates from natural experiments.[53] For example, Allen *et al.* (2024) finds suggestive evidence that increasing the minimum payment from 2 to 5% in Quebec results in lower revolving balances and higher delinquencies. Our model-implied results are in largely in line with Allen *et al.* (2024), and the increase in delinquencies, while not universal for all borrowers, is true for high credit-score individuals, where more defaults are driven by illiquidity rather than insolvency (see Figure B.8).

5.4 Qualitative Evidence of Lenders Optimizing Minimums

While our model does not rely on lenders being explicitly aware of a psychological anchoring mechanism (or cross-product mistake), it does rely on lenders using minimums to profit-maximize.[54] For example, as long as the correlation between repayments and default is used by lenders to optimize the minimum, anchoring will impact minimums.

Anecdotal examples suggest that lenders do actively use minimums to slow the repayments of liquid borrowers, weakening the correlation between repayments and default, and increasing profits. In one case, Guttman-Kenney *et al.* (2023) uses a lab experiment to show removing the minimum payment option among a set of repayment choices significantly increases repayments and lowers revolving balances.[55] The authors tried to implement their nudge in the field, but, "despite regulatory pressure, no UK lender was willing or able to test our treatment de-anchoring manual payments." They conclude, "From this resistance, we infer that lenders expect the lab results to extrapolate to the field."

A class-action lawsuit against Bank of America, settled in 2021, also provides evidence of lenders attempting to slow repayments.[56] The lawsuit describes how the bank provided four autopay options customers could choose from: "Amount Due", "Minimum Amount Due", "Account Balance", and "Fixed Amount". As the lawsuit describes:

> Reasonable consumers would expect "Amount Due" to mean the statement bal-

[52] Table B.7 also shows that credit card profits are hump-shaped by credit score, in line with Figure 3 in Guttman-Kenney and Shahidinejad (2023).

[53] For model-implied estimates, see for example, the green line in the bottom panel of Figure 10.

[54] We also do not claim that lenders would specifically target the cross-section of anchoring at the borrower level. More realistically, lenders might set a menu of cards.

[55] Borrowers could still pay the minimum, but it would be an active choice.

[56] Details of the lawsuit can be found here.

> ance...but in fact, under Bank of America's misleading construct, "Amount Due" means the same thing as "Minimum Amount Due"..."Amount Due" is a duplicative feature that serves no purpose except to confuse consumers and inflate Defendant's profits.

Similarly, industry insiders have themselves have corroborated the view that reducing minimum payments can increase profitability. In an interview, Andrew Kahr, a former credit card industry consultant, described his work with a client in the late '70s (PBS, 2004):

> Well, I convinced the client that instead of having 5 percent of the balance as a minimum payment, we should reduce that to 2 percent...Having a lower minimum payment allows you to offer higher credit lines...The high-balance accounts will be much more profitable than the low-balance accounts...they're paying interest on a higher balance.

6 Counterfactuals: Lender Response to Prioritization and Impacts on Aggregate Debt

How do credit card minimums, total debt, and default differ when borrowers are minimum sensitive (i.e., anchored)? We use our empirical model to estimate two counterfactuals. First, if borrowers became *un*anchored, lenders would set much higher minimums. Second, if lenders set higher minimums when borrowers are anchored, credit card debt and defaults would fall. Together, these counterfactuals allow us to quantify the extent to which lenders' choice of minimums amplifies the effect of consumer behaviors on total debt and default.

6.1 Behavioral Debt Repayment on Credit Card Contracts

How does anchoring affect lenders' choice of credit card minimums? To answer this question, we conduct a counterfactual in which we set $\gamma = 0$ for all borrowers, holding other parameters constant.[57] We then allow the lender to reoptimzie. Panel B of Table 8 shows that without anchoring, minimums (above the floor and conditional on balance) would be 1.2-3.3 times higher across the credit score distribution. In the top credit score bin a borrower at the credit limit would have a minimum of $330 instead of $100. Paying only the minimum would fully amortize their debt in 9 years instead of 23 years. For lower credit score borrowers, where

[57] Since we observe the distribution of γ in the data, in the future we could have heterogeneous γ across borrowers.

existing minimums are already higher, the increase is smaller. In the lowest score group, θ increases from 0.36 to 0.44.

In Section 6.3, we discuss the drivers of these minimum changes in more detail. Intuitively, one can view lenders as having two "strategies" to maximize profits: (1) reduce default costs by keeping balances low, giving up potential interest revenue from higher balances ("lender prefers to be paid") or (2) accept higher default rates and generate more interest from large balances ("lender prefers not to be paid"). When borrowers are anchored, the second strategy becomes more appealing. The next section provides evidence of this trade-off.

6.2 Behavioral Debt Repayment on Revolving Debt and Default

We next ask how much anchoring increases total debt and default, separating between the role of borrowers biases, a "demand-bias" effect, and lenders' response to these biases, a "supply-side amplification" effect. To illustrate how we do so, let current total credit card debt levels (analogously, defaults) be given by $D_{b,m}$. The subscripts denote that current borrowers are behaviorally anchored b and face minimums m. Define m' as the the minimum the lender sets after reoptimizing to borrowers who do not anchor. We estimate two counterfactuals:

(a) Total debt $D_{-b,m'}$ *without* anchoring, and the reoptimized minimum m'

(b) Total debt $D_{b,m'}$ *with* anchoring, and the reoptimized minimum m'

The total increase in debt in equilibrium from anchoring is equal to $D_{b,m} - D_{-b,m'}$. This object can be further decomposed into a demand- and supply-side effect. The demand-bias equals $D_{b,m'} - D_{-b,m'}$: this is the direct effect of anchoring on revolving debt, holding minimums constant. The supply-side amplification equals $D_{b,m} - D_{b,m'}$: this is the *additional* amount of revolving debt generated once lenders re-optimize in response to anchoring.[58]

Figure 8 shows how anchoring increases total revolving debt levels and default. Weighting by the mass of borrowers in each credit score bin, the model suggests that overall revolving debt levels are 24.3% higher due to anchoring. Using our two counterfactuals, we decompose this change, showing that 80.3% is driven directly by behaviors and 19.7% is driven by a supply-side response. Defaults increase by 4.7% with anchoring, where 85.0% is driven by the supply-side response. In general, the middle credit score groups are most affected by the supply-side reoptimizing.

[58] Appendix Figure B.7 depicts this counterfactual exercise visually.

6.3 Drivers of Amplification

Why would lenders lower minimums when borrowers are anchored? We first show that holding minimums constant, anchored borrowers are more likely to have high utilization rates; but *conditional* on utilization, they are *less* likely to default. As anchoring *lowers* the correlation between default and balances, all else equal, lenders "want" borrowers to revolve higher balances (increasing interest revenue). Consequently, with anchored borrowers, the marginal revenue of raising minimums decreases (is more negative) for the lender due to steeper losses from revolving interest. This implies lower minimums become more profitable.

Panel (A) of Figure 9 shows that holding minimums constant, borrowers who are anchored are more likely to have high utilization rates. For example, borrowers with credit scores between 660-699 are approximately 5 percentage points more likely to have a utilization greater than 90% in any given month the card is open. Higher utilization is due to the fact that borrowers pay less and closer to the minimum when anchored. However, *conditional* on balance, anchored borrowers are *less* likely to default. This is because low payments from an anchored borrower are a less informative signal of low income. As a result, high balances are more profitable for the lender once borrowers become anchored.

In Figures 10 we plot marginal (interest) revenue and marginal (chargeoff) cost curves for anchored versus unanchored borrowers.[59] The figure shows that when borrowers are anchored, minimums decrease and this effect is almost entirely due to additional interest from revolving that can be extracted from anchored borrowers.[60] The intersection of marginal revenue and marginal costs determines optimal minimums. In the top panel, point A marks optimal minimums when borrowers are unanchored. Anchoring shifts the marginal revenue curve to the left while not affecting the marginal cost curve substantially. Thus, the optimal minimum falls to point B. The middle and bottom panels illustrate the demand and supply-side contribution to revenue and costs. The supply-side contribution is small for revolving interest but much larger for chargeoffs, in line with Figure 8. The intuition is that anchoring increases balances a lot, but since revenue is concave, any additional amplification is low. However, chargeoffs decrease more quickly in minimums, so any amplification is high.

7 Conclusion

Despite credit cards being unsecured, lenders typically allow borrowers to make low minimum payments. In this paper, we study the forces which drive lenders' choice of low minimums. Using credit-bureau data, we first show that many borrowers make intra-temporal repayment

[59] Appendix Figure B.8 shows the figures for all credit score groups.

[60] Figure 10 shows the 660-699 credit score group. Appendix Figure B.8 shows all credit score bins.

mistakes, and pay the minimum not out of illiquidity constraints but behaviors consistent with anchoring to the minimum. This fact, combined with an empirical model, suggests that low minimums are largely driven by lenders' incentives to increase revenue through generating interest on revolving debt. When borrowers become anchored, lenders find it more profitable for borrowers to have large, interest-bearing balances, since low payments no longer a signal of default but a behavioral choice. Indeed, our counterfactuals suggest that without anchoring, minimums would be three times higher for many borrowers, revolving debt would be 24% lower, and defaults would be 5% lower. Of this, the supply-side response is 20% for revolving debt and 85% for defaults respectively.

Our results add to a mostly theoretical literature on how lenders optimize when faced with behavioral borrowers (e.g., Heidhues and Kőszegi, 2010), and a more recent literature on how lenders influence borrowing decisions through non-price channels (e.g., Foà *et al.*, 2019; Ru and Schoar, 2023). We show that the supply-side of consumer debt repayment can offer valuable insights into demand-side outcomes, including the credit-card overborrowing puzzle (Zinman, 2014). Providing evidence on the potential impacts of minimum regulations is not within the scope of this paper, but an important area for future work.

References

Agarwal, S., Chomsisengphet, S., Mahoney, N. and Stroebel, J. (2014). A simple framework for estimating consumer benefits from regulating hidden fees. *The Journal of Legal Studies*, **43** (S2), S239–S252.

—, —, — and — (2015). Regulating consumer financial products: Evidence from credit cards. *The Quarterly Journal of Economics*, **130** (1), 111–164.

—, —, — and — (2018). Do banks pass through credit expansions to consumers who want to borrow? *The Quarterly Journal of Economics*, **133** (1), 129–190.

Allen, J., Boutros, M. and Guttman-Kenney, B. (2024). Evaluating credit card minimum payment restrictions.

Amromin, G., Huang, J. and Sialm, C. (2007). The tradeoff between mortgage prepayments and tax-deferred retirement savings. *Journal of Public Economics*, **91** (10), 2014–2040.

Andersen, S., Campbell, J. Y., Nielsen, K. M. and Ramadorai, T. (2020). Sources of inaction in household finance: Evidence from the danish mortgage market. *American Economic Review*, **110** (10), 3184–3230.

Andrews, I., Gentzkow, M. and Shapiro, J. M. (2017). Measuring the sensitivity of parameter estimates to estimation moments. *The Quarterly Journal of Economics*, **132** (4), 1553–1592.

Argyle, B. S., Nadauld, T. D. and Palmer, C. J. (2020). Monthly payment targeting and the demand for maturity. *The Review of Financial Studies*, **33** (11), 5416–5462.

Ausubel, L. M. (1991). The failure of competition in the credit card market. *The American Economic Review*, pp. 50–81.

Avery, C. and Turner, S. (2012). Student loans: Do college students borrow too much—or not enough? *Journal of Economic Perspectives*, **26** (1), 165–192.

Bartels, D. M., Herzog, N. and Sussman, A. B. (2023). Distinguishing between anchors and targets. *Available at SSRN 4521038*.

Bernstein, A. and Koudijs, P. (2024). The mortgage piggy bank: Building wealth through amortization. *The Quarterly Journal of Economics*, p. qjae011.

Board of Governors of the Federal Reserve System (2003). Account management and loss allowance methodology for credit card lending. https://www.federalreserve.gov/boarddocs/srletters/2003/sr0301.htm.

Castellanos, S. G., Hernández, D. J., Mahajan, A., Prous, E. A. and Seira, E. (2018). *Contract terms, employment shocks, and default in credit cards*. Tech. rep.

CFPB (2021). The consumer credit card market. https://files.consumerfinance.gov/f/documents/cfpb_consumer-credit-card-market-report_2021.pdf.

Chetty, R., Friedman, J. N., Leth-Petersen, S., Nielsen, T. H. and Olsen, T. (2014). Active vs. passive decisions and crowd-out in retirement savings accounts: Evidence from denmark. *The Quarterly Journal of Economics*, **129** (3), 1141–1219.

Consumer Financial Protection Bureau (2020). Payment amount furnishing & consumer reporting.

Consumer Financial Protection Bureau (2022). *Credit Card Late Fees*. Tech. rep.

Consumer Financial Protection Bureau (2023a). *The Consumer Credit Card Market*. Tech. rep.

Consumer Financial Protection Bureau (2023b). Why the largest credit card companies are suppressing actual payment data on your credit report.

Conway, J. and Plosser, M. (2017). *When Debts Compete, Which Wins?* Tech. rep., Federal Reserve Bank of New York.

de Silva, T. (2023). Insurance versus moral hazard in income-contingent student loan repayment. *Available at SSRN 4614108*.

Department of Education (2023). Interest rates and fees for federal student loans. https://studentaid.gov/understand-aid/types/loans/interest-rates, accessed: 2023-12-27.

Einav, L., Jenkins, M. and Levin, J. (2012). Contract pricing in consumer credit markets. *Econometrica*, **80** (4), 1387–1432.

Federal Reserve Bank of New York (2023). Quarterly report on household debt and credit: Q3, 2023.

Federal Reserve Board (2024). Economic well-being of u.s. households in 2023.

Floden, M. and Lindé, J. (2001). Idiosyncratic risk in the united states and sweden: Is there a role for government insurance? *Review of Economic dynamics*, **4** (2), 406–437.

Foà, G., Gambacorta, L., Guiso, L. and Mistrulli, P. E. (2019). The supply side of household finance. *The Review of Financial Studies*, **32** (10), 3762–3798.

Gabaix, X. and Laibson, D. (2006). Shrouded attributes, consumer myopia, and information suppression in competitive markets. *The Quarterly Journal of Economics*, **121** (2), 505–540.

Gathergood, J., Mahoney, N., Stewart, N. and Weber, J. (2019a). How do americans repay their debt? the balance-matching heuristic". *Economics Bulletin*, **39** (2), 1458–1466.

—, —, — and — (2019b). How do individuals repay their debt? the balance-matching heuristic. *American Economic Review*, **109** (3), 844–875.

— and Weber, J. (2014). Self-control, financial literacy & the co-holding puzzle. *Journal of Economic Behavior & Organization*, **107**, 455–469.

Government Accountability Office (2023). *Credit Cards: Pandemic Assistance Likely Helped Reduce Balances, and Credit Terms Varied Among Demographic Groups*. Tech. rep.

Grodzicki, D. and Koulayev, S. (2019). Credit card revolvers. *Consumer Financial Protection Bureau Office of Research Reports Series*, (19-3).

Guerrieri, V. and Lorenzoni, G. (2017). Credit crises, precautionary savings, and the liquidity trap. *The Quarterly Journal of Economics*, **132** (3), 1427–1467.

Guttman-Kenney, B., Adams, P. D., Hunt, S., Laibson, D., Stewart, N. and Leary, J. (2023). *The semblance of success in nudging consumers to pay down credit card debt*. Tech. rep., National Bureau of Economic Research.

— and Shahidinejad, A. (2023). Unraveling information sharing in consumer credit markets. *Available at SSRN 4629496*.

Heidhues, P. and Kőszegi, B. (2010). Exploiting naivete about self-control in the credit market. *American Economic Review*, **100** (5), 2279–2303.

Katz, J. (2023). Saving and consumption responses to student loan forbearance. *Available at SSRN 4344262*.

Keys, B. J. and Wang, J. (2019). Minimum payments and debt paydown in consumer credit cards. *Journal of Financial Economics*, **131** (3), 528–548.

Kim, O. (2021). Credit and the family: The economic consequences of closing the credit gap of us couples. *Available at SSRN 3962414*.

Laibson, D., Chanwook Lee, S., Maxted, P., Repetto, A. and Tobacman, J. (2024). Estimating discount functions with consumption choices over the lifecycle. *The Review of Financial Studies*, p. hhae035.

Lee, S. C. and Maxted, P. (2023). Credit card borrowing in heterogeneous-agent models: Reconciling theory and data. *Available at SSRN 4389878*.

Liebersohn, J., Jambulapati, V. and Fitzpatrick, M. (2024). Understanding excess repayment. *Available at SSRN*.

Medina, P. C. and Negrin, J. L. (2022). The hidden role of contract terms: The case of credit card minimum payments in mexico. *Management Science*, **68** (5), 3856–3877.

Nelson, S. T. (2017). *Private information and price regulation In the US credit card market*. Ph.D. thesis, Massachusetts Institute of Technology.

Office of the Comptroller of the Currency (2003). Credit card lending: Account management and loss allowance guidance. https://www.occ.gov/news-issuances/bulletins/2003/bulletin-2003-1a.pdf.

Office of the Comptroller of the Currency (2005). Comptroller dugan expresses concern about negative amortization. https://www.occ.gov/news-issuances/news-releases/2005/nr-occ-2005-117.html.

PBS (2004). Secret history of the credit card. https://www.pbs.org/wgbh/pages/frontline/shows/credit/etc/script.html.

Ponce, A., Seira, E. and Zamarripa, G. (2017). Borrowing on the wrong credit card? evidence from mexico. *American Economic Review*, **107** (4), 1335–1361.

Ru, H. and Schoar, A. (2023). Do credit card companies screen for behavioural biases? *BIS Working Paper No. 842*.

Sims, C. A. (2003). Implications of rational inattention. *Journal of monetary Economics*, **50** (3), 665–690.

STANGO, V. and ZINMAN, J. (2016). Borrowing high versus borrowing higher: price dispersion and shopping behavior in the us credit card market. *The Review of Financial Studies*, **29** (4), 979–1006.

STEWART, N. (2009). The cost of anchoring on credit-card minimum repayments. *Psychological science*, **20** (1), 39–41.

TESCHER, J. and STONE, C. (2022). Revolving debt's challenge to financial health and one way to help consumers pay it off. *Brookings Institution*. https://www.brookings.edu/articles/revolving-debts-challenge-to-financial-health-and-one-way-to-help-consumers-pay-it-off/.

VIHRIÄLÄ, E. (2022). Intrahousehold frictions, anchoring, and the credit card debt puzzle. *Review of Economics and Statistics*, pp. 1–45.

XU, Y. (2023). *Essays on Mortgage Curtailment*. Ph.D. thesis, Georgetown University.

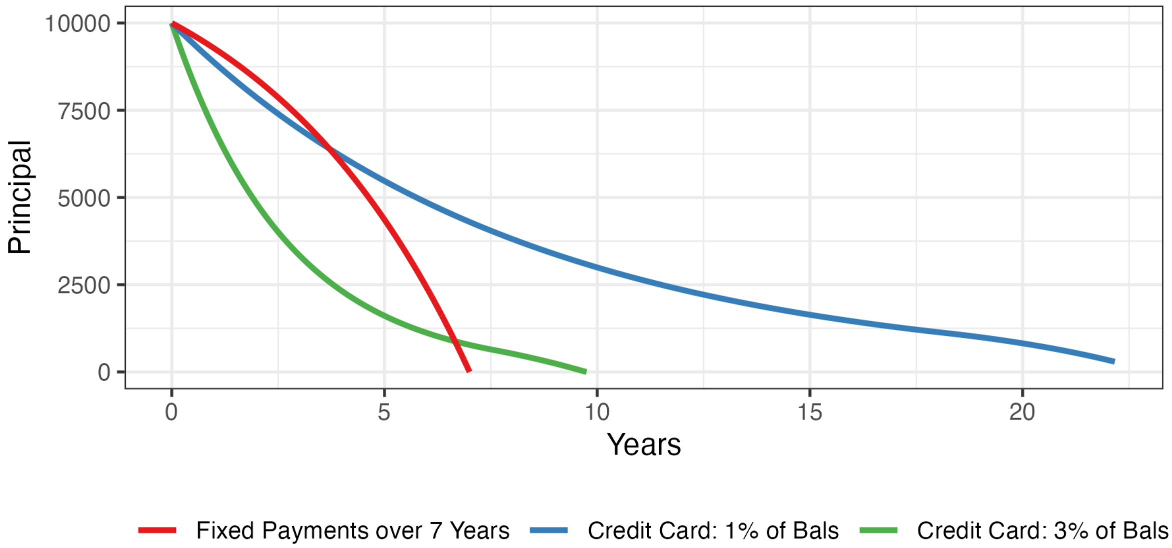
ZINMAN, J. (2009). Where is the missing credit card debt? clues and implications. *Review of income and wealth*, **55** (2), 249–265.

— (2014). Consumer credit: Too much or too little (or just right)? *The Journal of Legal Studies*, **43** (S2), S209–S237.

— (2015). Household debt: Facts, puzzles, theories, and policies. *Annual Review of Economics*, **7** (1), 251–276.

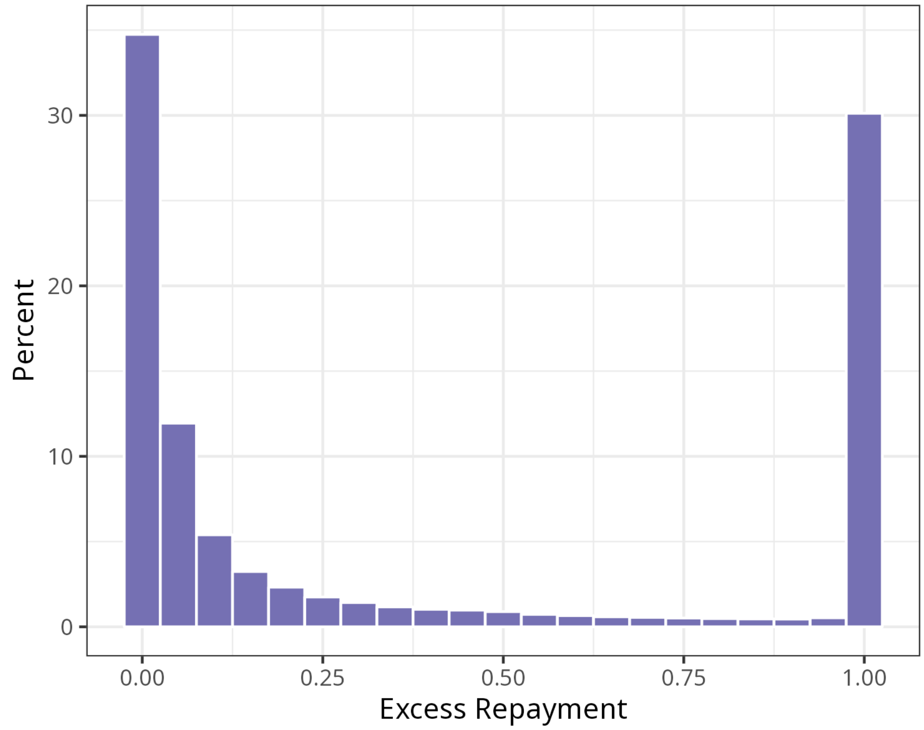
Figures

Figure 1: *Debt Repayment Schedules*



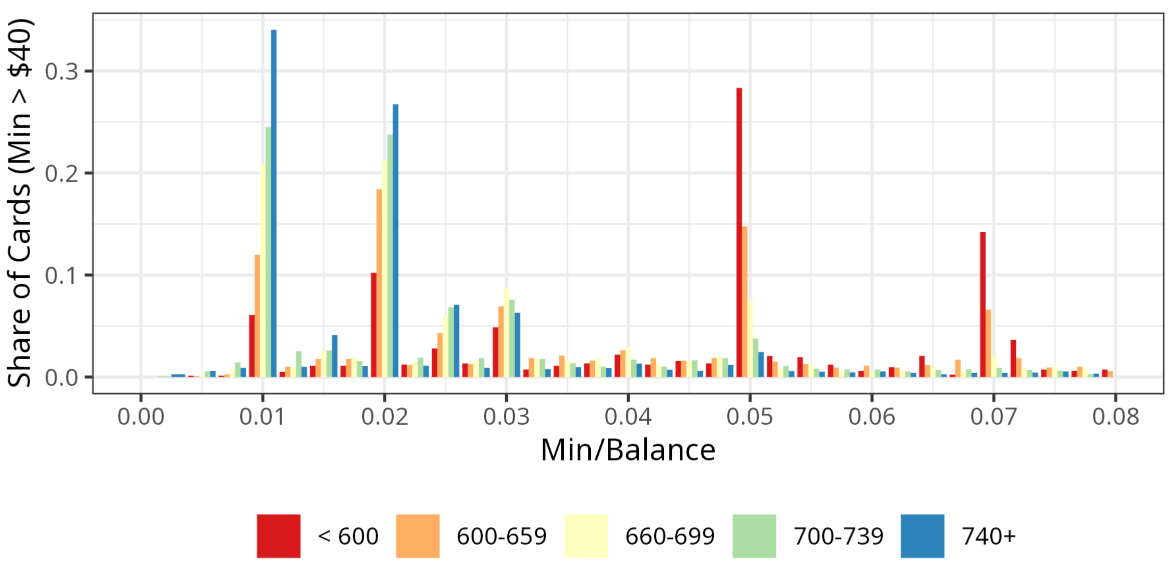
Note: Figure shows various amortization schedules of a debt with a \$10,000 principal and 15% APR. The red line shows the amortization schedule for a debt with fixed payments over seven years. The blue line shows the amortization schedule of a credit card with $\theta = 1\%$ (the share of balances due in addition to interest) and $\mu = \$30$ (the floor minimum) when the borrower makes only minimum payments and does not continue spending. The red line shows the amortization schedule for a similar credit borrower when $\theta = 3\%$.

Figure 2: *Excess Repayments as Share of Balance*



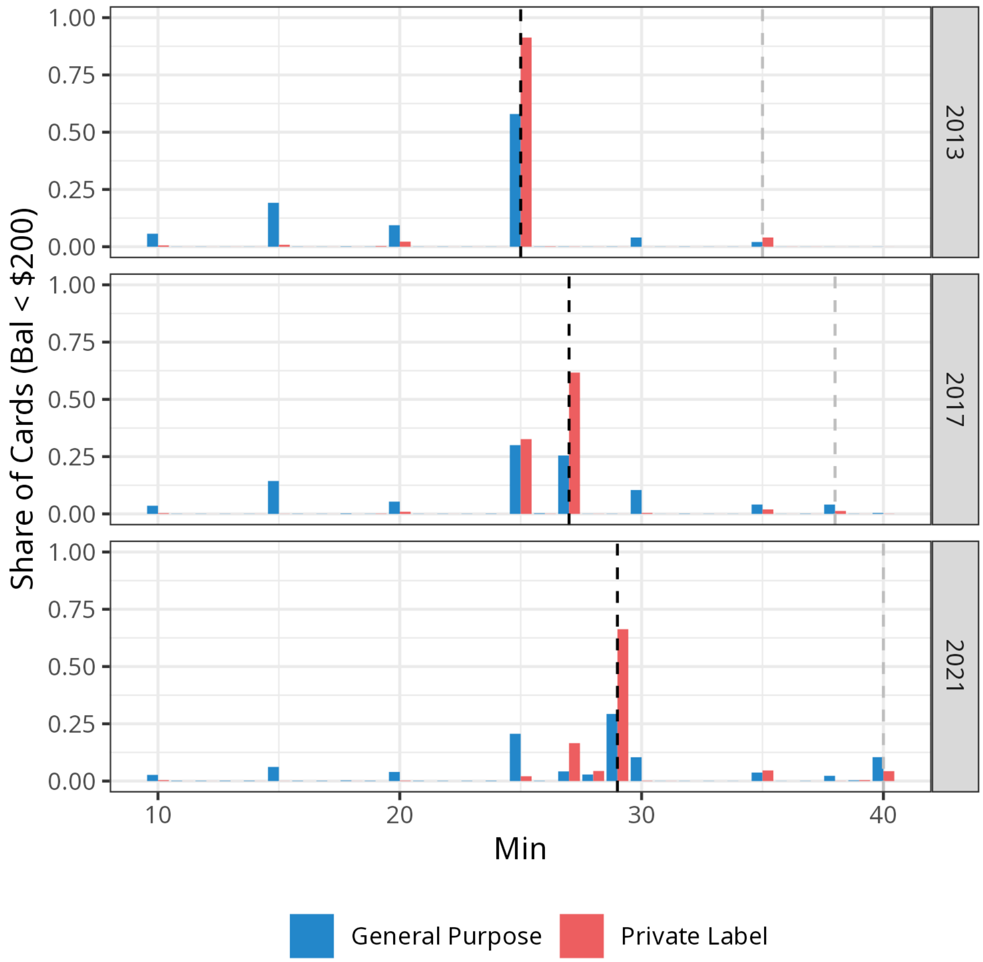
Note: Figure shows the distribution of credit card repayments in months when the borrower did not miss the minimum. The measure is the share of the balance in excess of the minimum the borrower paid. Formally, this is $\frac{\text{actual payment}_t - \text{minimum payment}_{t-1}}{\text{balance amt}_{t-1} - \text{minimum payment}_{t-1}}$. 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.

Figure 3: *Estimates of Credit Card Contract θ (Balance Slope) by Credit Score*



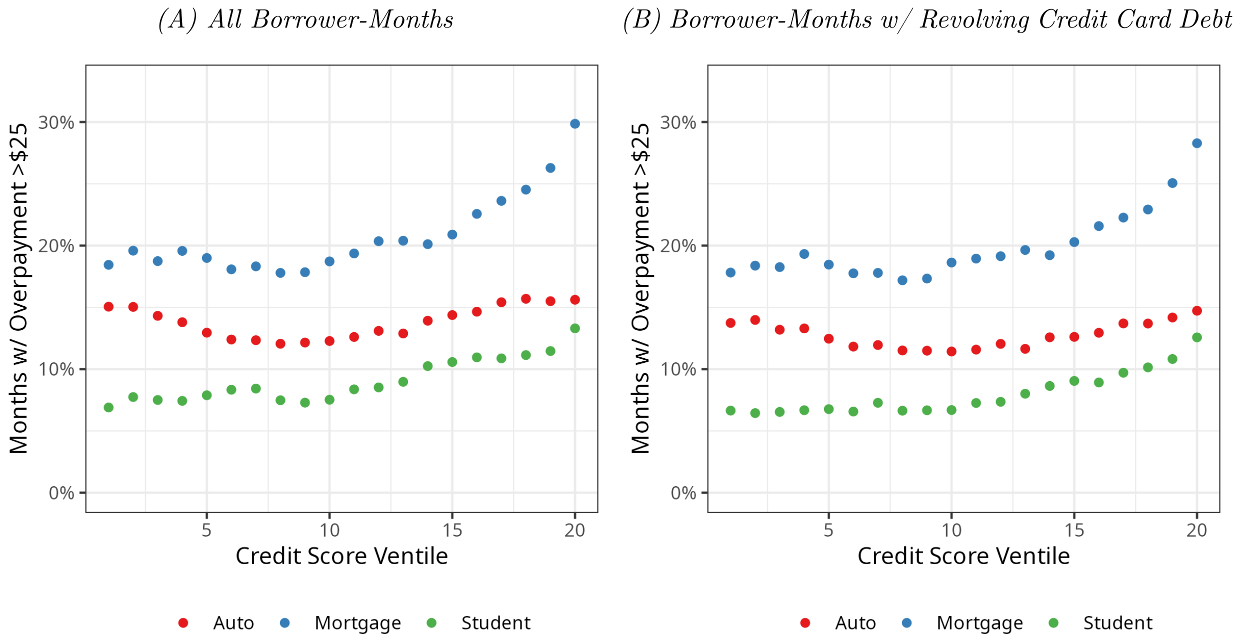
Note: Figure shows, across credit score bins, the distribution of cards' smallest $\frac{\text{Minimum}}{\text{Balance}}$. To estimate θ, the rate at which minimums increase in balances, the plot is only among months when individuals did not revolve debt and had a minimum larger than $40. Colors show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

Figure 4: *Estimates of Credit Card Contract μ (Floor) by Card Type*



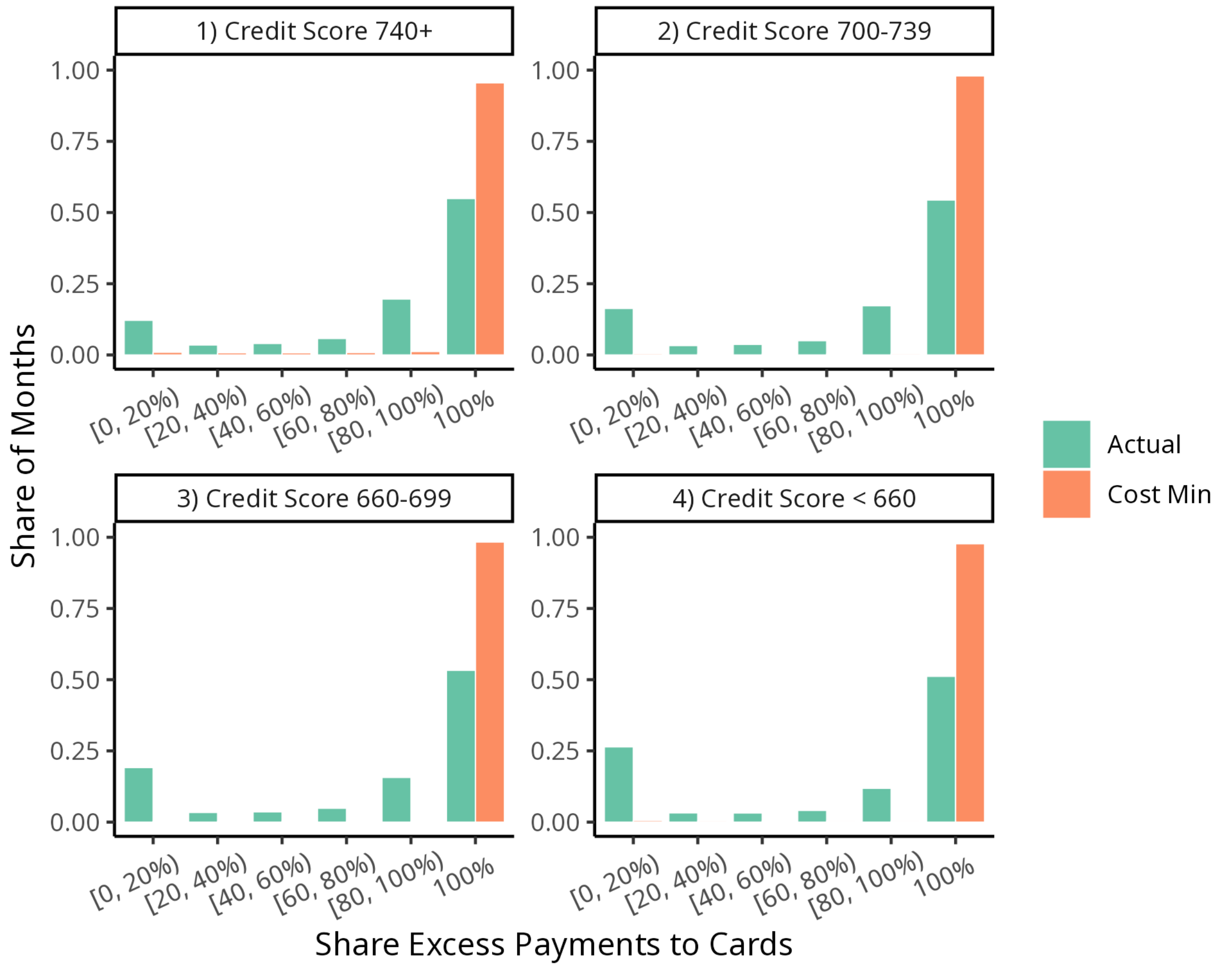
Note: Figure shows, across credit cards and private label cards, the distribution of cards' smallest minimum. To estimate μ, the "floor" of the minimum required payment formula, the plot is only among months when individuals did not revolve credit card debt from the previous month, had an end on month balance less than $200, and had a minimum larger than the balance. The dashed black line shows the largest late fee a lender could legally charge in that year for a first missed minimum. The dashed grey line shows the largest legal late fee for an additional miss within six months.

Figure 5: *Share of Borrower-Months with Overpayments by Credit Score and Product*



Note: Figure shows, by ventiles of borrower credit score, the share of borrower-months in 2017-2018 in which there was a payment at least $25 in excess of the monthly amount due. Data are a random sample of one million individuals in a major credit bureau, as described in Section 3.2. Panel (A) includes, for each product, all months in which borrowers made any positive payment. Panel (B) includes all months in which borrowers made a positive payment and revolved credit card debt.

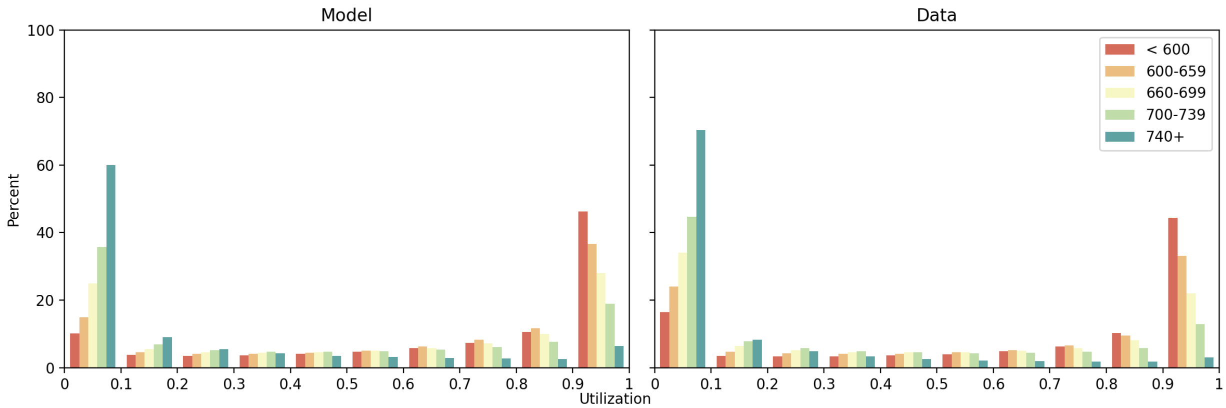
Figure 6: *Excess Debt Payments, Revolvers with Other Debt: Optimal vs Actual*



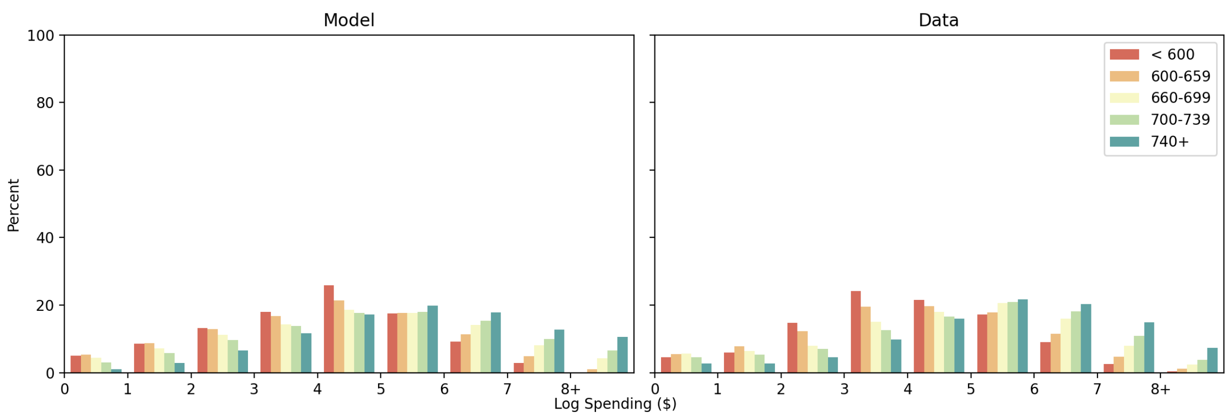
Note: Figure shows the share of debt payments in excess of the minimum amount due going to credit cards versus mortgages, student loans, and auto loans. The sample is consumer-months with revolving credit card debt plus one other debt and some excess payments, as described in Section 4.2.

Figure 7: *Unmatched Moments in the Model vs. Data*

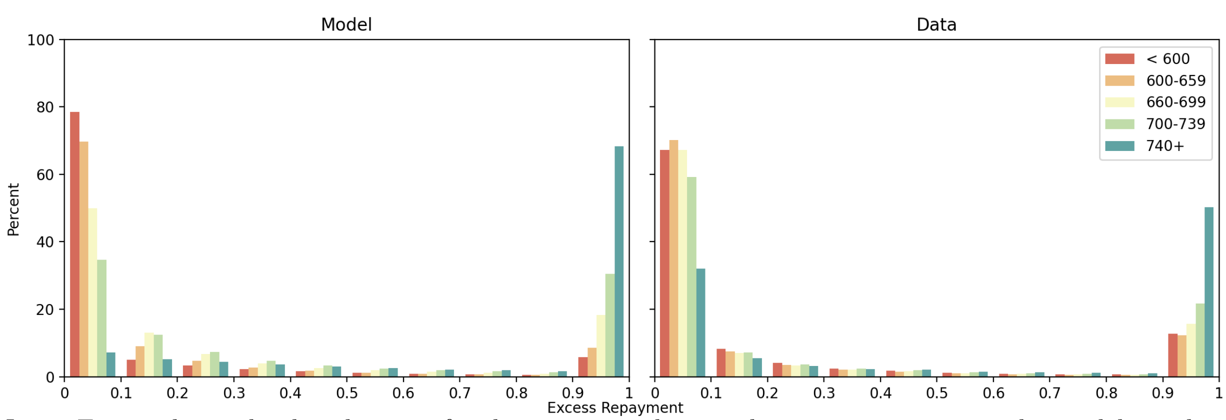
(A) Utilization



(B) Spending



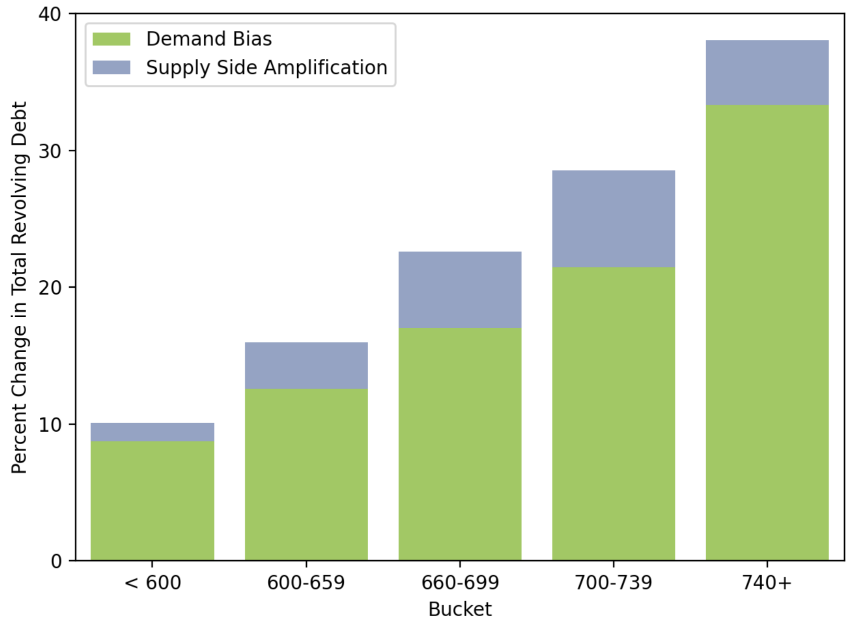
(C) Excess Repayment



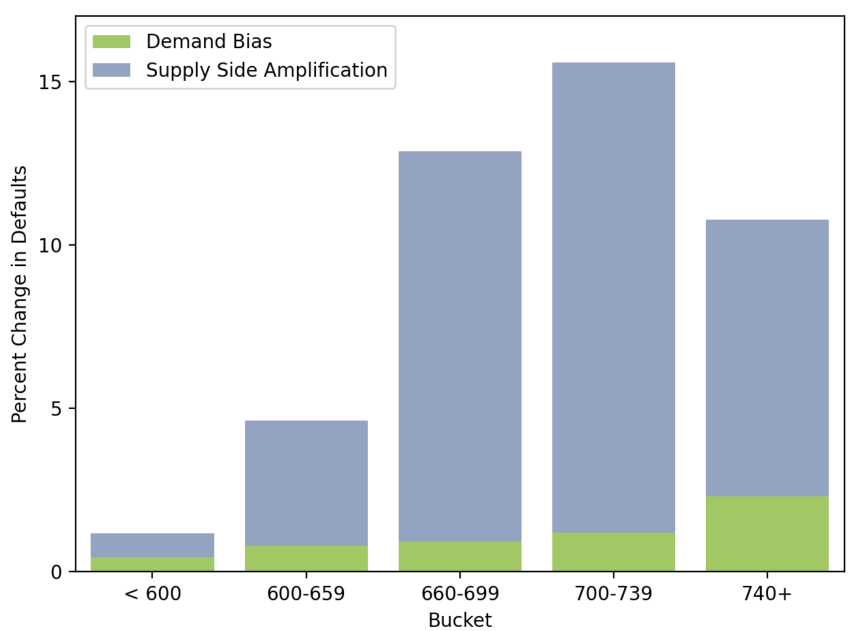
Note: Figure shows the distribution of utilization, spending, and excess repayment in the model vs. data. Utilization is the statement balance divided by the credit limit, spending refers to log spending (on the intensive margin), and excess repayment is the card repayment less the minimum divided by the statement balance less the minimum. While we match some utilization and spending moments, we do not match the full distribution of these variables.

Figure 8: *Increase in Revolving Debt and Defaults With Anchoring*

(A) Total Revolving Debt



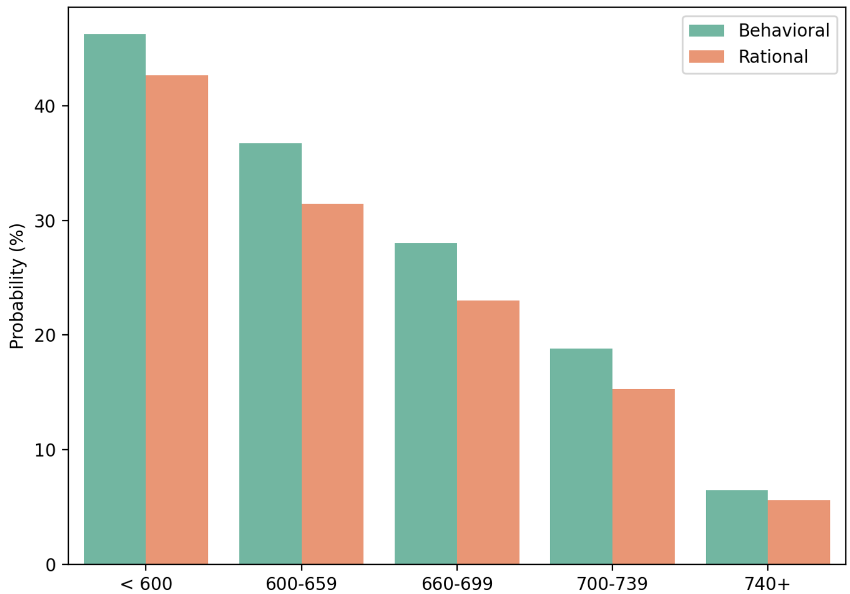
(B) Defaults



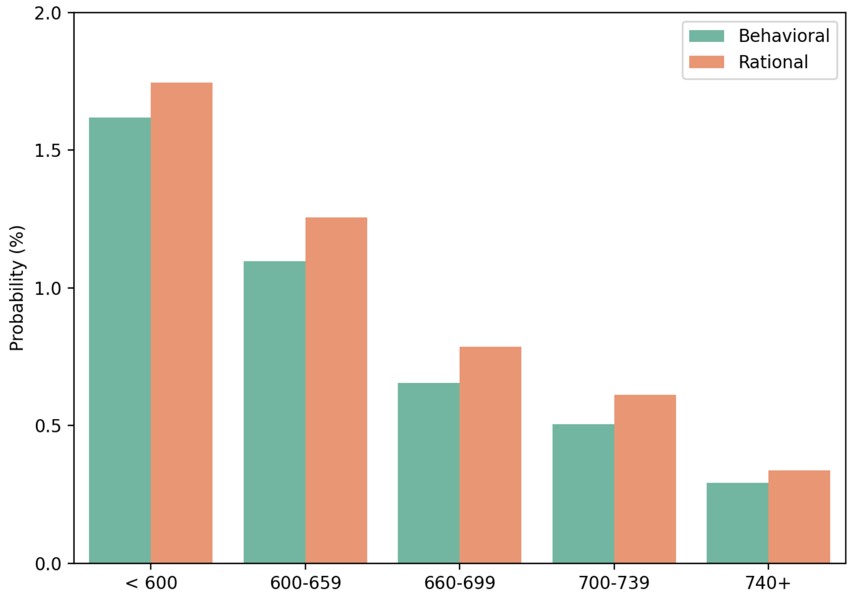
Note: Figure shows how total revolving debt and defaults change in a counterfactual going from unanchored to anchored borrowers. The "Demand Bias" is the change that would occur without the supply-side re-optimizing minimum payments. The "Supply Side Amplification" is additional debt or defaults incurred after the supply-side re-optimizes and pushes minimums to be even lower.

Figure 9: *Utilization and Defaults Among Anchored vs. Unanchored Borrowers*

(A) Probability Utilization ≥ 90%

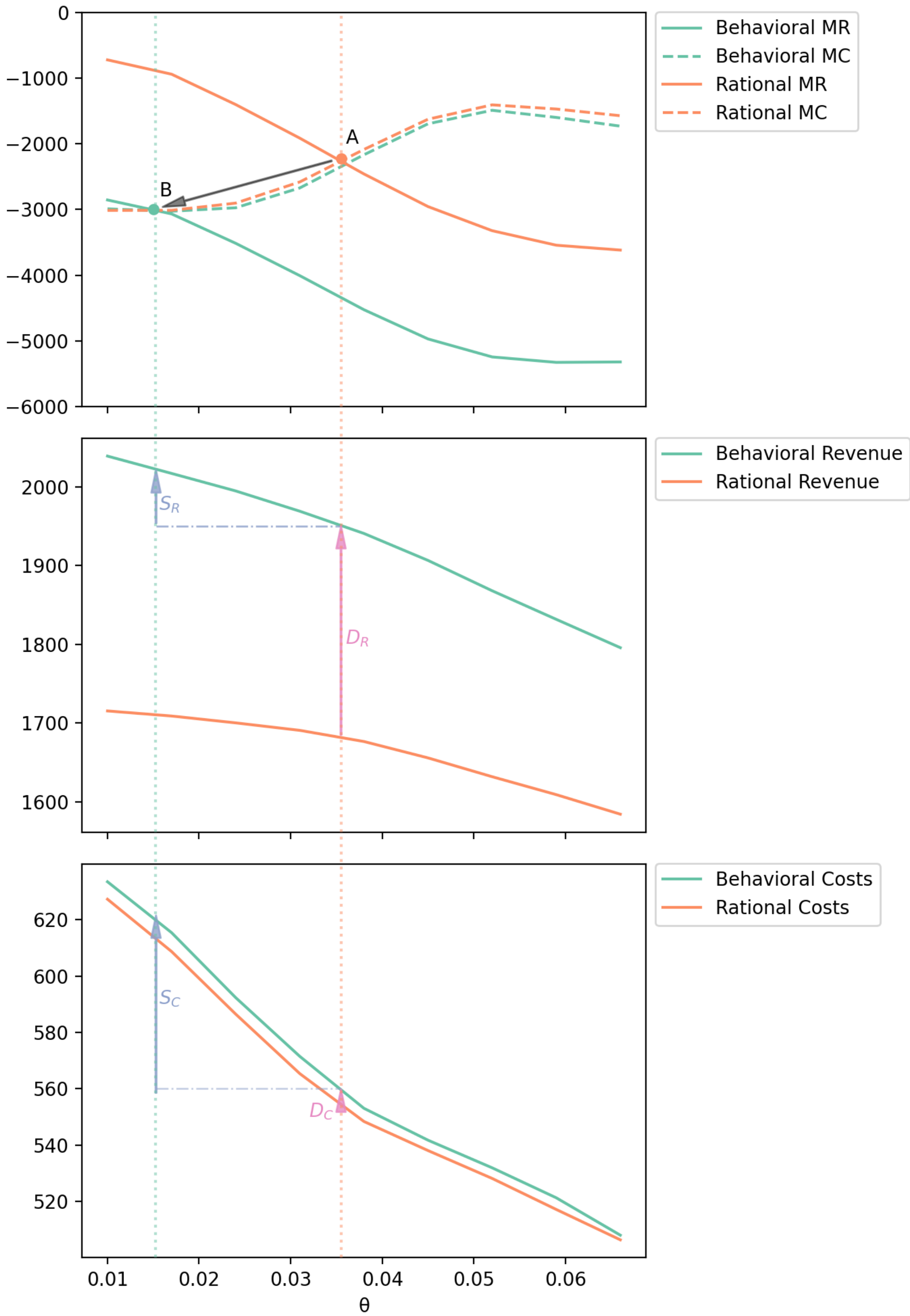


(B) Probability Default Given Utilization ≥ 90%



Note: Figure shows, by credit score group, the probability of having a utilization greater than 90%; and conditional on having a high utilization, the probability of default. "Behavioral" means borrowers are anchored, "rational" means borrowers are unanchored. This figure was made adjusting γ only (holding minimum payments constant at observed levels in the data).

Figure 10: *Revenue and Cost Curves for Example Credit Score Group (660-699)*



Note: Figure shows marginal revenue, marginal costs, revenue, and costs curves in levels, 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, and together, revenue minus costs is profits. Since there is some simulation error, to produce the top plot a spline was fitted to the cost and revenue curves before computing the numerical derivative.

Tables

Table 1: *Summary of "All Tradeline" Sample*

	Mean	SD	p10	p25	p50	p75	p90
Credit Card							
N Open	3.11	2.38	1	1	2	4	6
N Non-Zero Bal.	2.19	1.64	1	1	2	3	4
Total Credit Limit	$28,526	$31,648	$1,500	$6,200	$19,000	$39,950	$67,900
Total Balance	$6,124	$10,169	$247	$779	$2,563	$7,045	$15,821
Total Monthly Amt Due	$159	$257	$25	$41	$86	$184	$373
Mortgage							
Has 1+ Open	0.31	0.46	0	0	0	1	1
Total Balance	$66,659	$158,804	$0	$0	$0	$79,231	$228,156
Total Monthly Amt Due	$539	$1,734	$0	$0	$0	$817	$1,834
Total Bal. Cond. on > 0	$213,984	$222,327	$51,064	$92,986	$160,193	$266,263	$406,255
Auto Loan							
Has 1+ Open	0.35	0.48	0	0	0	1	1
Total Balance	$7,067	$13,901	$0	$0	$0	$10,280	$24,319
Total Monthly Amt Due	$179	$317	$0	$0	$0	$327	$574
Total Bal. Cond. on > 0	$20,129	$16,955	$4,647	$9,228	$16,214	$26,131	$39,475
Student Loan							
Has 1+ Open	0.17	0.37	0	0	0	0	1
Total Balance	$6,269	$24,997	$0	$0	$0	$0	$15,113
Total Monthly Amt Due	$38	$208	$0	$0	$0	$0	$95
Total Bal. Cond. on > 0	$37,158	$50,557	$3,504	$8,433	$20,565	$45,451	$86,284
All Four Types							
N Open	4.54	3.39	1	2	4	6	9
N Unique Types	1.84	0.82	1	1	2	2	3
Total Bal	$86,120	$165,312	$502	$2,576	$19,270	$107,575	$259,043
Total Monthly Amt Due	$915	$1,852	$27	$79	$430	$1,311	$2,454

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.

Table 2: *Summary of "Actual Payments" Sample*

	Mean	SD	p10	p25	p50	p75	p90
Credit Card							
N Open	1.53	0.94	1	1	1	2	3
N Non-Zero Bal.	1.41	0.84	1	1	1	2	2
Total Credit Limit	$12,125	$12,142	$1,000	$3,000	$9,000	$17,500	$27,000
Total Balance	$3,525	$5,541	$115	$400	$1,399	$4,298	$9,575
Total Monthly Amt Due	$98	$155	$20	$27	$51	$114	$236
Total Actual Monthly Pymnt	$879	$2,448	$25	$90	$250	$785	$2,200
N Revolving Bal	0.92	0.98	0	0	1	1	2
Total Revolving Bal	$2,745	$5,183	$0	$0	$508	$3,179	$8,394
Mortgage							
Has 1+ Open	0.31	0.46	0	0	0	1	1
Total Balance	$62,101	$144,122	$0	$0	$0	$75,115	$215,214
Total Monthly Amt Due	$507	$1,640	$0	$0	$0	$785	$1,740
Total Actual Monthly Pymnt	$557	$2,750	$0	$0	$0	$735	$1,830
Total Bal. Cond. on >0	$200,381	$198,277	$49,438	$89,318	$152,849	$251,774	$383,764
Auto Loan							
Has 1+ Open	0.36	0.48	0	0	0	1	1
Total Balance	$7,226	$13,926	$0	$0	$0	$10,738	$24,751
Total Monthly Amt Due	$183	$315	$0	$0	$0	$337	$582
Total Actual Monthly Pymnt	$217	$976	$0	$0	$0	$327	$602
Total Bal. Cond. on >0	$20,203	$16,734	$4,688	$9,303	$16,363	$26,316	$39,539
Student Loan							
Has 1+ Open	0.11	0.31	0	0	0	0	1
Total Balance	$3,346	$17,399	$0	$0	$0	$0	$2,429
Total Monthly Amt Due	$28	$131	$0	$0	$0	$0	$48
Total Actual Monthly Pymnt	$33	$438	$0	$0	$0	$0	$0
Total Bal. Cond. on >0	$30,438	$43,926	$2,652	$6,367	$15,907	$36,543	$71,604
All Four Types							
N Open	2.63	1.93	1	1	2	3	5
N Unique Types	1.78	0.79	1	1	2	2	3
Total Bal	$76,197	$148,613	$278	$1,385	$14,323	$94,376	$237,243
Total Monthly Amt Due	$816	$1,720	$25	$51	$382	$1,180	$2,225
Total Actual Monthly Pymnt	$1,686	$3,949	$60	$250	$810	$2,050	$3,935

Note: Table presents summary statistics on 2017-18 consumer-months in the credit bureau data, as in Table 1, but limits to only tradeline-months for which we observe payments and consumer-months for which there is at least one such credit card. We describe how we measure revolving balances in Appendix B.1.

Table 3: *Mortgage Overpayment Decomposition*

Prepayment Type	Share	N
1) Stickiness	0.2%	2,734
2) Double	14.7%	178,341
3) Round Up	23.6%	286,449
4) Total Payment Mult. of 100	15%	181,638
5) Excess Payment Mult. of 100	13.6%	165,186
6) Other < 1.1x	13.2%	160,328
7) Other 1.1x - 5x	18.9%	229,038
8) Other >5x	0.7%	8,137

Note: Table categorizes mortgage payments in 2017-2018 mortgage-months in which there was some excess payment $\geq$ \$25. "Stickiness" is paying the same amount as the previous amount due. "Round up" is paying an amount divisible by 5 that is $\leq$ 1.1x the amount due. "Double" is paying between 1.95x and 2.05x the amount due. "Total Payment Mult. of 100" is any other payment in which the total payment (excess plus required) is a multiple of 100. "Excess Payment Mult. of 100" is any other payment in which the excess payment is a multiple of 100. The "Other" categories are multiples of the amount due.

Table 4: *Partial Equilibrium Costs of Cross-Product Behaviors*

	Mean	SD	p50	p75	p90
Total Installment Excess Paid (2014-18)	\$4,969	\$14,381	\$1,690	\$5,058	\$11,380
Credit Card Debt Reduction	\$1,765	\$2,761	\$764	\$2,190	\$4,726
Annualized Interest Savings: 10pp APR-Δ	\$177	\$276	\$76	\$219	\$473
Annualized Interest Savings: 15pp APR-Δ	\$265	\$414	\$115	\$328	\$709

Note: Table provides estimates of the magnitude and costs of cross-product debt repayment behaviors. Estimates come from the counterfactual analysis described in Section 4.2. The sample is individuals who revolved credit card debt at the end of 2018 and made any payment (including only the required payment) on any mortgage, auto, or student loan debt in least two years between 2014 and 2018. We transfer installment loan excess payments from this period to the revolving credit card balance at the end of 2018. When excess payments exceed the revolving balance, the revolving balance is set to zero.

Table 5: *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 $\star$	μ	\$25	Our data
Minimum slope	θ	Median estimated θ	Our data
Max late fee $\star$	f_{max}	\$25	Regulation
Monthly installment min	m_{other}	Median installment min	Our data
Annual discount rate $\star$	$(R_l-1)*12$	0.06	Cost of equity
Income			
Average annual income (\$'000)	$\overline{Y}*12$	Mean household income	Our data
Persistence $\star$	ρ	0.989	GL (2017)
Variance $\star$	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/. All parameters marked with a $\star$ *do not* vary by credit score. For values of the other first stage parameters that do vary by credit score, see Table B.6.

Table 6: *Second Stage Moments and Parameters*

Description	Parameter	Moment
Insolvency default rule	ψ	Monthly default probability
Total debt repayment on income	β_y	Mean utilization
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
Corr(spend, total repayment shocks)	$\rho_{s,p}$	Corr(log spend, log total repayment)

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 5.1.1 provides more detail on the parameters.

Table 7: *Estimated Parameters*

	< 600	600-659	660-699	700-739	740+
First Stage					
γ	0.274	0.281	0.265	0.253	0.207
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
p_{nomin}	0.124	0.106	0.09	0.079	0.05
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
p_{close}	0.008	0.01	0.011	0.012	0.014
	(2e-04)	(2e-04)	(2e-04)	(2e-04)	(2e-04)
$p_{nospend}$	0.103	0.136	0.205	0.204	0.15
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
$\overline{Y} * 12$ ('000)	28.235	52.885	69.008	82.439	111.28
	(0.166)	(0.16)	(0.203)	(0.231)	(0.269)
Second Stage					
ψ	0.019	0.021	0.032	0.034	0.032
	(1e-04)	(2e-04)	(3e-04)	(4e-04)	(5e-04)
β_y	0.743	0.775	0.836	0.872	0.937
	(0.009)	(0.004)	(0.002)	(0.002)	(0.003)
σ_p	0.818	0.525	0.347	0.301	0.191
	(0.043)	(0.019)	(0.009)	(0.008)	(0.006)
s_0	4.362	4.374	4.766	5.026	5.55
	(0.023)	(0.023)	(0.027)	(0.027)	(0.023)
σ_s	2.223	2.28	2.397	2.297	2.022
	(0.017)	(0.014)	(0.016)	(0.016)	(0.015)
$\rho_{s,p}$	0.269	0.268	0.316	0.436	0.936
	(0.012)	(0.011)	(0.015)	(0.019)	(0.036)

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

Table 8: *Model-Implied vs. Real-World Minimums*

	< 600	600-659	660-699	700-739	740+
Panel A: Baseline Model					
θ Model	0.036	0.031	0.012	0.012	0.01
θ Real (Median)	0.05	0.03	0.02	0.02	0.02
θ Real (Mode)	0.05	0.02	0.02	0.01	0.01
Panel B: Counterfactuals					
Counterfactual θ	0.044	0.044	0.037	0.039	0.033
Min at CL (Behavioral)	\$59	\$102	\$65	\$84	\$100
Min at CL (Rational)	\$73	\$145	\$200	\$273	\$330

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" stands for the minimum amount due at the credit limit and is calculated by taking the credit limit for each credit-score group and multiplying by the model-implied optimal θ with anchoring (row 1) and no anchoring (row 4).

Appendix

A Theoretical Appendix

A.1 Derivation of Equation 1

Notation:

- Default: $\chi_t = \chi(B_t, m_t)$
- Repayments: $p_t = p(B_t, m_t)$
- Spending: $s_t = s(B_t)$
- Fees: $f_t = f(m_t)$
- Revolving balance: $B_{t+1} = RB_t + s_t + f_t - p_t$

Expected total profits are:

$$\Pi(B_t) = \max_m (1-\chi_t)\left(p_t - s_t + \delta\Pi(B_{t+1})\right)$$

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

$$(1-\chi_t)\left[\frac{\partial p_t}{\partial m} - \delta\Pi'(B_{t+1})\left(\frac{\partial p_t}{\partial m} + \frac{\partial f_t}{\partial m}\right)\right] = \frac{\partial \chi_t}{\partial m}\tilde{\Pi}(B_t)$$

The envelope condition is:

$$\begin{aligned}\Pi'(B_t) &= (1-\chi_t)\left[\frac{\partial p_t}{\partial B_t} - \frac{\partial s_t}{\partial B_t} + \delta\Pi'(B_{t+1})\left(R + \frac{\partial s_t}{\partial B_t} - \frac{\partial p_t}{\partial B_t}\right)\right] - \frac{\partial \chi_t}{\partial B_t}\tilde{\Pi}(B_t)\\ &= (1-\chi_t)\left[\frac{\partial \pi_t}{\partial B_t} + \delta\Pi'(B_{t+1})\left(R - \frac{\partial \pi_t}{\partial B_t}\right)\right] - \frac{\partial \chi_t}{\partial B_t}\tilde{\Pi}(B_t)\end{aligned}$$

Iterate forward:

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

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

$$(1-\chi_t)\left[\frac{\partial p_t}{\partial m} - \delta\left\{(1-\chi_{t+1})\frac{\partial \tilde{\Pi}(B_{t+1})}{\partial B_{t+1}} - \frac{\partial \chi_{t+1}}{\partial B_{t+1}}\tilde{\Pi}(B_{t+1})\right\}\left(\frac{\partial p_t}{\partial m} + \frac{\partial f_t}{\partial m}\right)\right] = \quad \frac{\partial \chi_t}{\partial m}\tilde{\Pi}(B_t)$$

Then we have:

$$\begin{aligned}
&\underbrace{(1-\chi_t)\frac{\partial p_t}{\partial m}}_{\uparrow\text{current pmt}} - \underbrace{\delta(1-\chi_t)(1-\chi_{t+1})\frac{\partial \tilde{\Pi}(B_{t+1})}{\partial B_{t+1}}\left(\frac{\partial p_t}{\partial m} + \frac{\partial f_t}{\partial m}\right)}_{\downarrow\text{net interest revenue + fees}} \\
&= \quad \underbrace{\frac{\partial \chi_t}{\partial m}\tilde{\Pi}(B_t)}_{\uparrow\text{illiquidity defaults}} \quad - \underbrace{\delta(1-\chi_t)\frac{\partial \chi_{t+1}}{\partial B_{t+1}}\tilde{\Pi}(B_{t+1})\left(\frac{\partial p_t}{\partial m} + \frac{\partial f_t}{\partial m}\right)}_{\downarrow\text{insolvency defaults + fees}}
\end{aligned}$$

B Empirical Analysis Appendix

B.1 Additional Details About Credit Bureau Outcome Measures

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

Measuring 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, we assign a zero balance. The use of the lagged balance captures the time between the statement being issued and the payment being due (generally 30 days and no less than 21 days). This measure is the same as the one in Guttman-Kenney and Shahidinejad (2023), who use similar credit bureau data.

Separating between zero payment and missing data. In our credit bureau data, missing payments data and zero payment are often both reported as missing. To separate between the two, we assign a month a zero payment when there are months within the two-year period both before and after that have non-missing payment information. We also require the credit limit to be non-missing in that particular month. This approach will not generally affect our two analyses that focus on excess payments, as these months are excluded. Appendix Table B.5 shows our approach generates missed payment frequencies that generally align well with Y-14 data on the frequency of credit card late fees.

Excluding "catch up" payments. When a borrower misses a payment for an installment loan, to avoid delinquency they are generally required to "catch up" by making this payment, even as new payments become due. These "catch up" payments are not always captured in the required monthly payment in the credit bureau data. We account for these in our installment debt analyses as follows. First, when a consumer misses a payment we start a running sum of the difference between their actual payments and the monthly amount due, only resetting this sum to zero once they make a full payment or more. When they make this first full or more payment, we calculate the excess payment as the actual payment net the monthly amount due and the running sum of the amount behind. This reduces the share of months in which consumers do not cost minimize from 49% to 46%, primarily due to consumers with double payments in the month following a missed payment.

B.2 Comparison to Cross-Card Repayment Behaviors

In this appendix, we compare cross-card repayment behaviors to the cross-product behaviors we document in Section 4.2. We first document, consistent with Ponce *et al.* (2017) and Gathergood *et al.* (2019b), 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 UK, we cannot directly observe interest rates.[61] Rather we look at a "best-case" scenario, in which the card that consumers prioritize most is their highest-APR card.

Following Gathergood *et al.* (2019a,b), 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 card payment; and total card payments are strictly between the total card balances and the total minimum payments due. Appendix Figure B.2 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.[62] 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.3 plots the distribution of *excess* payments for these consumer-months across the credit score distribution. The plot shows that, even in the "best-case" scenario in which the higher APR card is the one that receives the larger share of payments, borrowers do not cost-minimize by focusing repayments on a single highest-APR card first more than 60% of the time, more frequent than the 46% for the cross-product behaviors. However, per deviation from cost-minimization, the average amount mis-allocated is only \$102 for the cross-card behavior compared to \$203 for the cross-product behavior.

B.3 Optimal Inattention and Cross-Product Behaviors

In this appendix we explore the extent to which models of optimal inattention can explain the cross-product behaviors we document in Section 4.2. In these models, agents face fixed costs of attention and their behavior changes only if the costs of their behavior becomes higher than this cost (Sims, 2003). We test this theory in a manner by correlating 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 our 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

[61] Gathergood *et al.* (2019a), which includes a similar analysis in the US, notes "we are unaware of any US dataset that has interest rates on multiple cards for a broadly representative sample."

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

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.4 shows that the average mortgage overpayments from borrowers with revolving credit card debt did not substantially change as average outstanding credit card interest rates changed through 2017 and 2018. Appendix Table B.2 tests this using regressions with person fixed effects and monthly-level information on credit card balances and amounts due. Even in a sample of consumers with one 30-year mortgage through all of 2017 and 2018, the probability of making an overpayment of $25 or more on a mortgage is does not significantly fall as credit card interest rates increase.

B.4 Intra-Household Frictions and Cross-Product Behaviors

In this appendix, we explore the extent to which intra-household frictions may help explain the cross-product behaviors documented in Section 4.2. To do so, we use an imputed measure of whether of households are married, provided by the credit bureau and based on information including whether the individual holds joint accounts. Column 1 of Appendix Table B.3 shows that, among individuals who revolve credit card debt, married households are more likely to overpay their installment debts. Column 2 shows this result holds even after controlling for credit score and other debt characteristics.

However, these results may be driven by married households being more likely to overpay their installment debts in general, rather than due to intra-household frictions in repayments. To isolate the latter, Column 3 uses a two-way fixed effects design that includes indicators for being married, revolving credit card debt, and their interaction. The interaction is associated with a 1.03% increase in the propensity to deviate from cost-minimization across products, providing evidence that intra-household frictions play some role in explaining these behaviors. Columns 4-6 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.

B.5 Anchoring and Cross-Product Behaviors

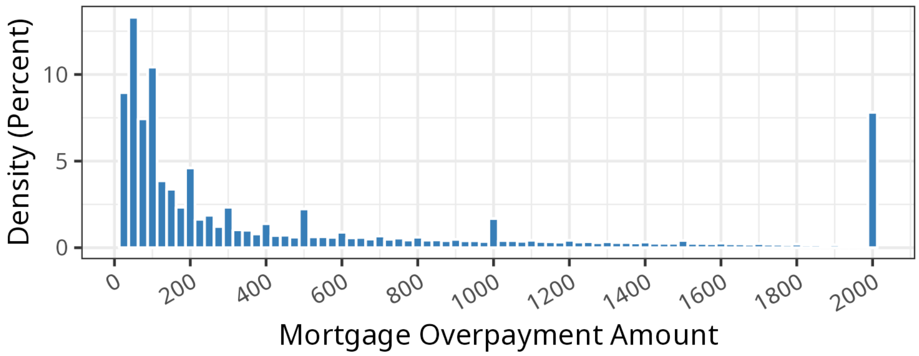
In this appendix, we explore the extent to which anchoring or minimum-based targets may help explain the cross-product behaviors documented in Section 4.2. To do so, we first analyze the credit card repayments of borrowers who do and do not make installment debt overpayments. Panel A of Appendix Figure B.5 shows that repayments are similarly U-shaped for both borrower groups, with many borrowers paying close to, but exactly, the minimum. Such a pattern is consistent with borrowers choosing repayment levels relative to the minimum. That this pattern exists even for borrowers overpaying installment debts, also provides evidence that liquidity constraints cannot fully explain repayment behaviors.

Panels B and C of Appendix Figure B.5 focus on the distribution of payments for borrowers paying between \$1 and \$100 from the minimum. Panel B shows that borrowers appear to frequently "round up" from the minimum, making round payments in multiples of \$10 or \$50. Panel C shows that borrowers also often make payments that are the minimum plus a round number. Both panels show that these patterns exist regardless of whether the borrower overpays installment debts, again suggesting that anchoring plays an important role in shaping repayment behaviors.

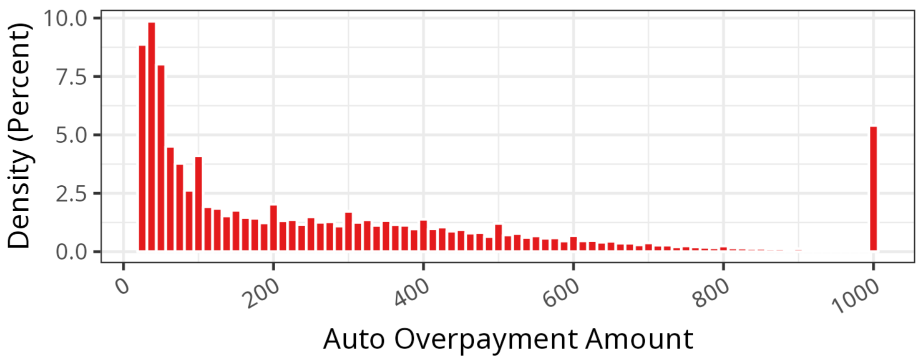
B.6 Additional Figures

Figure B.1: *Distribution of Overpayments ≥ $25 by Debt Type*

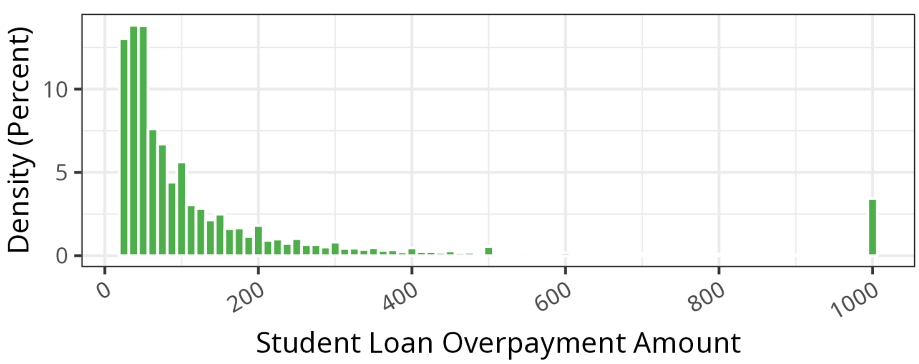
(A) Mortgage



(B) Auto Loan

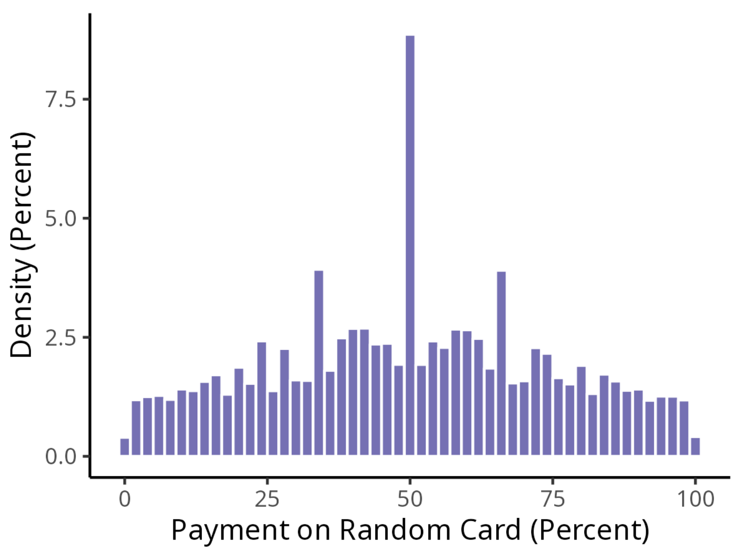


(C) Student Loan



Note: Figure shows the distribution of excess payments for all debt-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 last bars.

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

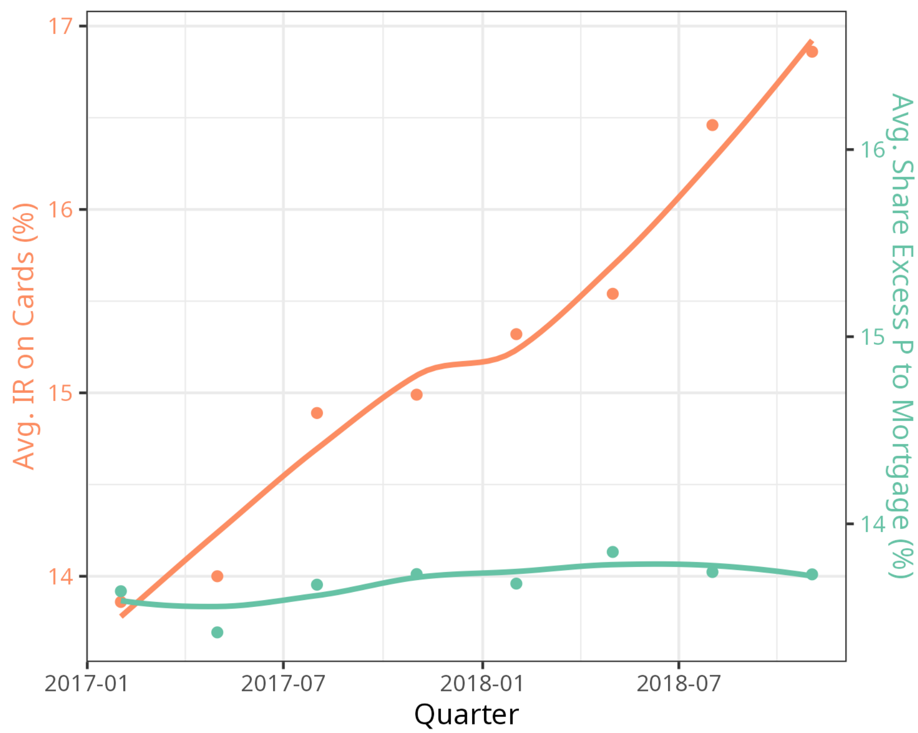


Note: Figure shows the share of credit card payments made on one card. The sample is consumer-months with actual payments for two credit cards and some excess payments, as described in Appendix B.2. The figure is similar to Figure 1 in Gathergood *et al.* (2019b) and Figure 1 in Gathergood *et al.* (2019a).

Figure B.3: *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 Figure B.2. The green bars display the actual data. The orange bars display the cost-minimizing strategy, as described in Appendix B.2.

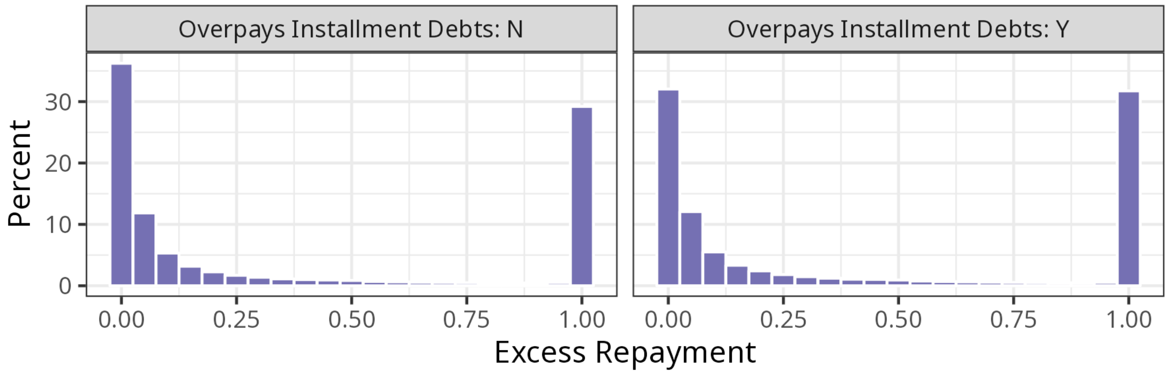
Figure B.4: *Mortgage Cross-Product Behavior Over Time*



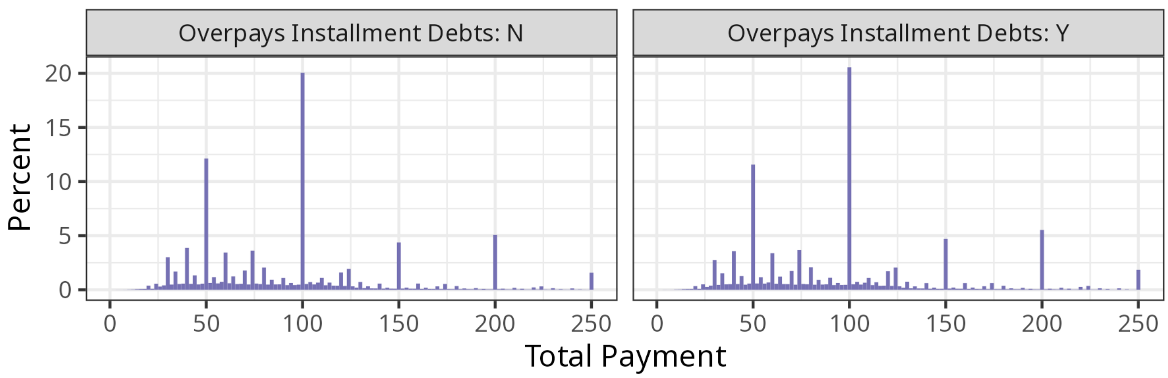
Note: Figure shows the share of excess payments on mortgages and credit cards going to mortgages (green) against the average interest rate on credit cards (orange). The sample is consumer-months with a positive mortgage and credit card balance and with total excess payments on these products that would not cover the credit card balance. The average interest rate comes from FRED series TERMCBCCINTNS.

Figure B.5: *Distribution of Repayments by Installment Debt Overpayments*

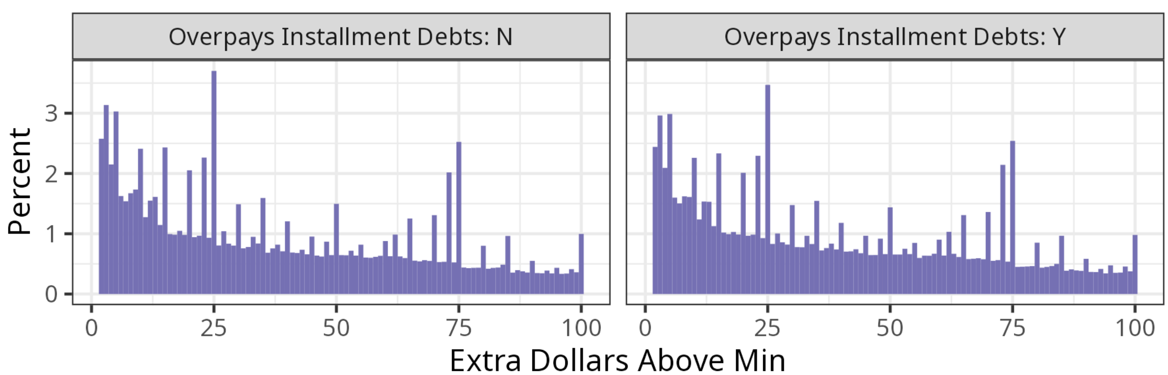
(A) Excess Repayments as Share of Balance



(B) Round-Up From Minimum



(C) Round Excess Payments



Note: Figure shows the distribution of credit card repayments in months when the borrower did not miss the minimum and also made a payment on one more installment debts. The left column shows repayments in months the borrower paid only the minimum required installment debt payment. The right column shows repayments in months the borrower paid more than the required payment. Panel (A) plots $\frac{\text{actual payment}_t - \text{minimum payment}_{t-1}}{\text{balance amt}_{t-1} - \text{minimum payment}_{t-1}}$. 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. Panel(B) plots actual payments for those who paid between \$1 and \$100 from their minimum payment. Panel (C) plots actual $\text{payment}_t - \text{minimum payment}_{t-1}$ for the same borrowers.

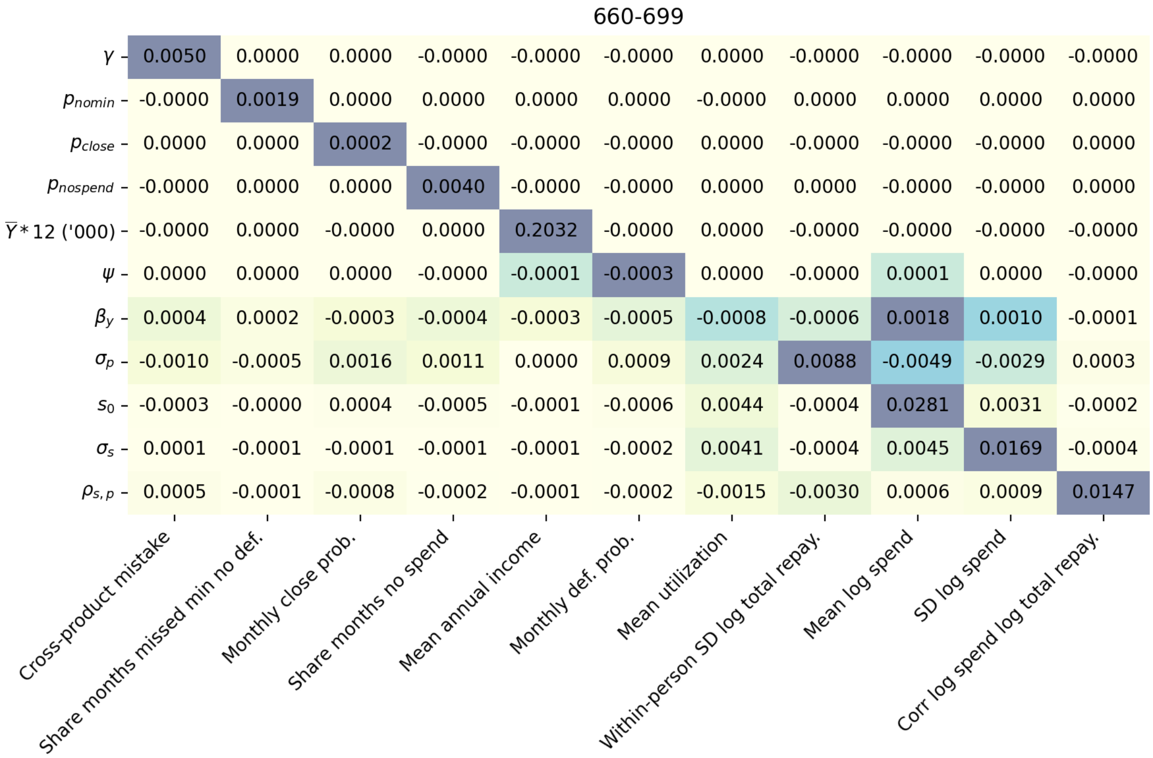
Figure B.6: *Sensitivity of Parameters to Moments*

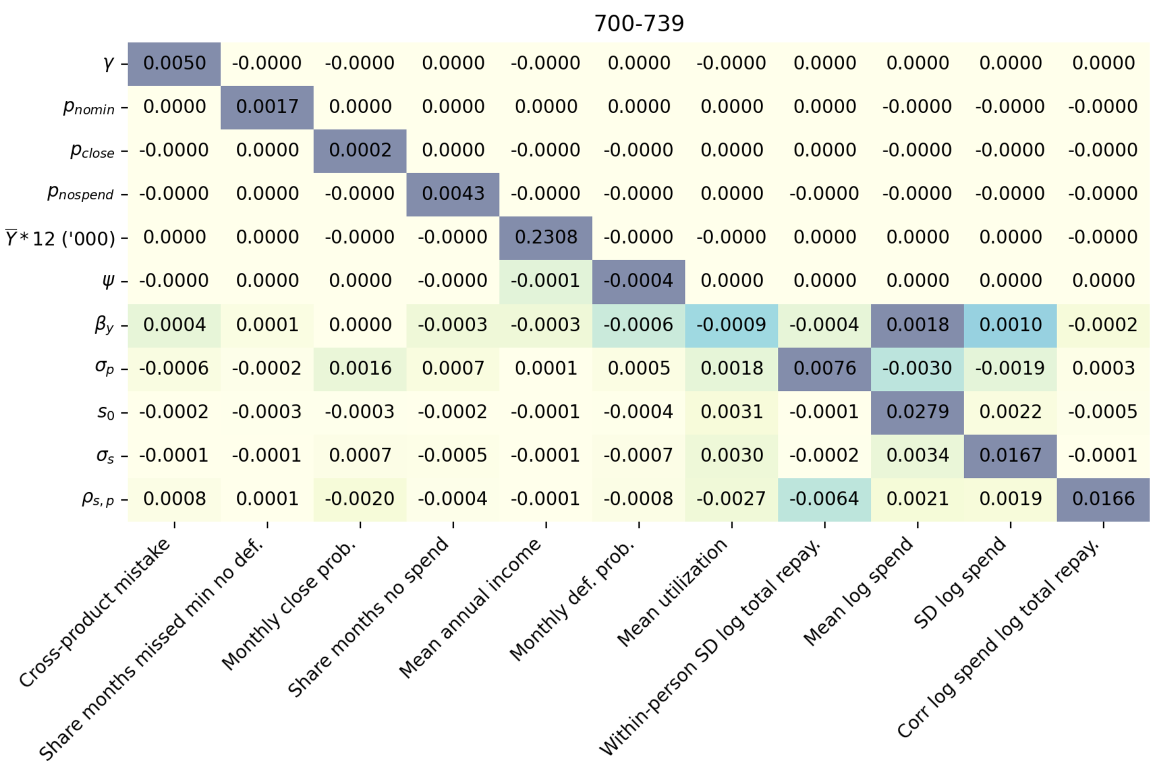
< 600

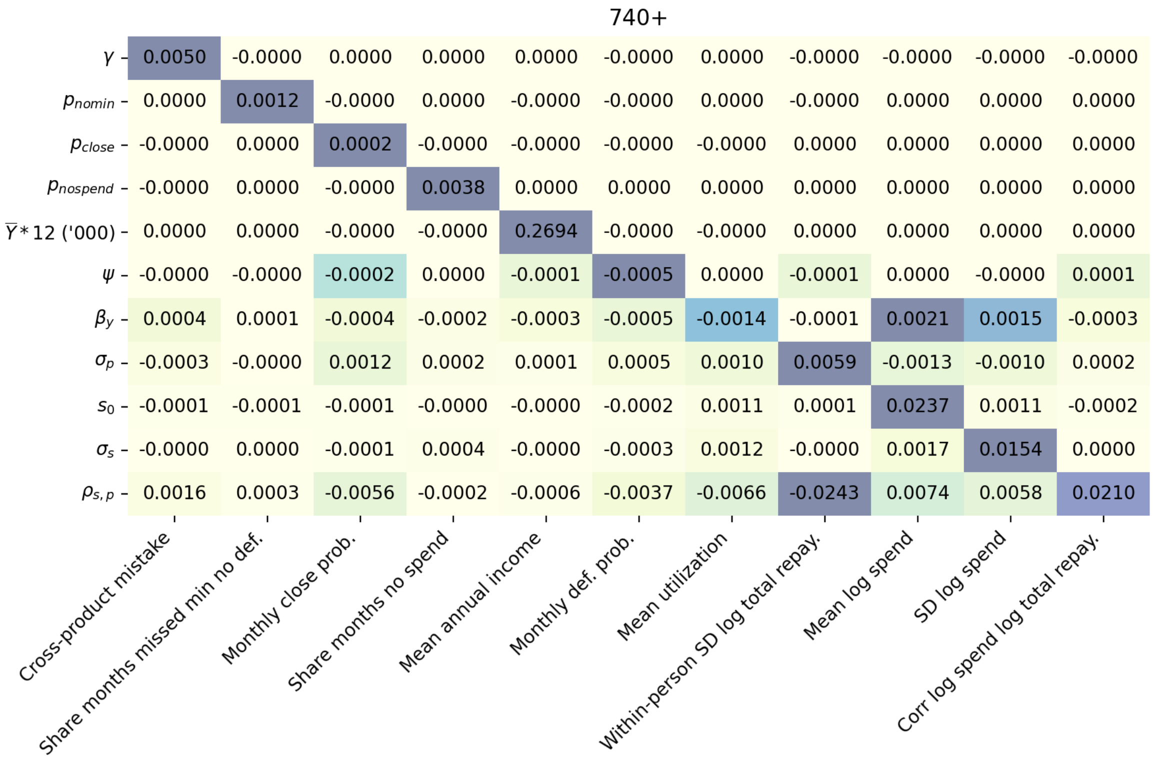
	Cross-product mistake	Share months missed min no def.	Monthly close prob.	Share months no spend	Mean annual income	Monthly def. prob.	Mean utilization	Within-person SD log total repay.	Mean log spend	SD log spend	Corr log spend log total repay.
γ	0.0054	-0.0000	-0.0000	0.0000	0.0000	0.0000	0.0000	-0.0000	-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
p_{close}	0.0000	0.0000	0.0002	-0.0000	-0.0000	-0.0000	0.0000	-0.0000	-0.0000	-0.0000	-0.0000
$p_{nospend}$	0.0000	0.0000	-0.0000	0.0026	-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	0.1663	-0.0000	0.0000	0.0000	-0.0000	-0.0000	-0.0000
ψ	-0.0000	0.0000	0.0000	-0.0000	-0.0001	-0.0001	0.0000	0.0000	0.0000	0.0000	-0.0000
β_y	0.0012	0.0007	-0.0006	-0.0011	-0.0005	-0.0009	-0.0024	-0.0044	0.0063	0.0037	-0.0004
σ_p	-0.0055	-0.0032	0.0030	0.0049	-0.0000	0.0032	0.0114	0.0299	-0.0293	-0.0175	0.0019
s_0	-0.0006	-0.0002	0.0002	0.0007	0.0000	0.0014	0.0077	0.0021	0.0224	0.0053	-0.0005
σ_s	-0.0004	-0.0006	0.0006	0.0007	-0.0000	0.0002	0.0073	0.0021	0.0045	0.0166	-0.0001
$\rho_{s,p}$	-0.0010	-0.0004	0.0008	0.0005	-0.0000	0.0005	0.0023	0.0028	-0.0043	-0.0028	0.0139

600-659

	Cross-product mistake	Share months missed min no def.	Monthly close prob.	Share months no spend	Mean annual income	Monthly def. prob.	Mean utilization	Within-person SD log total repay.	Mean log spend	SD log spend	Corr log spend log total repay.
γ	0.0050	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
p_{close}	0.0000	0.0000	0.0002	-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
$\overline{Y}*12$ ('000)	0.0000	0.0000	-0.0000	-0.0000	0.1602	0.0000	-0.0000	0.0000	0.0000	0.0000	0.0000
ψ	-0.0000	0.0000	0.0000	-0.0000	-0.0001	-0.0001	0.0000	0.0000	0.0000	0.0000	-0.0000
β_y	0.0006	0.0004	-0.0003	-0.0006	-0.0003	-0.0006	-0.0012	-0.0016	0.0029	0.0017	-0.0002
σ_p	-0.0027	-0.0016	0.0022	0.0028	-0.0000	0.0018	0.0058	0.0146	-0.0135	-0.0078	0.0009
s_0	-0.0002	0.0002	0.0011	-0.0003	-0.0000	0.0002	0.0047	0.0003	0.0236	0.0035	-0.0007
σ_s	-0.0002	-0.0002	-0.0003	-0.0003	-0.0001	-0.0001	0.0044	-0.0000	0.0043	0.0146	-0.0001
$\rho_{s,p}$	-0.0002	-0.0001	0.0005	0.0004	-0.0000	-0.0000	0.0005	0.0004	-0.0018	-0.0009	0.0120

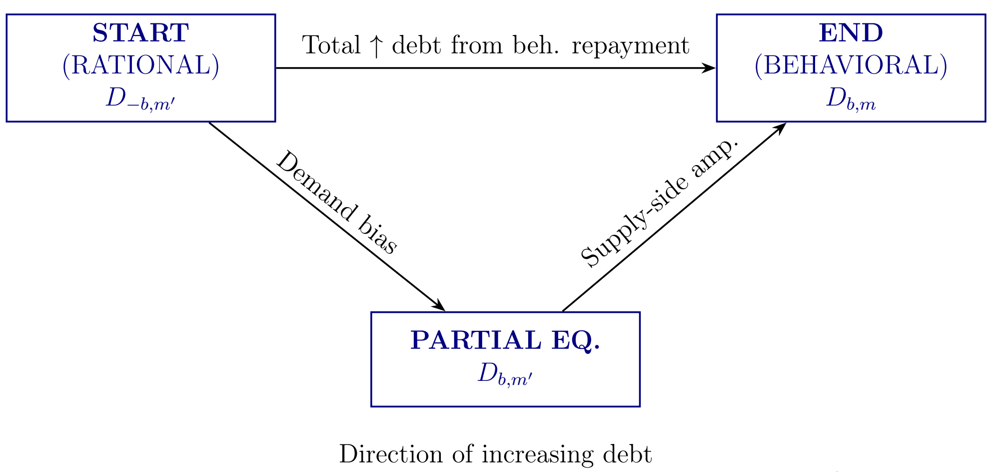

660-699
γ 0.0050 0.0000 0.0000 -0.0000 -0.0000 -0.0000 0.0000 -0.0000 -0.0000 -0.0000 -0.0000
p_{nomin} -0.0000 0.0019 0.0000 0.0000 0.0000 0.0000 -0.0000 0.0000 0.0000 0.0000 0.0000
p_{close} 0.0000 0.0000 0.0002 -0.0000 -0.0000 -0.0000 0.0000 -0.0000 -0.0000 -0.0000 0.0000
$p_{nospend}$ -0.0000 0.0000 0.0000 0.0040 -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 0.2032 -0.0000 0.0000 -0.0000 -0.0000 -0.0000 -0.0000
ψ 0.0000 0.0000 0.0000 -0.0000 -0.0001 -0.0003 0.0000 -0.0000 0.0001 0.0000 -0.0000
β_y 0.0004 0.0002 -0.0003 -0.0004 -0.0003 -0.0005 -0.0008 -0.0006 0.0018 0.0010 -0.0001
σ_p -0.0010 -0.0005 0.0016 0.0011 0.0000 0.0009 0.0024 0.0088 -0.0049 -0.0029 0.0003
s_0 -0.0003 -0.0000 0.0004 -0.0005 -0.0001 -0.0006 0.0044 -0.0004 0.0281 0.0031 -0.0002
σ_s 0.0001 -0.0001 -0.0001 -0.0001 -0.0001 -0.0002 0.0041 -0.0004 0.0045 0.0169 -0.0004
$\rho_{s,p}$ 0.0005 -0.0001 -0.0008 -0.0002 -0.0001 -0.0002 -0.0015 -0.0030 0.0006 0.0009 0.0147
Cross-product mistake
Share months missed min no def.
Monthly close prob.
Share months no spend
Mean annual income
Monthly def. prob.
Mean utilization
Within-person SD log total repay.
Mean log spend
SD log spend
Corr log spend log total repay.


700-739
γ 0.0050 -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
p_{close} -0.0000 0.0000 0.0002 0.0000 -0.0000 -0.0000 0.0000 0.0000 -0.0000 -0.0000 -0.0000
$p_{nospend}$ -0.0000 0.0000 -0.0000 0.0043 -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 0.2308 -0.0000 -0.0000 0.0000 0.0000 0.0000 -0.0000
ψ -0.0000 0.0000 0.0000 -0.0000 -0.0001 -0.0004 0.0000 0.0000 0.0000 0.0000 0.0000
β_y 0.0004 0.0001 0.0000 -0.0003 -0.0003 -0.0006 -0.0009 -0.0004 0.0018 0.0010 -0.0002
σ_p -0.0006 -0.0002 0.0016 0.0007 0.0001 0.0005 0.0018 0.0076 -0.0030 -0.0019 0.0003
s_0 -0.0002 -0.0003 -0.0003 -0.0002 -0.0001 -0.0004 0.0031 -0.0001 0.0279 0.0022 -0.0005
σ_s -0.0001 -0.0001 0.0007 -0.0005 -0.0001 -0.0007 0.0030 -0.0002 0.0034 0.0167 -0.0001
$\rho_{s,p}$ 0.0008 0.0001 -0.0020 -0.0004 -0.0001 -0.0008 -0.0027 -0.0064 0.0021 0.0019 0.0166
Cross-product mistake
Share months missed min no def.
Monthly close prob.
Share months no spend
Mean annual income
Monthly def. prob.
Mean utilization
Within-person SD log total repay.
Mean log spend
SD log spend
Corr log spend log total repay.



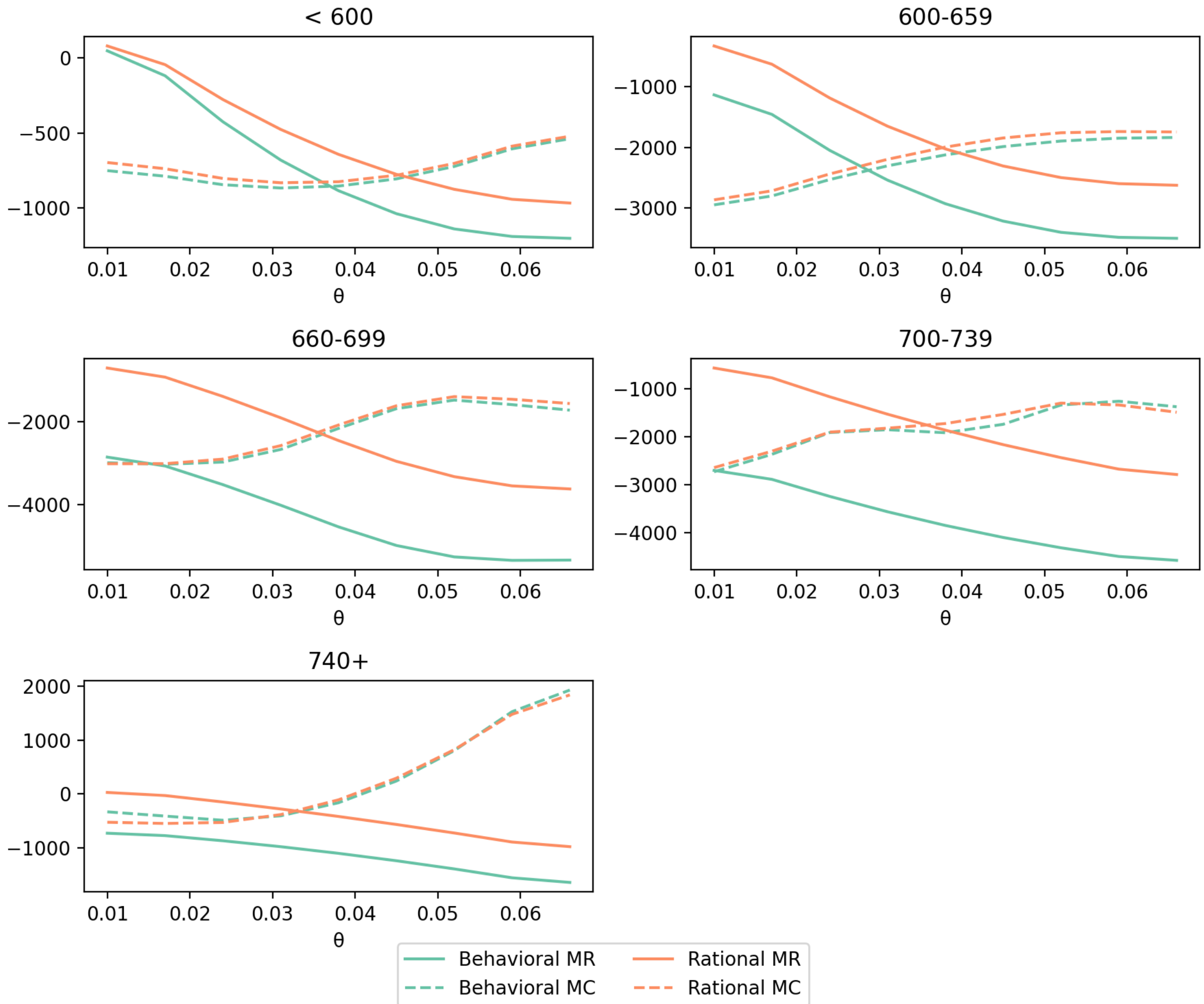
Note: Figure shows sensitivity analysis of parameters to moments following Andrews *et al.* (2017). For each credit score bin we report $\Lambda \cdot \sqrt{(1+D/S)\Omega_g}$, where $\Lambda = (G'WG)^{-1}G'W$ (same notation as in Appendix C.2) as recommended by Andrews *et al.* (2017) for classical minimum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

Figure B.7: *Flow Chart for Counterfactuals*



Note: Figure shows a flow chart for the counterfactuals of interest. $D_{-b,m'}$ is total debt with no behavioral repayment $-b$ and optimal minimums m'. $D_{b,m'}$ is total debt with behavioral repayment b and (sub-optimal) minimums m'. $D_{b,m'}$ is total debt with behavioral repayment b and optimal minimums m.

Figure B.8: *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, and together, revenue minus costs is profits. Since there is some simulation error, to produce this plot a spline was fitted to the cost and revenue curves before computing the numerical derivative.

B.7 Additional Tables

Table B.1: *Summary of Cards With and Without Actual Payments*

	Mean	SD	p10	p25	p50	p75	p90
Has Actual Payments							
Monthly Balance Amount	$1,856	$3,159	$39	$183	$638	$2,083	$5,088
Credit Score	718.72	101.76	591	655	734	800	825
No Actual Payments							
Monthly Balance Amount	$2,166	$3,838	$26	$189	$806	$2,556	$5,674
Credit Score	730.97	101.97	606	676	757	806	830

Note: Table provides 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.2: *Optimal Inattention and Cross-Product Behavior*

Dependent Var: 100 × Overpays Mortgage ≥ $25				
	(1)	(2)	(3)	(4)
Avg. IR on Cards	−0.05	0.07*	0.02	0.02
	(0.03)	(0.04)	(0.04)	(0.09)
Log(Balance Amt Card)			1.43***	1.36***
			(0.04)	(0.11)
Log(Monthly Amt Due Card)			0.37***	0.25
			(0.08)	(0.23)
Sample	Baseline	Baseline	Baseline	One 30-Year
Person FE		Y	Y	Y
Observations	1489292	1489292	1489292	191620
R2 Adj.	0.000	0.491	0.492	0.471

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

Note: Table shows results from regressions described in Appendix B.3. 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 lager. The sample in the final column is borrowers who had one 30-year mortgage through all of 2017 and 2018. The average interest rate come from FRED series TERMCBCCINTNS.

Table B.3: *Intra-Household Frictions and Cross-Product Behavior*

	Dependent Var: 100 × Overpays Installment ≥ $25					
	(1)	(2)	(3)	(4)	(5)	(6)
Is Married	2.12***	0.31***	−0.72***	−0.35	−1.23**	0.09
	(0.10)	(0.08)	(0.11)	(0.21)	(0.35)	(0.17)
Credit Score	0.04***	0.03***	0.03***	0.03***	0.04***	0.03***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Log(Bal Amt Card)		0.03	−0.01	−0.05	−0.13	0.11**
		(0.06)	(0.02)	(0.04)	(0.07)	(0.03)
Log(Month Amt Due Card)		−0.53***	−0.37***	−0.35***	−0.47**	−0.31***
		(0.07)	(0.05)	(0.05)	(0.15)	(0.06)
Log(Bal Amt Install)		1.56***	1.10***	2.81***	1.42***	−2.00***
		(0.23)	(0.22)	(0.39)	(0.25)	(0.47)
Log(Month Amt Due Install)		2.88***	3.26***	2.65***	2.10***	3.35***
		(0.37)	(0.36)	(0.67)	(0.33)	(0.81)
Is Revolving			−5.22***	−4.78***	−6.91***	−4.55***
			(0.14)	(0.24)	(0.33)	(0.24)
Is Married × Is Revolving			1.03***	0.55*	2.36***	0.20
			(0.12)	(0.20)	(0.40)	(0.21)
Sample	Revolves	Revolves	All	Has Auto	Has Edu	Has Mort
Observations	1727526	1727526	2439187	1549015	456514	1382662
R2 Adj.	0.009	0.021	0.025	0.035	0.029	0.010

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

Note: Table shows results from regressions described in Appendix B.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 a mortgage overpayment of $25 or lager. The sample in columns 1-2 filters to those who are revolving credit card debt. The sample in columns 4-6 filters to those who are overpaying auto, student, and mortgage loans, respectively.

Table B.4: *Share of Balance and Actual Payments on Cards vs Installment Loans*

	Mean	SD	p10	p25	p50	p75	p90
Share Balance on Credit Card	9.7%	15.5%	0.2%	0.8%	3.2%	10.8%	28.7%
Share Actual Pymnt on Credit Card	34%	25.9%	5.3%	11.9%	27.1%	52.7%	74.8%

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

Group	Share Missed Min	CFPB: Share Late Fee
1) Superprime	20%	15%
2) Prime	35%	32%
3) Near-prime	42%	43%
4) Subprime	52%	53%
5) Deep Subprime	63%	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: $\geq$ 720 is superprime; 660-719 is prime; 620-659 is near-prime; 580-619 is subprime; $\leq$ 580 is deep subprime.

Table B.6: *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 ($)	$\overline{L}$	[1651, 3305, 5406, 6994, 10006]
Minimum floor ($)	μ	25
Minimum slope	θ	[0.05, 0.03, 0.02, 0.02, 0.02]
Max late fee ($)	f_{max}	25
Monthly installment min ($)	m_{other}	[475, 567, 753, 957, 1284]
Annual discount rate	$(R_l-1)*12$	0.06
Income		
Average annual income ($'000)	$\overline{Y}*12$	[28, 53, 69, 82, 111]
Persistence	ρ	0.989
Variance	σ_y	0.078
Spending		
No spending probability	$p_{nospend}$	[0.1, 0.14, 0.2, 0.2, 0.15]
Card Closure		
Card closing probability	p_{close}	[0.008, 0.01, 0.011, 0.012, 0.014]
Repayments		
Missed min probability	p_{nomin}	[0.12, 0.11, 0.09, 0.08, 0.05]
Anchoring	γ	[0.27, 0.28, 0.26, 0.25, 0.21]

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

Table B.7: *Expected Profits and Minimum Floors*

Floor (μ)	< 600	600-659	660-699	700-739	740+
0	141	592	1390	1305	476
25	146	600	1403	1322	494
50	141	594	1401	1320	495

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 fixed at the values observed in the data (no counterfactuals).

Table B.8: *Model Fit*

	< 600	600-659	660-699	700-739	740+
Real (Data)					
Annual Default Prob	0.099	0.052	0.023	0.012	0.003
Mean Utilization	0.728	0.663	0.574	0.464	0.239
Std Log Total Payments (FE)	0.342	0.34	0.347	0.354	0.326
Mean Log Spending	3.945	4.101	4.531	4.877	5.501
Std Log Spending	1.788	1.97	2.126	2.101	1.934
Corr Log Spending and Log Total Repayments	0.187	0.21	0.234	0.273	0.352
Fit (Model)					
Annual Default Prob	0.099	0.052	0.023	0.012	0.003
Mean Utilization	0.728	0.663	0.574	0.464	0.239
Std Log Total Payments (FE)	0.342	0.34	0.347	0.354	0.326
Mean Log Spending	3.945	4.101	4.531	4.877	5.501
Std Log Spending	1.788	1.97	2.126	2.101	1.934
Corr Log Spending and Log Total Repayments	0.187	0.21	0.234	0.273	0.352

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

C 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

Fixed Parameters: For a given set of borrower parameters, the model simulates $N = 10,000$ borrowers over $T = 240$ months.

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):

$$\begin{aligned}
m_1 &= \left(\frac{1}{12}\right)^2 \left(12 + 2\sum_{i=1}^{11}(12-i)(\rho_m)^i\right)\left(\frac{\sigma_m^2}{1-\rho_m^2}\right) \\
m_2 &= \left(\frac{1}{12}\right)^2 \left(\sum_{i=1}^{12} i(\rho_m)^i + \sum_{j=13}^{23}(24-j)(\rho_m)^j\right)\left(\frac{\sigma_m^2}{1-\rho_m^2}\right) \\
m_1 &= \frac{\sigma_a^2}{1-\rho_a^2} \\
m_2/m_1 &= \rho_a
\end{aligned}$$

We simulate all income processes starting off at mean income, but have a $10 \times T$ month burning period (so that in the model all simulated individuals have a different starting income). The net present value of income is calculated using the credit card APR as the discount rate and going forward 1000 months.

C.2 Second Stage Estimation and Standard Errors

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 $\Theta_2 = (\psi, \beta_y, \sigma_p, s_0, \sigma_s, \rho_{s,p})$:

$$\text{Bounds} = [(0,1),(0,1),(0,1.5),(0,10),(0,5),(-0.9999,0.9999)]$$

We first run DE, and then refine the solution with five Nelder-Meads with no bounds on any parameter except $\rho_{s,p} \in (-0.9999, 0.9999)$. We also have a set of manual starting points (which we also refine using five Nelder-Meads), and ensure that the global optimum achieves a solution better than the manual one. Note that since our system is just-identified, if the optimizer finds a zero we can be fairly confident that a solution has been found.

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 $M_{\Theta_2} \times (N_{\Theta_2} + N_{\Theta_2})$ 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.

D CFPB Credit Card Agreement Database

In this appendix, we describe our analyses usings 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 Contract 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 Contract Database.

Table D.1: *Minimum Payments in CFPB Credit Card Contract 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 Contract 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 2. 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 describe a pilot survey to better understand the mechanisms underlying the debt repayment patterns we document in Section 4.2. The pilot was conducted on Prolific in December 2023 and contains two parts: hypothetical vignettes and open-ended questions about personal debt repayment.[63] In the vignettes, participants were asked to allocate $100 across two cards. Card A had an account balance of $1,200, a minimum payment of $25, and 10% APR in the baseline vignette. Card B had a lower account balance of $1,000, a minimum of $20, but a higher 20% APR. In the open-ended questions, participants were asked to think about how they paid their credit card and mortgage in the last few weeks. We collected 100 responses and filtered to 96 after screening for attention.

The survey's hypothetical vignettes were intended to explore whether limited knowledge of the interest rates across their debts drives cross-product behaviors. Appendix Figure E.1 shows that, even with clearly displayed APRs, fewer than 30% of baseline respondents fully cost minimize, suggesting a lack of knowledge on one's APR is not a key driver.

A second set of questions invited participants to "think about the payments you've made on your credit cards [or mortgage] in the last few weeks." Many respondents report repayment strategies relative to minimum amounts. A smaller set of borrowers mentions housing security in payment prioritization. We provide examples of each below. Future versions of this pilot will provide more evidence on the frequency of different explanations.

Repayments Strategies Relative to the Minimum

- *I have a set amount (a little over the minimum payment) that I pay. If the balance is under $400, I usually try to pay the whole amount.*

- *I paid a little more than minimum on the lowest card, but this is only to get it to $0 and then cancel it.*

- *Paid minimum +15% as always til paid off.*

- *I pay my credit card payment...when I get paid. I usually pay a little more than the minimum, so usually 60 a month.*

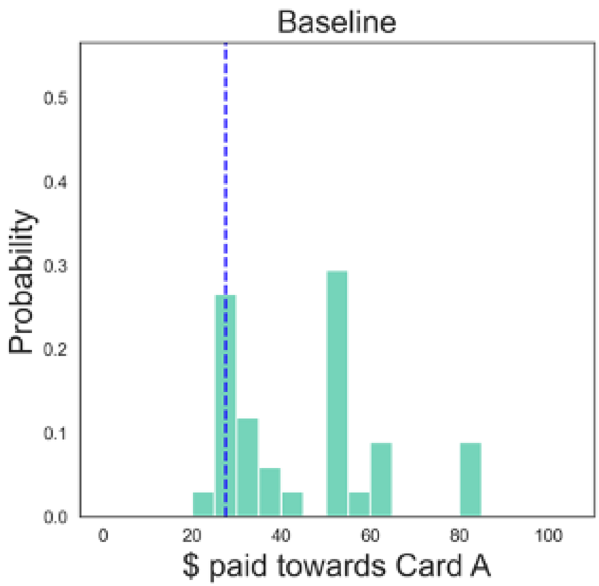
- *I set up the payment the day I receive the bill. I always pay a few dollars more than the minimum payment always rounding it to end in either 0 or $5.*

[63] The survey can be found here. Appendix Table E.1 shows the sample demographics. The sample somewhat skews female and more educated.

Housing Security

- *Always pay required mortgage first; don't want to put my house in jeopardy since it's the biggest investment of my life.*
- *You don't screw with your mortgage payment!*

Figure E.1: *Survey Baseline Vignette Results*



Note: Figure shows the distribution of responses from the credit card vignettes. Card A had an account balance $1200, a minimum payment of $25, and a 10% APR. Card B had a lower account balance of $1000, a minimum payment of $20, but a higher 20% APR. The blue line shows the cost-minizing repayment strategy: paying only the minimum on Card A.

Table E.1: *Survey Demographics*

	Proportion	Mean	Median
Age		42.34	37.00
Gender			
Female	0.62		
Male	0.36		
Education			
4-year college degree	0.41		
Some college	0.21		
Master's degree, MBA	0.14		
2-year college degree	0.10		
High school degree/GED	0.06		
PhD, JD, MD	0.04		
Some high school	0.03		
Race			
European American/White	0.76		
Asian/Asian American	0.09		
Hispanic/Latino	0.07		
African American/Black	0.05		
Other	0.02		
Income			
$ 50,000-$ 74,999	0.19		
$ 100,000-$ 149,999	0.18		
$ 75,000-$ 99,999	0.18		
$ 40,000-$ 49,999	0.15		
$ 10,000-$ 19,999	0.08		
$ 30,000-$ 39,999	0.08		
$ 20,000-$ 29,999	0.06		
$ 150,000+	0.05		
$ 0-$ 9,999	0.02		
Responsibility			
A great deal	0.61		
A lot	0.19		
A moderate amount	0.15		
A little	0.05		

Note: Table shows the demographics of survey participants. "Responsbility" refers to a question that asked: "In your household, how much responsibility do you have for paying monthly bills?" $N = 96$.