Minimum Payments and Debt Paydown in Consumer Credit Cards*

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Abstract

Using a dataset covering one quarter of the U.S. general-purpose credit card market, we document that 29% of accounts regularly make payments at or near the minimum payment. We exploit changes in issuers' minimum payment formulas to distinguish between liquidity constraints and anchoring as explanations for the prevalence of near-minimum payments. Nine to twenty percent of all accounts respond more to the formula changes than expected based on liquidity constraints alone, representing a lower bound on the role of anchoring. Disclosures implemented by the CARD Act, an example of one potential policy solution to anchoring, resulted in fewer than 1% of accounts adopting an alternative suggested payment. Based on back-of-envelope calculations, the disclosures led to $62 million in interest savings per year, but would have saved over $2 billion per year if all anchoring consumers had adopted the new suggested payment. Our results show that anchoring to a salient contractual term has a significant impact on household debt.

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I Introduction

Borrowing and repayment choices have significant impacts on the path and level of consumption over the lifecycle, but relatively little is known about how consumers make these decisions in many large debt markets. With $712 billion in total outstanding balances as of May 2016, credit cards represent one of the largest sources of liquidity for household consumption in the United States. In this paper, we examine the drivers of debt repayment in a dataset covering 25% of the U.S. general-purpose credit card market.

In particular, we focus on the role of minimum payments. Minimum payments indicate the smallest payment necessary to remain current on an account in a given month, and are dictated by formulas under the discretion of credit card issuers.[1] Anecdotal and experimental evidence suggest that minimum payments may affect payment choices due to anchoring, a bias toward salient (but sometimes irrelevant) cues.[2] Because the minimum payment is a lower bound on the optimal payment amount for the vast majority of consumers, anchoring would downwardly bias payment amounts and lead to suboptimally high debt levels, lower average consumption, and greater consumption volatility for affected consumers. To our knowledge, ours is the first empirical study to estimate the economic significance of anchoring in the credit card market.

We analyze the effect of minimum payments on payment decisions using the CFPB credit card database (CCDB), which contains the near-universe of credit card accounts for a number of large U.S. credit card issuers.[3] The CCDB includes monthly account-level data from 2008 through 2013, and is merged to credit bureau data that provides an overview of each borrower's credit portfolio on a quarterly basis. We observe the exact amounts of minimum and actual payments in each month,

[1]Regulatory rules and guidance set some boundaries on the disclosure and amortization schedule of minimum payments, but issuers exercise substantial discretion within these boundaries. Typical minimum payments are between 1-4% of the balance. Alongside the full statement balance, minimum payments are prominently featured at the top of credit card statements, in the payment slip, and on online and mobile payment interfaces.

[2]Thaler and Sunstein (2008) write that minimum payments "can serve as an anchor, and as a nudge that this minimum payment is an appropriate amount." Stewart (2009) shows that including a minimum payment on hypothetical credit card statements significantly decreases payment size. Navarro-Martinez, Salisbury, Lemon, Stewart, Matthews and Harris (2011) find that hypothetical statements with higher minimum payments result in lower average payments, and Hershfield and Roese (2014) find evidence that including both a minimum payment and three-year payment amount disclosure similar to that required by the CARD Act leads to lower payments than presenting only one payoff scenario.

[3]The CCDB is confidential supervisory information, and the statistics in this paper have been aggregated to maintain the confidentiality of both issuers and consumers in the underlying data. We omit information about the total number of issuers and exact samples sizes included in the analysis to preserve confidentiality. Confidential supervisory information has only been shared in aggregated form with Benjamin Keys.

and can track accounts over time. Thus, the database allows us to estimate the high-frequency effects of policy changes and control for both account fixed effects and a rich set of time-varying characteristics.

We divide our empirical analysis into three sections. First, we describe consumer payment behavior by classifying accounts based on their history of payments relative to the minimum payment and the full balance. We find that 29% of accounts pay exactly or close to (i.e. within $50 of) the minimum in most months. The remainder either pay in full most of the time or make a mix of intermediate payment amounts. Neither individual income nor age strongly correlate with payment behavior, but both credit score at origination and account balance are correlated with the propensity to make near-minimum payments. The large fraction of accounts paying close to the minimum provides prima facie evidence that either many consumers are liquidity constrained at amounts that happen to be near the minimum, or that repayment decisions are influenced by anchoring.

A key challenge with interpreting the role of minimum payments is that they are both a potential anchor and a corner solution. Consumers who fail to pay the minimum incur substantial late fees and can also face penalty interest rates, credit score damage, and credit supply reductions. These penalties provide strong incentives for liquidity-constrained borrowers to pay at least the minimum. Nonetheless, some consumers whose optimal repayment is higher than the minimum may underpay due to anchoring. Without detailed information on consumers' wealth and income dynamics, it is difficult to disentangle these two effects.

We address this challenge in the second part of our empirical analysis, which takes advantage of the fact that several issuers changed their minimum payment formulas during the sample period. We start with a simple framework for interpreting how formula changes should affect the distribution of payments. Our identifying assumption is that liquidity-constrained borrowers should respond to a formula increase by either bunching mechanically at the new minimum or becoming delinquent if they are sufficiently constrained. In contrast, some anchoring borrowers may choose to always pay a certain amount more than the minimum regardless of changes in its dollar value. This framework allows us to estimate the fraction of anchoring consumers by measuring the degree of bunching at the minimum payment before and after formula changes.

We implement our estimates using a difference-in-differences approach based on the four increases and one decrease in minimum payment formulas observed in our sample, including accounts from several issuers that did not change their formulas as controls. Consistent with the presence of anchoring, we find a 9 to 20% gap in the degree of observed bunching at the new minimum payment compared to what is expected based on liquidity constraints alone. This estimate is a lower bound for the fraction of anchoring accounts, since it does not include consumers who move from exactly the old to exactly the new minimum in strict adherence to the anchor. Most of the anchoring effect occurs immediately when the formulas change, and the effect is observed for both formula increases and decreases. A significant fraction of accounts anchor to the minimum payment across the credit score spectrum and within each quartile of income and age. Changes in the minimum payment are not associated with changes in card usage or delinquency in our sample.

One potential way to de-bias anchoring consumers while preserving liquidity for constrained consumers is through disclosures or "nudges" that encourage higher payments. The third and final part of our empirical analysis explores the effect of one such disclosure required by the Credit Card Accountability Responsibility and Disclosure (CARD) Act of 2009. The disclosure was mandated on more than half of all statements, and presents a calculation of the payment needed to amortize the outstanding balance in three years. Exploiting regulatory rules that exempt some consumers from receiving the disclosure, we estimate the effects of this policy change using a difference-in-differences framework.[4]

In contrast to the large fraction of accounts that anchor to the minimum payment, we find that fewer than 1% of accounts adopt the three-year repayment amount, and the effect decays by one-third within one year. The modest effects we observe could be due to a number of factors. First, the substantial fraction of consumers who make online or mobile payments without opening their statements never observe the new disclosure. Second, those who do view the disclosure may not find it to be salient among other information present on statements, and it may not have remained salient during the lag between viewing the statement and making a payment.[5] Finally,

[4]In related work, Agarwal, Chomsisengphet, Mahoney and Stroebel (2015) compare repayment patterns across personal and small business cards, which were differentially impacted by the CARD Act, to analyze the impact of this three-year payment calculation.

[5]Based on conversations with industry participants, many consumers who continue to receive paper statements make payments online. Thus, consumers may not remember the information on the disclosures by the time they make their payments.

the minimum payment, which is still present on all statements, may continue to exert a stronger influence than the three-year repayment amount. Although we cannot disentangle the relative importance of these potential explanations, the results show that a prominent policy change aimed at de-biasing consumers failed to yield a large economic effect relative to the influence of anchoring.

We conduct a back-of-envelope estimate of the economic significance of anchoring by comparing the observed effects of the disclosure to the counterfactual effect if all anchoring consumers had adopted the new suggested payment. We estimate that in steady-state, the disclosures reduced interest payments by a total of $62 million per year marketwide, given the distribution of customers in 2013. In contrast, if the disclosures had caused all anchoring consumers to move from the minimum payment to the three-year repayment amount, total interest costs would have declined by between $2.7 and $4.7 billion.

Our findings contribute to and build connections between three strands of literature, which focus on the regulation of consumer financial markets, the role of anchoring in real-world decision-making, and the effects of default options on household balance sheets. In particular, Campbell (2016) presents a framework for consumer financial regulation based on the observation that a sizable share of households behave suboptimally when interacting with retail financial markets. The literature on behavioral biases and credit use proposes a number of factors that could lead consumers to take on too much debt relative to rational benchmarks, including hyperbolic discounting, naivete, and cost misperception.[6] Our paper outlines one source of suboptimal decision-making, highlights the importance of the repayment margin of credit use, and estimates several of the key parameters laid out by Campbell (2016) as applied to the optimal regulation of payment structures for revolving debt.[7]

Although a substantial psychological literature starting from Tversky and Kahneman (1974) shows that anchoring can significantly affect individual responses in laboratory experiments, ours

[6]On naivete and hyperbolic discounting, see Ausubel (1991), Angeletos, Laibson, Repetto, Tobacman and Weinberg (2001), Della Vigna and Malmendier (2004), Shui and Ausubel (2004), Skiba and Tobacman (2008), Heidhues and Kőszegi (2010), and Kuchler (2015). On cost misperception, see Stango and Zinman (2009) and Bertrand and Morse (2011). A related literature examines the role of adverse selection in consumer choices (e.g. Agarwal, Chomsisengphet, and Liu 2010).

[7]The key parameters are the fraction of behavioral households who are misusing a credit product, the benefits of the product when properly used, the deadweight cost of intervention, and the effectiveness of an intervention that encourages proper usage. Zinman (2015) also highlights the need for more empirical research on the relationship between borrowing and consumer preferences, beliefs, and cost perceptions.

is one of surprisingly few studies that provide evidence of anchoring in the real world.[8] While our paper is one of the first to analyze the role of anchoring in credit use, related effects have received careful study in the literature on household savings. Seminal work by Madrian and Shea (2001) showed that default options in employer-sponsored retirement savings plans have dramatic effects on employee enrollment, contribution rates, and portfolio choice. Subsequent studies confirm that default effects and consumer passivity are widespread across different types of retirement savings decisions, and that passive decisions pass through to overall savings and consumption levels.[9] Despite the influence of this literature in both research and policy, few papers have applied its insights to the liabilities side of household balance sheets. Minimally-amortizing loan contracts exist in many credit markets (e.g. adjustable-rate mortgages, home equity lines of credit, and payday loans), so anchoring to minimum payments and other salient contract features may well extend beyond credit cards to other types of liabilities.

Interest-only loans and other "risky" loan structures have received significant attention from policymakers in recent years, and a number of papers have analyzed the effects of regulations that restrict the types of loans that can be offered to consumers.[10] However, we know of few that attempt to disentangle the effects of restrictions on the contract space from the reduced-form effects of changes in credit supply. In particular, our paper is one of the first to study the effects of regulatory guidance that encourages higher minimum payments on credit cards.[11] Recent work has also examined a number of dimensions of the CARD Act.[12] Our identification strategy for the impacts of the CARD Act disclosures complements the approach taken by Agarwal et al. (2015), and yields a new estimate of the demand response to information disclosure.

[8] Notable examples include Simonsohn and Loewenstein (2006) and Beggs and Graddy (2009).

[9] See, for example, Choi, Laibson, Madrian and Metrick (2002), Choi, Laibson, Madrian and Metrick (2004), Choi, Laibson, Madrian and Metrick (2006), Beshears, Choi, Laibson and Madrian (2009), and Carroll, Choi, Laibson, Madrian and Metrick (2009) for evidence on default effects, passive decision-making, and related effects in retirement savings in the U.S. Chetty, Friedman, Leth-Petersen, Nielsen and Olsen (2014) use comprehensive Danish data to show that the majority of individuals are passive savers, and automatic contributions to retirement savings are almost fully passed through to total savings. While anchoring can potentially explain some of the effects documented in this literature, the savings literature has thus far not attempted to distinguish the role of anchoring from other psychological factors.

[10] See, for example, Di Maggio and Kermani (2014), Ding, Quercia, Reid and White (2012) and Bond, Musto and Yilmaz (2009) on the effects of anti-predatory loan provisions in the mortgage market.

[11] A concurrent paper by d'Astous and Shore (2014) finds evidence of liquidity constraints in the context of a increase in minimum payments at a single financial institution. Seira and Castellanos (2010) explore the role of minimum payments in credit card choice in Mexico.

[12] On the impacts of the CARD Act, see Agarwal et al. (2015), Debbaut, Ghent and Kudlyak (2013), and Jambulapati and Stavins (2014). On consumer financial regulation, see Campbell (2006), Bar-Gill and Warren (2008), Barr, Mullainathan and Shafir (2013), and Campbell (2016).

The remainder of the paper is organized as follows. Section II provides background on credit card minimum payments and describes our dataset. Section III presents a descriptive analysis of consumer payment patterns. Sections IV and V estimate the prevalence of anchoring and the impact of the CARD Act disclosures, respectively. Section VI discusses the economic significance of anchoring, Section VII provides a discussion of the theoretical explanations and implications of our findings, and Section VIII concludes.

II Data and Background on Minimum Payments

II.A Minimum Payments and Government Policy

Minimum payments are a universal feature of credit cards, and indicate the lowest payment necessary to remain current on an account in a given month. In the 1970s, typical minimum payments were about 5% of the outstanding balance.[13] By the 2000s, the average minimum payment had fallen to 2% (Kim 2005). While this decline could have resulted from competitive pressure to attract customers and maintain customer loyalty, industry insiders also report that issuers lowered minimums in order to extend repayment periods and increase interest revenue.[14]

Beginning in the mid-2000s, minimum payments came under increasing scrutiny of regulators and consumer groups for their role in high interest costs and debt burdens. Most notably, in 2003 the Office of the Comptroller of the Currency (OCC) and other prudential regulators issued guidance on minimum payments, stating that they "expect lenders to require minimum payments that will amortize the current balance over a reasonable period of time."[15] Several issuers have raised their formulas in the years since the guidance was issued, and our identification strategy exploits these changes.

Regulatory interest in the credit card industry continued throughout the 2000s, culminating

[13]Testimony of Travis B. Plunkett, Legislative Director of the Consumer Federation of America, in U.S. Congress, Senate Committee on Banking, Housing, and Urban Affairs, Examining the Current Legal and Regulatory Requirements and Industry Practices for Credit Card Issuers With Respect to Consumer Disclosures and Marketing Efforts, hearings, 109th Cong., 1st sess., May 17, 2005, p.8.

[14]Interview with Andrew Kahr, credit card industry consultant, "Secret History of the Credit Card," *Frontline*, PBS, 2004.

[15]The other regulators issuing the interagency guidance were the Federal Reserve Board, Federal Deposit Insurance Corporation, and Office of Thrift Supervision. See Office of the Comptroller of the Currency et al. (2003).

in the passage of the CARD Act in May 2009.[16] The CARD Act instituted dramatic changes to industry practices, including restrictions on fees, interest rate re-pricing, payment allocation, and billing practices. In addition, the CARD Act and its implementing regulation instituted disclosures aimed at warning consumers about the costs of making only the minimum payment. These disclosures were mandated starting in February 2010, and introduced a new payment suggestion on many consumers' monthly statements equalling the amount that would amortize the existing balance over the next three years.

During our sample period, we observe four increases and one decrease in issuers' minimum payment formulas. Issuers have discretion to set their own formulas in compliance with regulator guidance, and we do not know the exact reasons why they made these changes.[17] From an issuer's perspective, the optimal formula balances interest revenues, credit risk, and regulatory risk. Based on news reports and conversations with regulators and industry insiders, direct and indirect regulatory concerns are likely to be the main reason for the formula changes. Some issuers reportedly changed their formulas when changing regulators (e.g. when moving from state to national charters), potentially under the direct guidance of their new regulators.[18] Even without direct advice from regulators, issuers whose formulas are below the market norm may elect to voluntarily increase them in anticipation of future regulatory action (Knittel and Stango 2003, Stango 2003). Finally, issuers may also have business reasons to modify their formulas. The CARD Act changed the payment hierarchy such that payments in excess of the minimum must be applied to balances with the highest interest rates first. Thus, increasing minimum payments may yield higher interest revenue for some issuers. Increasing the minimum could also help issuers mitigate default risk, an area of concern for both banks and regulators during our sample period.

The formulas used for determining minimum payment amounts can be found on issuer websites, in credit card agreements, and on a number of commercial comparison-shopping websites. Minimum payment formulas generally follow a consistent format, with a flat "floor" region for lower balances

[16]In December 2008, the Federal Reserve Board, Office of Thrift Supervision, and National Credit Union Administration amended their regulations to parallel many aspects of the CARD Act, and were later modified to have concurrent effective dates as the CARD Act provisions.

[17]To protect the confidentiality of the identities of the issuers included in our analysis, we omit the details of the exact timing of the formula changes and the circumstances of the issuers that changed their formulas.

[18]Although all of the major bank regulators jointly issued the 2003 interagency guidance, individual regulators may have different standards of compliance and provide different feedback to supervised entities.

and sloped regions based on a percentage of the balance for higher balances. Figure 1 shows a simplified version of a typical minimum payment formula and illustrates the two types of formula changes we observe in our sample. Under the "old" formula in both panels, the minimum payment is given by the following:

$$minimum = \max\{floor, 2\% \cdot balance\}$$

Panel A shows the impact of an increase in the floor portion of the formula. In this example, the floor is raised from \$20 under the old formula (solid line) to \$40 under the new formula (dashed line). For a floor increase, only consumers with balances below a given threshold experience changes in their minimum payments. Thus, for this type of formula change, only some consumers are treated with changes in their minimum payments, and a given consumer may be treated in some months and not treated in others depending on their balance.

Another way to adjust the minimum payment formula is to shift the entire schedule. Panel B of Figure 1 shows a shift in the schedule from the old formula to a new formula with $minimum = \$20 + \max\{floor, 2\% \cdot balance\}$. In the case of a schedule increase, all consumers are treated by the formula change, and experience increases in the minimum payment of a fixed amount (here \$20). Minimum payment formulas could also change in other ways, such as changing the slope (e.g. from 2% of the balance to 3%), but the examples shown in the figure reflect the two types of changes we observe in our sample.

Actual minimum formulas are often more complex than those in our simple example. For very low balances less than the floor amount, the minimum payment is generally equal to the balance due. While our example shows typical minimum payments for transactors, i.e. consumers who do not have any interest charges in the current month, actual formulas may have a third component in the *max* function that incorporates interest charges (e.g. $1\% \cdot balance + interest$). Thus, minimum payments can also depend on whether a consumer is revolving debt and the interest rate they face. Late and overlimit fees and past due amounts are also typically added to the minimum payment. Despite these complications, similar intuition about the subsets of accounts that are treated and the relationship between the minimum and the balance applies to the formulas we actually observe in our data.

Our identification strategy focuses on the sharp changes in consumer payments that occur during the months around the formula change. Our approach uses two groups of consumers that did not experience minimum payment changes as control groups to pin down time fixed effects, account fixed effects, and the coefficients on control variables. The first control group consists of consumers with accounts at issuers that did not change their minimum payment formulas. The second control group includes accounts that were not affected by the changes made by their issuer to the minimum formula, such as high-balance accounts with issuers that increased their formula floors. As long as consumer characteristics evolve smoothly across the timing of the formula changes, we can identify causal estimates of consumer responses to these changes, regardless of the precise motivation of issuers. We discuss this strategy in more detail below.

II.B CFPB Credit Card Database (CCDB)

This is the first research paper to use data from the CFPB Credit Card Database (CCDB), which includes account-level data for a number of large credit card issuers in the United States. The data are collected under the CFPB's supervisory authority over the credit card market as prescribed by the Dodd-Frank Act.[19] The data used here cover February 2008 to December 2013, and the issuers in the full dataset comprise over 85% of credit card industry balances.

The dataset includes information on the near-universe of consumer and small business credit card accounts from included issuers. The variables include monthly account-level details on balances, payments, fees, interest rates, and delinquency. For each account-month, we observe the minimum payment and the actual payment made by the consumer. In addition, the CCDB includes FICO scores and individual income both at origination and based on periodic updates by issuers. Each account is linked to credit bureau data that provide a summary of the borrower's overall credit portfolio on a quarterly basis. While we cannot link separate accounts to the same consumer or household, we can observe total credit card activity for each individual (including any joint accounts with other household members) in the credit bureau variables. The CCDB does not contain data on individual purchase transactions.

We apply three restrictions to the full CCDB to arrive at our analysis sample. First, we

[19]The dataset also includes nine institutions that fall under the purview of the U.S. Office of the Comptroller of the Currency (OCC). For additional information on the CCDB, see Consumer Financial Protection Bureau (2013).

restrict our analysis to general-purpose cards, so that the cards offered by different issuers can be considered close substitutes. Unlike cards associated with specific retailers, airlines, or other affiliates, general-purpose cards are not targeted at highly specific demographics that might not be representative of the general population of cardholders. Furthermore, general-purpose cards represent the largest portfolio segments for most issuers, and have only one or at most a few different minimum payment formulas that are applied across millions of cards. Second, we keep only issuers that report consistent data on minimum payments due, actual payments made, and matching cycle-ending balances. This leaves us with a sample of several issuers covering approximately 25% of total outstandings in the general-purpose card market. Third, in order to observe meaningful repayment outcomes, we only consider active accounts as flagged by issuers and statement months with positive balances. Our analysis is based on a 1% random sample of active accounts from included issuers, leaving us with about 40 million observations.

Table 1 presents summary statistics on the full analysis sample. The top panel reports basic statistics about the account and borrower. Account-holders have an average income of $66,000. Individual income is reported by borrowers at the time they apply for a credit card, and is updated by lenders periodically (e.g. if the borrower requests an increase in their credit line).[20] Throughout this paper, we use FICO at origination as our measure of a consumer's credit score. The average FICO score at origination is 701. Because our credit score measure is based only on past credit activity prior to account opening, we eliminate any direct causal relationship between FICO and repayment activity in our analysis.[21]

The second panel reports information on all credit cards for each borrower based on credit bureau data. On average, consumers have three credit cards, with a total balance of $11,000. The third panel reports balances for the accounts in our monthly dataset. Consistent with a typical consumer holding several active credit cards simultaneously, the average balance on a given account is $3,200, and consumers make positive purchases in 63% of account-months. The average account

[20]Income is generally self-reported and not always verified by lenders. Although it is possible for consumers to inflate their incomes in an effort to gain more credit access or better terms, income is not used in underwriting and credit line assignment models by major credit card issuers. Therefore, consumers have little incentive to systematically mis-represent their income.

[21]FICO scores at origination would in part reflect borrowers' past repayment behavior on other credit card accounts. Thus, within-person persistence in repayment behavior can lead to correlation between FICO at origination and the payments we observe.

utilization (balance as a fraction of total credit limit) is 45%.

The final panel presents measures of payment behavior. The average payment is $570, compared with a minimum required payment of $82. Borrowers pay 42% of balances on average. However, the median fraction of balances paid is only 11%, suggesting a highly bimodal distribution with some paying in full and many paying much less of their balance. The actual payments made on the accounts are less than the minimum payment due in 9% of cases. Any payments less than the minimum are considered late, and in nearly all of these cases borrowers are assessed late fees that typically range from $25–$35. Payments are exactly equal to the minimum payment due in 15% of account-months, and are near the minimum in an additional 20% of account-months. Throughout the paper, we define near-minimum payments as those within $50 of the minimum. Given the tight clustering of many payments near the minimum, our results are robust to alternative definitions of near-minimum payments, and we evaluate this sensitivity in Appendix Figure A-4. At the other end of the spectrum, payments are equal to or greater than the outstanding balance in 33% of account-months.

III Descriptive Analysis

This section presents descriptive evidence of account-level payment behavior. First, we classify accounts based on their history of payment amounts relative to the minimum payment and full balance, and the consistency of these payment amounts over time. We then examine whether proxies for liquidity constraints can explain the prevalence of minimum and near-minimum payments.

We classify accounts based on whether they pay in full, pay the minimum, or pay near the minimum in at least 50% of positive-balance months. Those who do not consistently pay within one of these categories at least half the time are categorized as mixed payers. Figure 2 presents the composition of accounts and account-months according to this taxonomy. As shown in Panel A, 9% of accounts pay exactly the minimum in most months, while 20% pay close to, but not exactly, the minimum in most months. The remainder make full payments in most months or pay a mixture of intermediate amounts. Appendix Table A-1 provides summary statistics for each of the payer types.

Panel B of Figure 2 shows that payment behavior is largely persistent over time within an account. Full payers pay in full over 90% of the time, and exact minimum payers pay exactly the minimum 78% of the time. The persistence of payment behavior may be due in part to features such as automatic payments tied to bank accounts, but are also likely to reflect consistency in the active choices made by borrowers. While we are not aware of systematic data on how often autopay features are used to pay credit card bills, discussions with industry representatives suggest that only a minority of customers use autopay for their credit card bills, and an even smaller minority use autopay for the minimum payment amount. Thus, we interpret the majority of payments by minimum and near-minimum payers as the result of active choices.

Providing further evidence that even those who actively pay more than the minimum tend to stick relatively close to the minimum amount, Figure 3 shows the distribution of payments as a fraction of balances for each payer type. The figure shows a highly bimodal distribution. The majority of payments for exact minimum, near minimum, and mixed payers are less than 10% of balance, and only 16% of all payments lie between 10% and 99% of the balance.

We next consider several potential proxies for liquidity constraints and examine their relationship to repayment behavior. Figure 4 presents the distributions of fraction paid (Panel A) and payer type (Panel B) by income, age, balance, and FICO score. Consistent with the bimodal distribution presented above, the vast majority of payments across all four distributions in Panel A are either close to the minimum (between 0-9% of the balance) or at 100% of the balance. In the discussion below, we compare how the fraction of low payments (those below 10% of the balance) vary with four potential proxies for liquidity constraints.

We first examine income and age, which are likely to correlate with the severity of liquidity constraints in the cross-section of consumers. The top-left figure of Panel A shows that payments increase only modestly by income, and a substantial fraction of consumers across the income spectrum make low payments. Consumers making less than $50,000 per year make low payments about half of the time, while those making more than $150,000 per year make low payments 38% of the time. This is a striking result: high-income consumers make near-minimum payments more than one third of the time, accumulating debt at relatively high interest rates. The top-left figure in Panel B confirms the weak relationship between income and payment behavior, showing similar income distributions for all four payer types.

The top-right of Figure 4A presents the relationship between borrower age and the composition of payments. The lifecycle / permanent income hypothesis suggests that while younger consumers may optimally decide to borrow when their income is below their expected lifetime level, the share of borrowers should decline significantly as they enter middle and old age.[22] Similarly, if the explanation for the high frequency of minimum payments was simply related to the age profile of experience with unsecured credit (Agarwal, Driscoll, Gabaix and Laibson 2009), we would expect to see a sharp increase in the fraction of full payments as accounts aged through the lifecycle. While we observe a decrease in the share of low payments with age, even accountholders over age 60 make low payments 34% of the time. The top right figure of Panel B shows that while full payers skew toward the higher end of the age distribution, we identify substantial shares of all four payer types in all age categories.

Next, we turn to two variables that reflect a combination of potential liquidity constraints and past credit use behavior. First, the bottom-left of Figure 4A shows that the share of low payments increases sharply with balance. While low payments are made 20% of the time on accounts with less than $500, by $1,500 in balance, the majority of payments are low. This pattern results from a combination of two effects. Greater cashflows are needed to pay off a given fraction of the balance as balances increase, and high balances arise endogenously due to low prior payments. Consistent with the second channel, the bottom-left figure of Panel B documents that full payers are most prevalent at low balances.

Finally, the bottom-right figure of Panel A shows that consumer payments vary dramatically by FICO at origination, which takes into account payment behavior on past debts. Consumers with FICO scores less than 700 make low payments more than 67% of the time, while those with scores above 800 make low payments only 18% of the time. However, even some consumers with very high FICO scores display low-payment behavior. Some of these low payments are likely due to "rate surfing" or exploitation of promotional offers, which we attempt to control for in the analysis that follows.

Consistent with Panel A, the bottom-right figure of Figure 4B shows that full payers are clus-

[22]For a recent example, Kaplan and Violante (2014) present a model in which borrowing occurs early in the lifecycle and after income shocks, followed by periods of repayment which reduce debt to zero relatively quickly.

tered at FICO scores between 700–850, while minimum and mixed payers span a greater range, with minimum payers having lower scores on average than mixed payers. FICO scores are a predictive measure of the probability of future default based on a consumer's past credit activity, including measures such as delinquency, account age, and utilization. Many of these measures may indicate past liquidity constraints that persist into the measurement period. However, the correlation between FICO at origination and the propensity to make low payments could also be due to other drivers of persistence such as consumer preferences, beliefs, and decision-making heuristics.

This section has shown that while payment behavior is highly persistent over time both within and across accounts, it is only weakly correlated with traditional proxies for liquidity constraints. The next two sections of the paper explore quasi-experiments intended to disentangle liquidity constraints from anchoring as potential explanations for the repayment patterns we observe.

IV Impact of Changes to Minimum Payment Formulas

In this section, we exploit changes in issuers' minimum payment formulas to estimate the fraction of accounts that anchor to the minimum payment. We first describe a conceptual framework for interpreting how changes in the formula should affect the distribution of payments for borrowers who are liquidity constrained versus those who anchor on the minimum. We then describe our strategy for testing the key predictions of the framework, and finally, present our estimates of the parameters that describe the extent of anchoring.

IV.A Conceptual Framework

We consider the impacts of a change in the minimum payment from an old value Min_1 to a new value Min_2. While all of our notation refers to the case where $Min_2 > Min_1$, the intuition is analogous for decreases in the minimum. In Figure 5A, we present a stylized illustration of how the cumulative distribution of payments near the minimum would change if all consumers were fully rational and chose their payment amounts based on a tradeoff between liquidity constraints and the costs of borrowing. Before the formula change, a fraction F_1 of consumers are delinquent due to severe liquidity constraints. Consumers choosing to pay as little as possible while remaining in good standing bunch at the minimum payment, leading to a discontinuity in the CDF at Min_1. For some consumers, the solution to their intertemporal choice problem is an amount that is greater than the minimum but still fails to pay off their debt completely, leading to an upward-sloping CDF above Min_1. Aggregating across consumers with different optimal repayment amounts, a fraction F_2 of consumers pay less than or equal to Min_2 under the old formula.

If all consumers chose their payment amounts optimally under the old formula, then an increase from Min_1 to Min_2 would change the payment distribution in two ways. First, some consumers may suffer from severe liquidity constraints and be unable to afford Min_2. As shown in the figure, severe constraints may lead to an increase in delinquencies from F_1 to F_1'. Because delinquency leads to costly late fees, penalty interest rates, and other negative consequences, most consumers previously paying less than Min_2 would choose to remain current and bunch at Min_2. The amount of bunching would be determined by the density of payments between Min_1 and Min_2 and by the fraction of severely-constrained consumers.[23] Overall, we predict that the formula change should shift the cumulative distribution of payments from the solid to the dotted lines shown in Figure 5A. Our key prediction is that if all near-minimum payments were driven by liquidity constraints, the fraction of consumers paying less than or equal to Min_2 should remain at F_2 after the formula change (i.e. the solid and dotted lines would coincide starting at Min_2).

In contrast, if some consumers locate near the minimum due to anchoring, then the formula change could also affect the distribution of payments greater than Min_2. Figure 5B illustrates the distribution of payments predicted by classical anchoring-and-adjustment models (Tversky and Kahneman 1974). Under these models, consumers choosing an interior repayment amount start with the minimum and adjust upward, leading to an upward shift in the entire distribution of payments when the minimum payment increases. Following this intuition, the figure shows the case where a fraction $-(F_2' - F_2)$ of all accounts pay less than Min_2 prior to the formula change and pay strictly more than Min_2 after the formula change. Relative to a scenario where all near-minimum payments are due to liquidity-constraints as shown in Panel A, there is less bunching at the new minimum Min_2 when some consumers anchor.

By imposing some normalizations, we can translate the change in the distribution of payments

[23] For an overview of the recent literature that has used settings where consumers are expected to "bunch" at a point in the distribution for obtaining identification, see Kleven (2016).

to estimates of the fraction of anchoring accounts. Let $\beta = F_2' - F_2$. If θ denotes the fraction of accounts affected by the formula change that anchor to the minimum payment, then $-\beta/F_2$ is a lower bound on θ. This estimate is a lower bound because while it includes all accounts that move from paying Min_2 to paying more than Min_2 after the formula change, it does not contain accounts that move from Min_1 to Min_2 in strict adherence to the anchor. Here, we define those "affected" by the formula change as accounts whose payment amounts under the old formula are less than or equal to Min_2.

To estimate the fraction of all accounts that anchor to the minimum payment, we need to make additional assumptions about the payment behavior of anchoring accounts. For simplicity, we assume that there is some interval $(\underline{X}, \overline{X}]$ for which the fraction of anchoring accounts among those paying between $[1, Min_1 + x]$ is approximately constant for $x \in (\underline{X}, \overline{X}]$, and that anchoring accounts make no payments above $Min_1 + \overline{X}$. These assumptions are based on the observation that a large fraction of accounts make payments close to the minimum, yet few payments are made between \$50 above the minimum and the full payment. Furthermore, as described in Section III, accounts that typically pay close to the minimum very rarely pay in full. Under these assumptions, the fraction of anchoring accounts among those with payments in the interval $[1, Min_1 + \overline{X}]$ is equal to θ, and the fraction of all accounts that anchor to the minimum is $\theta^* = \theta\delta$, where $\delta = CDF(Min_1 + \overline{X})$. Thus, $-\beta\delta/F_2$ provides a lower bound on θ^*. Appendix Figure A-1 presents an illustration of the parameters used in these calculations. We present estimates of the lower bounds on θ and θ^* in our empirical results below. We use $\bar{X} = \$50$ for our main calculations, and show how our estimates of anchoring vary with different thresholds of $\bar{X} \in [1, 200]$ in the appendix.

For completeness, Panel C shows the hypothetical case of "excessive" bunching at the new minimum, which would occur if an increase in the minimum caused some borrowers who were previously paying more than Min_2 to subsequently pay less. While some prior evidence lends support to this mechanism (Stewart 2009, Navarro-Martinez et al. 2011), our estimates show that the bunching effects shown in Panel B dominate in practice. The possibility that increases in the minimum could cause some consumers to move down to Min_2 from higher amounts is another reason why our estimates represent a lower bound on the extent of anchoring.

As suggested by our framework, we first focus our empirical analysis on estimating β. A finding that $\beta = 0$ would indicate that liquidity constraints alone drive consumer payments, whereas a negative value indicates that some consumers anchor on the minimum payment and yields an estimate of the size of this group.[24] We then use our estimates of β, along with direct measurements of F_2 and δ, to estimate lower bounds on the fraction of anchoring borrowers near the minimum, θ, and the fraction of anchoring borrowers overall, θ^*.

IV.B Estimation Strategy

We examine the effects of minimum payment formula changes using a difference-in-differences research design that estimates high-frequency changes in payments in the months surrounding the formula changes. Our design uses accounts unaffected by minimum payment changes to pin down the effects of time trends and control variables.

We measure exposure to the formula changes by computing the minimum payment for each account-month using both the old and new formulas. We define $I_{ij\tau}$ as an indicator for whether account i in issuer j would experience a change in its minimum payment in month τ due to issuer j's formula change. Specifically,

$$I_{ij\tau} = \begin{cases} 1 & \text{if } min_{ij\tau} \neq min'_{ij\tau} \\ 0 & \text{if } min_{ij\tau} = min'_{ij\tau} \end{cases}$$

where $min_{ij\tau}$ denotes account i's minimum payment based on issuer j's old formula, and $min'_{ij\tau}$ denotes its minimum payment under issuer j's new formula. As described above, a given issuer's formula change may not affect the minimum payments for all accounts in all months, depending on the nature of the formula change and characteristics of the account. We define this indicator for all months both before and after the formula changes in order to test for spurious pre-trends in minimums and payments. When control issuers are included that did not change their formulas, $I_{ij\tau} = 0$ for all accounts from these issuers.

[24] In section VII, we also discuss other potential interpretations of our findings.

Our baseline difference-in-differences model takes the following form:

$$Y_{ijt} = \alpha_i + \eta_t + \sum_{\substack{\tau=-12 \\ \tau\neq-1}}^{6} \beta_\tau \times I_{ij\tau} + \zeta I_{ij\tau} + \gamma X_{ijt} + \epsilon_{ijt} \tag{1}$$

where Y_{ijt} is an outcome for account i from issuer j in month t, α_i and η_t are account and month fixed effects, and X_{ijt} is a vector of controls described below. The β_τ's are the coefficients of interest, where τ is a measure of "event time" such that $\tau = 0$ denotes the first month after issuer j implemented a formula change. All periods prior to $\tau = -12$ are absorbed into $\tau = -12$, and all periods after $\tau = 6$ are absorbed into $\tau = 6$, so β_5 can be viewed as an estimate of the "medium-run" effects of the formula changes.[25] The $\zeta \times I_{ijt}$ term absorbs time-invariant differences between accounts that would be affected by formula changes versus those that would not.[26] The $\zeta \times I_{ijt}$ term is included separately and β_{-1} is omitted, so all of the β_τ coefficients can be interpreted as changes relative to the month prior to the formula changes.

As described below, we present results both with and without time-varying account-level controls. Our identification relies on discrete changes in issuer formulas that are not related to simultaneous sharp changes in underlying consumer characteristics, so the results are similar whether or not we include these controls. Throughout our analysis, we include time fixed effects, as well as fixed effects for the interaction of issuer formula type and FICO decile. In the full-controls specification, we also include a rich set of variables in X_{ijt}: dummies for deciles of balance, account age, credit limit, FICO score, purchases, and APR, and dummies for 0% APR and nonzero promotional balance. The full-controls specification also includes control issuers that did not change their formulas during our sample period to help identify the time fixed-effects. To account for serial correlation in account outcomes within similar customer demographics, we cluster all standard errors by the interaction of FICO decile and issuer formula type.[27]

[25]We show results for twelve months before and six months after the formula changes because that is the longest window where we have balanced observations on all treated issuers. As a result, β_6 includes the impacts of the compositional change in issuers, so we use β_5 for our medium-run estimate. In results not shown, estimates are qualitatively similar if we drop one issuer with a post-change window of less the one year and expand post-formula-change window according to availability.

[26]Even when account fixed effects are included, this term is needed because an account's treatment status can vary each month.

[27]Despite our millions of account-month observations, our goal using this level of clustering is to conservatively account for both the joint determination of credit card contract characteristics (Agarwal et al. 2015) and serially correlated outcomes across similar types of consumers (Bertrand, Duflo and Mullainathan 2004). In all specifications,

In practice, due to the large number of observations and rich covariates in some specifications, we estimate the model on data collapsed into cells by month × issuer formula type × potential treatment status × deciles of balance, credit limit, FICO score, purchases, and APR × indicators for 0% APR and nonzero promotional balance. By weighting the regressions by the number of accounts in each cell, our estimates on the collapsed data yield results that are identical to those using microdata. One drawback to the collapsed specification is that we cannot include account fixed-effects. However, we show below that account attributes and activity do not change sharply around formula changes, and in Appendix Table A-3 that regressions using the microdata that include account fixed-effects yield very similar results.

The identifying assumption for our research design is the parallel trends assumption: In the absence of the changes in minimum payment formulas, consumer payments would have evolved in parallel over time across treated and control groups. We assess the validity of this assumption by plotting the β_τ coefficients over time both before and after the formula changes to see whether treated accounts were moving along a different trend before the formula change.

We also test the robustness of our results by defining the control group in two different ways. First, we run the difference-in-differences specification using only accounts with $I_{ij\tau} = 1$, so that the control group includes potentially-treated accounts for other issuers whose formula changes occurred at different times. Our second approach includes all accounts of our sample issuers. The two implicit control groups in this specification are accounts with issuers that changed their formulas but that were outside of the range where the formula change applied (See Figure 1), and accounts with issuers that never changed their formulas.[28]

Column (1) of Table 2 shows the first stage of the specification in equation (1), with the dollar value of the minimum payment as the dependent variable. The coefficients in Panel A correspond to a specification with potentially treated accounts only, time and issuer formula type × FICO decile fixed effects, and no time-varying controls. Panel B shows our preferred specification, including all accounts from both treated and control issuers, time and issuer formula type × FICO decile fixed effects, and the full suite of time-varying controls. The average account's minimum payment

our regression samples for our main results contain at least 40 clusters.

[28]Our results are robust to a number of other variations such as including all accounts from treated issuers, separately estimating the coefficients for each issuer individually, and either including or excluding the full suite of time-varying controls. We only show two sets of representative results for brevity.

increased by \$12 to \$14 in the month of the change for the pooled positive formula changes, with similar point estimates under both specifications. While Panels A and B show results that pool the effects for four different formula changes that increased minimum payments, Panel C applies the full-controls specification to the one formula change that decreased minimum payments. Accounts from the issuer that reduced the required minimum payment saw an average decrease of about \$30 in the month of the formula change.

Figure 6A shows graphs of the corresponding difference-in-differences coefficients from Table 2B and C. Graph a) shows the results for positive formula changes, while graph b) shows the results for the negative change. These results confirm the absence of pre-trends in minimum payments. The two figures in Panel A also show that the formula changes occur immediately and are effectively permanent. Lending further credence to our approach, Appendix Figures A-2 and A-3 show that there is no systematic change in the composition of our sample across account or borrower characteristics, respectively, around the timing of formula changes.

IV.C Response to Changes in Minimum Payment Formulas

The framework described above suggests that β, the change in the fraction of accounts paying at or below the new minimum after a formula change, provides a test for whether some consumers anchor to the minimum payment. In order to estimate β, we first compute the minimum payments that an account would face under both the old and new formulas. We construct an indicator $P_{ij\tau}$ that is equal to one if the actual payment amount is less than or equal to the minimum payment under the larger of the two formulas, and zero otherwise:[29]

$$P_{ij\tau} = I(payment_{ij\tau} \leq \max\{min_{ij\tau}, min'_{ij\tau}\}) \tag{2}$$

For minimum payment increases, the average value of this indicator is equal to the fraction of payments at or below the minimum payment under the new formula, and its conditional mean is analogous to F_2 in the pre-period and F'_2 in the post-period from our conceptual framework. Our key test is whether the conditional mean of the indicator variable changes when the formula change

[29] For example, for accounts with balances $\leq$ \$2000 in the example shown in Figure 1A, this variable would be equal to 1 for payments $\leq$ \$40, and 0 otherwise.

occurs. In our model, this is equivalent to testing whether $\beta_\tau = 0$ for $\tau \geq 0$ when the dependent variable is $P_{ij\tau}$. The framework also predicts that if some consumers are so liquidity constrained that they are unable to afford the new minimum when the formula changes, then we should observe $\beta_\tau > 0$ when delinquencies are the dependent variable.

Columns (2) and (3) of Table 2 show the results of regressions for delinquencies and P. The three rows in each panel report the coefficients $\hat{\beta}_0$, $\hat{\beta}_3$, and $\hat{\beta}_5$ from each regression. The samples and controls included in each panel are the same as those for the first-stage results described above. The formula changes did not significantly affect delinquencies, which is unsurprising given the significant late fees triggered by delinquency and the relatively modest changes in the minimums. This result suggests that severe liquidity constraints are not a major driver of near-minimum payments.

Subfigure (c) of Figure 6 shows the $\hat{\beta}_\tau$ coefficients corresponding to Panel B of the table. The figure documents a sharp decline in the fraction paying at or below the new minimum when the minimum payment is increased. Consistent with the presence of anchoring, 3 to 4% of accounts that were paying less than or equal to the new minimum move to paying strictly more than the new minimum five months after the formula change occurs. We soundly reject the null hypothesis that all near-minimum payments are driven by liquidity constraints.

The intuition is analogous for interpreting the effects for minimum payment formula decreases. A finding that $\hat{\beta}_\tau > 0$ for $\tau \geq 0$ implies that some consumers who previously paid more than the minimum decrease their payments in response to a decrease in the formula. Subfigure (d) of Figure 6 shows the $\hat{\beta}_\tau$ coefficients for the one formula change that decreased the minimum payment. Instead of continuing to pay the same amount, 12 to 15% of accounts *lower* their payments when the minimum payment decreases. The effect for formula decreases is particularly striking because the incentives for consumers paying more than the old minimum payment are completely unaffected by the formula change. The behavioral response is immediate and persistent for both positive and negative formula changes.

To interpret the magnitudes of these effects, we turn to estimates of the prevalence of anchoring among accounts close to the minimum, θ, and among all accounts, θ^*. As described above, $-\beta/F_2$ and $-\beta\delta/F_2$ are lower bounds for θ and θ^*. We use the $\hat{\beta}_\tau$ coefficients as empirical analogs to β, comparing the results both for the immediate effect of the formula changes ($\hat{\beta}_0$) and the longer-run estimates ($\hat{\beta}_3$ and $\hat{\beta}_5$). We estimate $\hat{F}_2$ using the mean of P among accounts affected by the formula change (i.e. $I = 1$), and we estimate $\hat{\delta}$ using the fraction of all accounts paying less than or equal to $min + \$50$. Both $\hat{F}_2$ and $\hat{\delta}$ are estimated using the 12 months prior to the formula changes, and we obtain that $\hat{F}_2 = 0.42$ and $\hat{\delta} = 0.18$ for the pooled positive formula changes, and $\hat{F}_2 = 0.51$ and $\hat{\delta} = 0.39$ for the negative formula change. We discuss the robustness of our estimates to the definition of δ in the next section.

Columns (4) and (5) of Table 2 show the estimated lower bounds for θ and θ^*. For the pooled estimates of $\hat{\beta}_5$ using four positive formula changes in Panel B, we find that at least 22% of accounts paying close to the minimum and at least 9% of all accounts anchor to the minimum payment. The results from the formula decrease are larger than the estimates from formula increases, due both to the larger first stage effect on minimum payments and compositional differences in the treated population. As shown in Panel C, we estimate lower bounds of 38% and 20% for for θ and θ^*, respectively. Notably, the behavioral response is consistent, yielding a significant fraction of anchoring consumers in response to both minimum payment increases and decreases. In all specifications, we estimate an upper bound for the fraction of liquidity-constrained accounts at about one third (LC^*, shown in Column (6)).

In this section, we have established that consumers' repayment choices are sensitive to changes in minimum payment formulas. Our identification strategy allows us to rule out that this sensitivity can be explained solely by liquidity constraints. In the next two sections we explore heterogeneity in anchoring by borrower characteristics and the robustness of the anchoring result.

IV.D Heterogeneity and Robustness

IV.D.1 Heterogeneity

To examine heterogeneity in the prevalence of anchoring in the consumer population, Table 3 presents estimates of $\hat{\beta}$, θ^* and LC^* stratified by a number of borrower characteristics. Panel A shows the stratification by credit score at origination. While super-prime borrowers (those with FICO scores above 720) are relatively unlikely to anchor, the rest of the credit score groups yield similar estimates of θ^* ranging from 13% to 15%. In contrast, LC^* decreases monotonically with credit score as expected. This result suggests that the drivers of anchoring are distinct from the drivers of credit risk, consistent with our main results that distinguish anchoring from liquidity constraints.

The estimates in Panel B stratify the sample based on the descriptive payer types defined in Section III.[30] Full payers, who pay in full in more than 50% of account-months, unsurprisingly do not anchor to the minimum payment. Near-minimum payers are the most likely to anchor, with a lower bound of $\theta^* = 32\%$. Near-minimum payers are defined as those who actively pay more than the minimum payment, but nonetheless choose payment amounts that are very close to the minimum. The prevalence of anchoring in this group suggests that habitual near-minimum payment behavior is an observable correlate of anchoring and could be used to target consumers who are more likely to use anchoring heuristics. Panels C and D show that θ^* decreases only moderately with income and age. Overall, the results support our descriptive finding that traditional proxies for liquidity constraints do not seem to be strong drivers of payment behavior near the minimum.

IV.D.2 Robustness

In Appendix Table A-2, we explore the robustness of our results to alternative estimation approaches. Our baseline specification uses an indicator variable $I_{ij\tau}$ to specify accounts that would experience any change in their minimum payment as a result of issuer formula changes, and estimates the average change in payments across all accounts with $I_{ij\tau} = 1$. An alternative approach takes into account variation in the intensity of treatment (i.e. the dollar change in the minimum payment), which we define as

$$\Delta Min_{ijt} = min'_{ijt} - min_{ijt}$$

where min_{ijt} denotes account i's minimum payment based on issuer j's old formula and min'_{ijt} denotes the minimum payment under issuer j's new formula. In Panel A of the table, we present the results of the following specification:

$$Y_{ijt} = \alpha_i + \eta_t + \sum_{\substack{\tau=-12 \\ \tau\neq-1}}^{6} \beta_\tau \times \Delta Min_{ijt} + \zeta \times \Delta Min_{ijt} + \gamma X_{ijt} + \epsilon_{ijt} \tag{3}$$

[30] To avoid look-ahead bias in the definition of payer types, payer types are defined using only data prior to the formula changes.

This approach utilizes both the timing of the formula changes and variation across issuers in the nature of the formula changes. It also provides evidence on the sensitivity of our results to the assumption that the fraction of anchoring consumers (θ) remains constant across a range of payments near the minimum by explicitly imposing the restriction that the change in P scales linearly with dollar changes in the minimum payment. Columns (4) and (5) show that this approach leads to similar estimates of anchoring as our baseline model.

One concern with our findings is that promotional introductory offers (e.g. 0% APR for the first 18 months after opening an account) can drive payment behavior separately from either liquidity constraints or anchoring. An optimal response to 0% introductory offers for many consumers is to make the minimum payment for the duration of the introductory period, and then pay off the balance just before the promotion expires. Several pieces of evidence suggest that promotional offers cannot account for our results. As shown in Figure A-2(c), 0% APR offers do not change discretely at the time of formula changes, and do not vary enough to account for our results. Our baseline specification also includes time-varying controls for accounts with 0% APR and promotional balances. To provide a further test, Panel B of Table A-2 shows the anchoring estimates when excluding all observations with positive promotional balances, 0% APR, \$0 minimum payment, or less than 2 years since account opening. The results remain similar to our baseline specification.

A related concern is that increases in the minimum payment may cause consumers to transfer their balances or purchases to cards with lower minimum payments. This behavior is unlikely to explain our results, since we find that most of the effect occurs in the month immediately following the formula change with no pretrend. In contrast, we would expect consumers to transfer their balances more gradually over the months just before and after the formula changes to take advantage of incoming promotional offers. Nonetheless, as further tests, Panels C and D of Table A-2 re-run the analysis on consumers with only one active credit card account during the entire sample period, and those with multiple credit cards. Our estimates of θ^* remain similar in both of these subsamples, suggesting that our result is not driven by strategic balance-shifting across existing credit cards in response to minimum payment changes. We examine changes in purchases and balances around the formula changes in more detail below.

Appendix Figure A-4 shows the sensitivity of our estimates of θ^* to the definition of δ. The tables and figures thus far have relied on the assumption that all anchoring accounts make payments within \$50 of the minimum payment, i.e. that $\bar{X} = \$50$ and $\delta = CDF(Min_1 + \$50)$. Subfigure (a) shows the sensitivity of our results to this assumption for each FICO band, re-estimating the fraction anchoring for $\bar{X} \in [\$1, \$200]$. Subfigures (b), (c), and (d) shows the sensitivity analysis by payer type, income quartile, and age quartile. The consistent pattern in figures (a), (c), and (d) is that the share of anchoring accounts increases only moderately above $\bar{X} = \$50$, because relatively few payments fall into the range between \$50 above the minimum and the full payment.

In subfigure (b), we show that the estimates of θ^* converge to 36% for near-minimum payers, 11% for exact minimum payers, and 1% for full payers in the region $\bar{X} \in [\$1, \$200]$, which are close to the values obtained with $\bar{X} = \$50$. However, the estimate for mixed payers increases from 8% at $\bar{X} = \$50$ to 19% at $\bar{X} = \$200$. The steady increase suggests that although many mixed payers actively choose to pay amounts more than \$50 above the minimum, the values they choose may still be influenced by anchoring. Instead of paying an optimal amount that is invariant to changes in the minimum payment formula, some mixed payers may start from the minimum and adjust upward. Since most of the variation we exploit results in minimum payment changes of less than \$50, the sensitivity of θ^* to $\bar{X}$ should be interpreted with caution. However, this result suggests an additional channel through which our main results underestimate θ^* by potentially undercounting mixed payers.

Finally, a natural question is whether the formula changes affect account activity other than repayment. For instance, as discussed above, borrowers might switch their purchases and balances to other accounts in order to minimize their overall debt service burden. In Appendix Figure A-5, we replicate the analysis from Panel A of Figure 2 for other account outcomes.[31] We find no significant or consistent change in purchases and balances on the credit card accounts affected by formula changes (Panels A and B, respectively). Using the credit bureau data appended to each account, we find no evidence that consumers systematically open new accounts (Panel C), or change overall borrowing across accounts (Panel D). While these estimates are relatively imprecise due to the small size of the minimum payment formula changes relative to overall credit card purchases and balances, we do not observe any patterns that are consistent with purchase- or balance-switching

[31] Because purchases and balances are used as control variables in our full-controls specifications, we present these results using time and account-cell fixed effects only. The results are similar when including time-varying controls.

behavior.

V Impact of Changes to Disclosure Requirements

Starting on February 22, 2010, credit card issuers were required by the CARD Act to include a new disclosure on credit card statements that presented a comparison between the costs and repayment duration of making the minimum payment versus paying an amount that would amortize the outstanding balance in three years. An example of this disclosure is shown in Figure 7. In this case, paying $103 per month (and making no additional charges) instead of the minimum payment yields a reduction of over $1,000 in total interest payments and allows the borrower to pay off the debt eight years earlier.

The impact of this disclosure represents a distinct test of the role of anchoring in repayment choices. The disclosures present no new information, and no changes were made to the economic incentives around repayment. Consumers who begin paying the three-year amortization amount as a result of the disclosure are unlikely to be doing so because of liquidity constraints, since the three-year payment suggestion is greater than the required minimum (in most cases) and was within their choice set prior to the disclosure. Perfectly-informed rational consumers would not be expected to respond to the disclosures, and we interpret the fraction of accounts that adopt the three-year repayment amount as an estimate of the ability for mandated disclosure to establish new anchors for consumer payments.[32]

To estimate the causal impact of the disclosures, our regression approach exploits the details of the amendments to Regulation Z that implemented the CARD Act. In particular, the regulation specified that consumers who paid their balances in full for two months in a row and those whose minimum payments are higher than the three-year repayment amount are exempt from the disclosures. All of the variables needed to determine an account's exemption status in a given month and the amount of the three-year repayment amount are observable in the dataset, and our strategy compares the payments of exempt accounts with those of accounts exposed to the disclosures.

[32] While the disclosure does not present any new information that could not be calculated from information already available, it lowers the costs of calculating the payment needed to amortize the balance in three years. Although amortization of the existing balance in three years is an arbitrary benchmark which is unlikely to be the optimal payment for most consumers, part of the observed effect may be driven by lowered information acquisition costs.

To illustrate our approach, we first run difference-in-differences regressions restricted to three months before and three months after February 2010. We run the following specification:

$$Y_{ijt} = \alpha_i + \eta_t + \beta \times RequiredDisc_{ijt} \times Post_{ijt} + \zeta \times RequiredDisc_{ijt} + \gamma X_{ijt} + \epsilon_{ijt} \quad (4)$$

where $RequiredDisc_{ijt}$ is an indicator for observations which would have been required to receive the disclosures based on the criteria described above, and $Post_{ijt}$ is an indicator for the period after February 2010. We define $RequiredDisc$ both before and after the actual CARD Act effective date to account for systematic, time-invariant differences between accounts that are required to receive the disclosure and those that are not. The coefficient of interest is β, which captures the effect of the disclosure rules after the law went into effect. The regressions include the same rich set of controls described in Section IV, as well as an additional control for the level of the minimum payment. As above, we collapse the microdata into cells by month $\times$ issuer $\times$ potential treatment status $\times$ deciles of balance, credit limit, FICO score, purchases, and APR $\times$ indicators for 0% APR and nonzero promotional balance and weight each observation by the number of accounts in each cell.

Panel A of Figure 8 shows estimates from equation (4) where the dependent variables are indicators for the payment duration of a consumer's actual payment rounded to the nearest month. We restrict our attention to repayment durations between 25 and 45 months to observe changes around the three-year payment amount.[33] The figure shows a clear increase in payments around the three-year payment amount, with significant bunching at exactly 36 months. Smaller increases are detected between 31-35 months, which are generally very close in dollar amount to the three-year repayment amount and likely reflect rounding up. Unlike with minimum payments, there is very little diffusion of repayment amounts further away from the suggested payment amount.

Our main difference-in-differences specification for the effects of the CARD Act disclosure mir-

[33] Repayment periods are calculated using the following formula, rounded to the nearest integer:

$$\text{Repayment period} = -ln(1 - Balance/Payment \times r)/ln(1 + r)$$

where r is the monthly interest rate.

rors our approach in Section IV:

$$Y_{ijt} = \alpha_i + \eta_t + \sum_{\substack{\tau=-12 \\ \tau\neq-1}}^{12} \beta_\tau \times RequiredDisc_{ij\tau} + \zeta \times RequiredDisc_{ijt} + \gamma X_{ijt} + \epsilon_{ijt} \tag{5}$$

We include α_i and η_t representing issuer by FICO decile and month fixed effects in all regressions. The β_τ's are the coefficients of interest, where $\tau = 0$ denotes February 2010, the first month during which the disclosures requirements were in effect. Within our sample period from February 2008 through December 2013, all periods prior to $\tau = -12$ are absorbed into $\tau = -12$, and all periods after $\tau = 12$ are absorbed into $\tau = 12$.

Panel B of Figure 8 presents the difference-in-differences results for the share of payments with repayment durations between 30-36 months over a two-year window around the implementation date. There are no pre-trends in the period prior to the implementation of the disclosure, in large part because very few consumers actively chose the three-year repayment amount in the absence of the disclosure. The absence of pre-trends provides support for our identifying assumption that the payments of consumers required to receive the disclosures were moving on a parallel trend to those exempt from receiving the disclosures prior to the CARD Act effective date. The lack of pre-trend also confirms that no issuers in our sample implemented the disclosures prior to the law's effective date.

In the five months following the CARD Act, we observe a sharp increase in the share of accounts paying the three-year disclosure amount. Although the economic impact is small, with treatment effects of less than 1%, the effect is statistically significant. Unlike the immediate effects observed for changes in the minimum payment, the disclosures take several months to take full effect. This short lag could reflect issuers missing the deadline to present the disclosure on credit card statements (although we have not heard reports of such incidents), or consumers gradually noticing the disclosure on their statements and taking time to adopt the new payment amount.

Another trend visible in the figure is a deterioration of the effect of the disclosure over time. The coefficient at $\tau = 12$ absorbs all periods starting 12 months after the CARD Act effective date until the end of 2013, so reflects the medium-run effect of the disclosures. One reason for the decline in the disclosure's effect could be habituation as consumers become accustomed to seeing the disclosure and "tune out" after its novelty wears off. We use this medium-run effect as the benchmark estimate of the disclosure's overall impact.

Panel A of Table 4 presents the coefficient estimates corresponding to the figure. We show the effects of the disclosures at three different horizons: three months after implementation, six months after implementation, and the medium-run effect pooling dates that are twelve or more months after the effective date. The columns report effects for different windows around the disclosed 36-month repayment duration, which from above show smaller increases after the disclosure. For our most inclusive measure of payments at durations between 30-36 months, we find an immediate response of 0.7% of accounts at the three-month horizon, with a medium-run effect of 0.5%.

Panel B of Table 4 stratifies the specification from column (4)A by credit score bin. Panel C stratifies by payer type as defined in Section III, based only on payments prior to the implementation date. We find that subprime consumers and exact and near minimum payers are the only account types that respond significantly to the disclosures. Five percent of exact minimum payers continue to pay the three-year amount 12 or more months after the disclosure effective date, suggesting that some consumers who typically made exactly the minimum payment prior to the CARD Act were not strictly liquidity constrained, choosing to pay more when presented with a new suggested payment. The significant effect among exact minimum payers provides further evidence that our estimates of anchoring from Section IV may represent a lower bound.

In sum, the effects of the CARD Act disclosures were modest overall and within all of the subgroups we considered. This could be due to a number of factors. Consumers making online payments without opening their statements were not exposed to the disclosure. Consumers may not have found the new disclosure to be salient among other information regarding balances, purchases, fees, and interest rates present on statements. Finally, the minimum payment, which was still present on all statements, may continue to exert a stronger influence than the new repayment amount.

VI Economic Significance

To conduct a back-of-envelope calculation on the economic significance of anchoring, we compare the realized effects of the CARD Act disclosures with the counterfactual effects if the disclosures had caused all anchoring consumers to move from the minimum payment to the suggested three-year payment amount. We conduct this calculation given the distribution of consumers in 2013, using $\hat{\beta}_{12} = 0.5\%$ as the estimated steady-state adoption rate of the disclosures. Assuming that consumers who adopt the three-year payment amount would have otherwise made the minimum payment, we find that the disclosures led to an \$0.18 per month increase in payments averaged across all accounts.

Assuming further that affected consumers carry balances at an APR of 16% and scaling up the average increase in payments by the 44 million active accounts represented by the issuers in our sample and their market share of 25% in the general-purpose card market, we estimate that the disclosures saved consumers \$62 million (= \$0.18 × 12 × 16%× 44 million ×4) in interest charges in 2013. This estimate is remarkably close to that of Agarwal et al. (2015), who estimate an upper bound of \$57 million per year in interest savings due to the CARD Act disclosures using a different sample, different control group, and different set of assumptions.

In contrast, by replacing $\hat{\beta}_{12}$ with our estimates of θ, we repeat the calculation to estimate the interest savings if the disclosures had instead caused *all* anchoring consumers to move from the minimum payment to the three-year payment amount.[34] Based on the estimated range of θ between 22% and 38% from Panels B and C of Table 2, we find that the interest savings in 2013 would have been two orders of magnitude larger, between \$2.7 and \$4.7 billion, if the disclosures had affected all anchoring consumers. Depending on the costs of implementing the disclosures, even the relatively modest realized interest savings could make them a cost-effective policy for increasing consumer payments. Nonetheless the effect of the disclosures is substantially smaller than the economic role of anchoring.

[34]We make this calculation under the assumption that the fraction of anchoring accounts among customers affected by the formula changes and those who were required to receive the disclosures is roughly the same.

VII Discussion and Interpretation

In this section, we discuss the implications of our findings for rational and behavioral theories of consumer financial decision-making.

Active vs. Passive Choice

An influential literature on consumer savings decisions shows that consumers tend to follow the path of least resistance, and are strongly influenced by defaults and salient suggestions. Madrian and Shea (2001) show that automatic enrollment significantly increases 401(k) participation, and the majority of consumers stay with default contribution rates and asset allocations even though few of them chose these values prior to automatic enrollment. Chetty et al. (2014) find that the majority of consumers are passive savers, accepting employer-specific default retirement contribution rates instead of adopting individualized savings targets. As an alternative to passive defaults, Carroll et al. (2009) show that requiring consumers to make active savings choices also substantially increases the fraction of savers, and present a model showing that active choice can be optimal when consumer preferences are highly heterogeneous.

For consumers who carry revolving balances, debt repayment is an inherently active choice; heavy penalties for delinquency make inaction an unattractive option. While autopay features are available through most checking accounts and credit cards, conversations with issuers suggest that their use remains limited among revolvers. One reason for limited adoption of autopay is that consumers who borrow at substantial interest rates are likely to have limited liquid wealth (Stango and Zinman 2013). Automatic Clearing House (ACH) bank transactions typically require several days to clear, so consumers with low liquidity must actively manage their checking account balances in order to avoid costly overdraft and insufficient-funds fees.[35] As a result, automatic repayment is largely confined to transactors who use credit cards for convenience and rewards instead of as debt instruments.

Our results suggest that despite making active choices, consumers nonetheless follow the path of least resistance when making repayment choices. The minimum payment is a salient and attractive option for those carrying revolving debt, with nearly one in three accounts paying exactly or close

[35] See, e.g., the advice given on automatic bill payments, including credit card payments, on financial advice website creditcards.com: `http://www.creditcards.com/credit-card-news/pros-cons-automatic-payments-1580.php`.

to the minimum payment amount on a regular basis. Within this group, twice as many accounts consistently pay close to but more than the minimum as pay exactly the minimum. Despite actively choosing to repay more than the minimum, at least one third of near-minimum payers anchor to the minimum payment amount. In contrast to retirement savings instruments where defaults and active choice may serve as substitute choice architectures, our results suggest that many consumers rely on defaults even when forced to make active debt repayment choices.

Liquidity Constraints and Lifecycle Borrowing

A novel aspect of our approach is that we use exogenous variation in minimum payment formulas to distinguish between anchoring and liquidity constraints. Liquidity constraints are an important reason for consumers to make minimum or near-minimum payments on their credit cards. Traditional drivers of liquidity constraints include transitory income or expenditure shocks and lifecycle income dynamics (Hayashi 1985, Deaton 1991). However, we show that the role of anchoring in the propensity to make near-minimum payments varies surprisingly little with income and age.

Previous work related to credit cards and liquidity constraints, most notably Gross and Souleles (2002), has found evidence that consumers are overly-sensitive to the credit limit. While consumers near the credit limit are likely responding to the relaxation of a binding (or near-binding) constraint, this work also suggests that consumers who are not especially close to the limit still respond to raises in credit limits by increasing their borrowing. Beyond the traditional interpretation of precautionary behavior, consumers may alternatively be targeting a certain credit utilization rate or certain dollar amount of balances relative to the limit, even if such heuristics fail to approximate the optimal consumption path. In other words, the credit limit may also serve as an anchor when considering how much to borrow.

One explanation for the lack of correlation between minimum payments and income is that "wealthy hand-to-mouth" households persist over the lifecycle due to investment in illiquid assets (Kaplan, Violante and Weidner 2014). However, this hypothesis does not explain why consumers would voluntarily choose to pay more than the minimum and continue to pay more when the formula increases. Investments in illiquid assets also do not explain why some consumers begin paying the three-year repayment amount after the CARD Act mandated the provision of new disclosures. Our results suggest that in the spirit of the spender-saver model of Campbell and

Mankiw (1989), a significant share of consumers behave as if liquidity-constrained because they follow simple heuristics.

Present bias and Inattention

One explanation that has been proposed for the amount of revolving consumer debt in the economy is impatience and time-inconsistency (Laibson 1997). Present-biased individuals over-consume in the absence of commitment devices, leading to an accumulation of credit card debt. Kuchler (2015) and Shui and Ausubel (2004) explore this phenomenon empirically, and Angeletos et al. (2001) calibrate a model to reconcile credit card indebtedness and income over the lifecycle. Present bias is unlikely to explain the repayment patterns we observe, although it may contribute to the choice of borrowing in the first place. We would expect present-biased consumers to repay as little as possible to increase consumption in the short term. Instead, we observe consumers continuing to pay more than the minimum when minimum payments increase.

Our results are also unlikely to be driven by temporary attention effects. We find that anchoring consumers immediately adjust to increases in the minimum payment formula, and we find no evidence of reversal. Thus, our evidence of anchoring to the minimum payment is unlikely to be driven by novelty or "Hawthorne" effects. In contrast to the changes in minimum payment formulas, we find that the effects of disclosures attenuate over time, and are only 60-70% as large 1-2 years after the disclosures went into effect as they were immediately after implementation. These findings provide suggestive evidence of a novelty effect and consumer inattention with respect to the CARD Act disclosures.

Anchoring and Rules of Thumb

Tversky and Kahneman (1974) first introduced the notion of anchoring and insufficient adjustment in the psychology literature. When presented with irrelevant numerical cues, individuals' answers to general knowledge questions (such as the percentage of African countries in the United Nations) are biased in the direction of the starting value. More recent psychological research on anchoring has been skeptical of the adjustment mechanism, and has instead supported a view that the initial value "activates" or "primes" information that is consistent with the starting value when the value is relevant or salient to the question at hand (Chapman and Johnson 1999, Epley and Gilovich 2006). Some studies, such as Jacowitz and Kahneman (1995), explore the idea that the anchor can be perceived as a suggestion, and becomes a potential option in the choice set as an answer to the question. Although the initial value only temporarily enters the choice set, this can distort the individual's final answer toward the anchor.

We find some evidence consistent with both adjustment and activation in credit card repayment decisions. Our finding that many consumers index their payments to the minimum regardless of arbitrary changes in its dollar value is consistent with the classical anchoring-and-adjustment theory. One example of behavior that could generate our finding is the use of rules of thumb such as paying the minimum plus $20 each month. The consumer may adopt this rule of thumb because paying more than the minimum is desirable, but still use the minimum as a starting point for upward adjustment, a form of classical anchoring. In contrast, the CARD Act disclosure causes some consumers to adopt the three-year payment amount when there was no bunching at this amount beforehand, suggesting that the disclosure increases the salience of this payment amount and emphasizes it in the choice set.[36] This behavior is more in line with the modern literature on anchoring as activation.[37]

Overall, our results suggest a model in which some consumers are not fully aware of the utility value of their payment choices. Instead of calculating the solution to an intertemporal choice problem, consumers start with salient numerical cues available on their monthly credit card statements, and adjust or adopt these cues based on their views of whether the cues represent desirable or acceptable payment amounts.[38] The minimum payment may be an especially powerful anchor because it signifies staying in good standing with the issuer and avoiding late fees. This feature may create the perception that the minimum is a suggested payment amount, as the most prominent amount besides the full balance featured on credit card statements and payment interfaces (Thaler and Sunstein 2008). We interpret consumers' reduced-form responses to these "informative" anchors as capturing a set of psychological rules, one of which may be an implicit advice channel. While many consumers realize that making only the minimum payment would fail to significantly

[36] We find no evidence that consumers use other heuristics such as paying twice the three-year amount, rounding the amount to the nearest $50 or $100, etc.

[37] Other recent empirical research on anchoring, such as Beggs and Graddy (2009) has found a role for the adjustment-based mechanism, while Chapman and Johnson (1999), for instance, find support for anchoring-as-activation.

[38] Choi, Haisley, Kurkoski and Massey (2012) find evidence that cues play a significant role in 401(k) savings choices using randomized field experiments.

amortize their debt, they may nonetheless be at a loss for how much more they should pay, and use anchoring heuristics to choose their ultimate repayment amounts.

VIII Conclusion

Using a sample covering one quarter of the U.S. general-purpose credit card market, we examine whether anchoring to the minimum payment causes consumers to make smaller payments toward their outstanding balance. Our identification strategy relies on changes to issuers' minimum payment formulas, and we estimate that at least 10% of all consumer accounts anchor to the minimum payment. This anchoring response is immediate, and occurs for both increases and decreases in the minimum payment. An attempt by the CARD Act to introduce an alternative suggested repayment amount resulted in fewer than 1% of accounts adopting the new suggested payment, more than an order of magnitude smaller than the impact of anchoring.

Our findings provide novel real-world evidence of anchoring, and have implications for models of lifecycle consumption and savings behavior. Our finding that a sizable fraction of consumers anchor on the minimum payment lends support to heterogeneous-agent models that include consumers that are "boundedly rational" (Gabaix 2014) or follow simple heuristics in the presence of costly information acquisition (Gabaix, Laibson, Moloche and Weinberg 2006). Lifecycle models that have attempted to calibrate the share of consumers with outstanding credit card debt (and the amount of that debt) fall well short of their empirical benchmarks, even when allowing for relatively extreme hyperbolic preferences (see, e.g. Angeletos et al. 2001). Our results suggest that anomalies related to repayment behavior may influence the stock of outstanding consumer debt, and help to explain the calibration gaps in these consumption models.

By improving our understanding of consumer behavior, these findings have significant implications for designing optimal defaults in credit markets. As discussed by Choi, Laibson, Madrian and Metrick (2003) and Carroll et al. (2009) in the context of retirement saving, under some conditions defaults should be set such that they are optimal for the largest fraction of individuals possible, whereas in others the default should be deliberately suboptimal in order to force active choice. Our work suggests that while a large fraction of near-minimum payers appear to treat the minimum as an anchor, others may be liquidity constrained. In the presence of significant heterogeneity in consumer circumstances, tools for optimizing consumer choice may be preferable to unilaterally increasing payment requirements (Campbell 2016). However, the modest effects we document of the CARD Act disclosures illustrate the challenges of changing real-world behavior using traditional forms of disclosure. Developing further evidence on ways to help imperfectly-rational consumers amortize their debts while minimizing the impact on liquidity-constrained consumers is an important area for future research.

Exploring the role of anchoring and related behaviors in other contexts within the consumer credit market provides another fruitful avenue for future research. There have been few existing studies of anchoring in consumer credit markets, and prior work has also largely focused on minimum payments on credit cards. Minimum payments are a feature of many mortgage contracts (such as the popular “Option-ARM” contract during the housing boom), as well as auto loans, student loans, and payday loans. Credit limits and maximum borrowing amounts may also serve as salient anchors. Studying these effects could help explain repayment behavior, aggregate debt levels, and consumption dynamics, and yield useful parameters for evaluating the effects of government intervention in credit markets.

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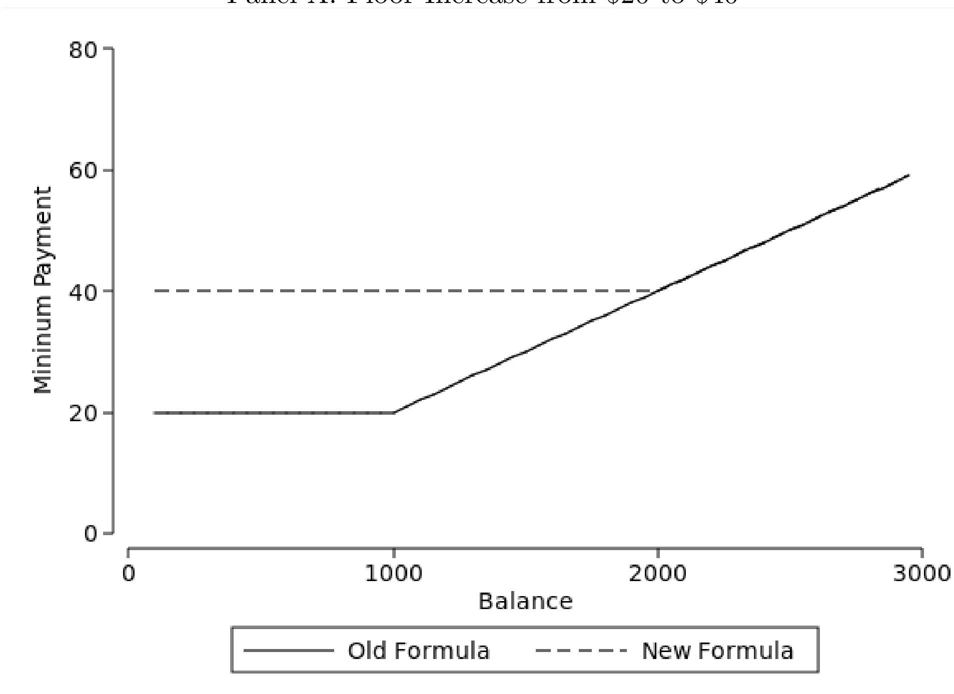
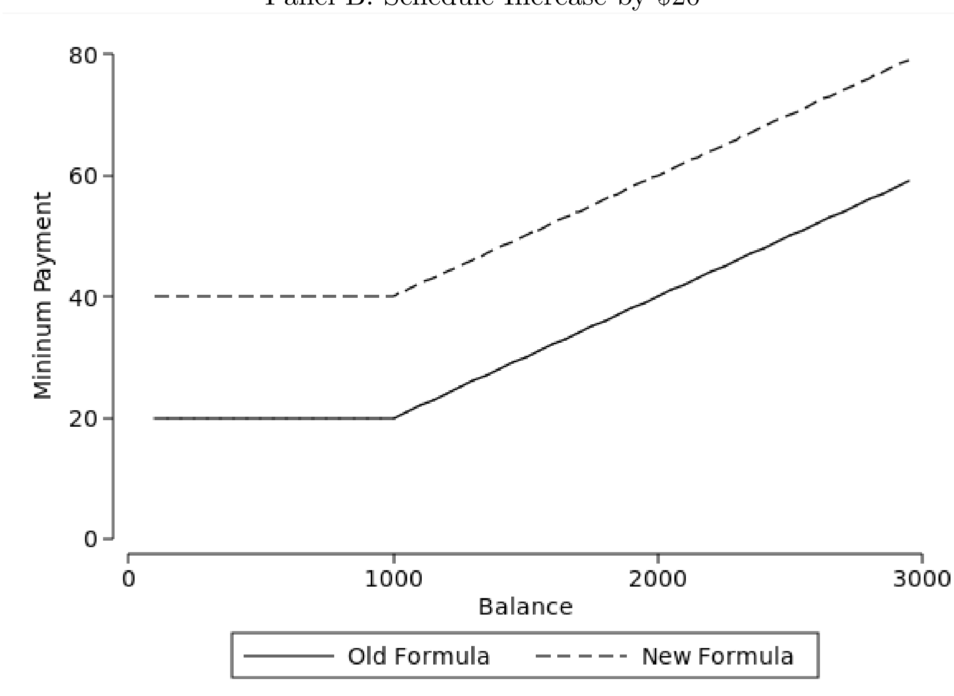
Figure 1: **Stylized Minimum Payment Formula Changes**

Panel A: Floor Increase from \$20 to \$40



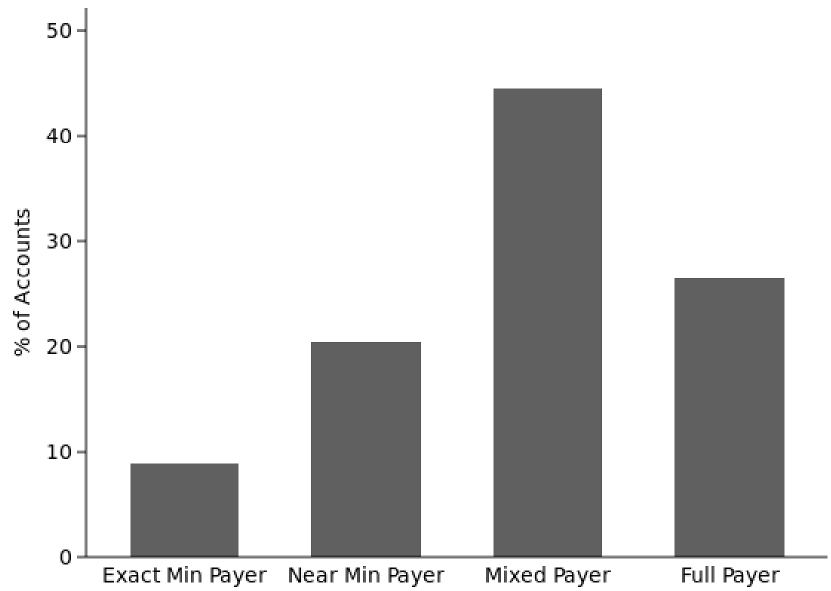
Panel B: Schedule Increase by \$20



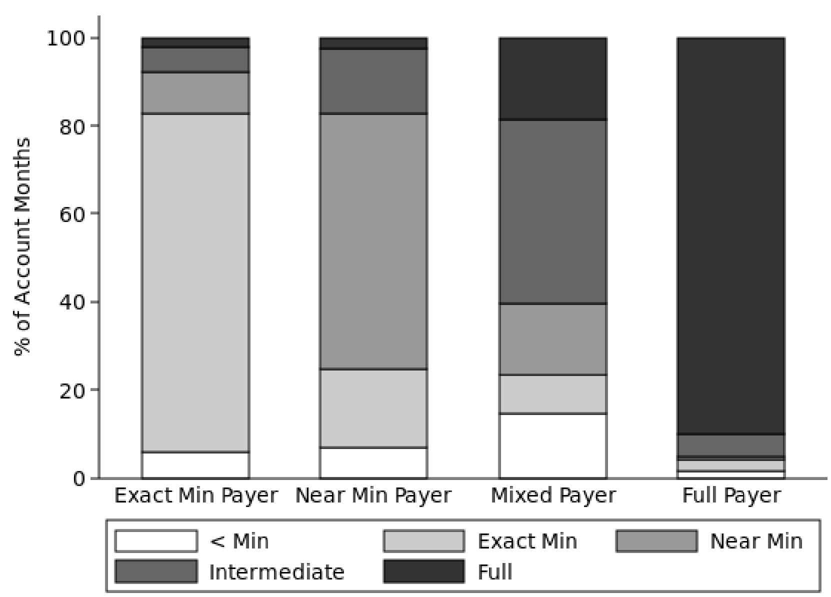
Note: The figure presents a simplified example of a typical credit card minimum payment formula and the two types of formula changes we observe in our sample. The "old" formula in both panels is $minimum = \max\{floor, 2\% \cdot balance\}$. In Panel A, the floor is \$20 for the old formula and \$40 for the new formula. In Panel B, the formula is shifted from the old formula to a new formula with $minimum = \$20 + \max\{floor, 2\% \cdot balance\}$, in both cases with $floor = \$20$.

Figure 2: **Prevalence of Minimum and Near-Minimum Payments**

Panel A: Distribution of Payer Types

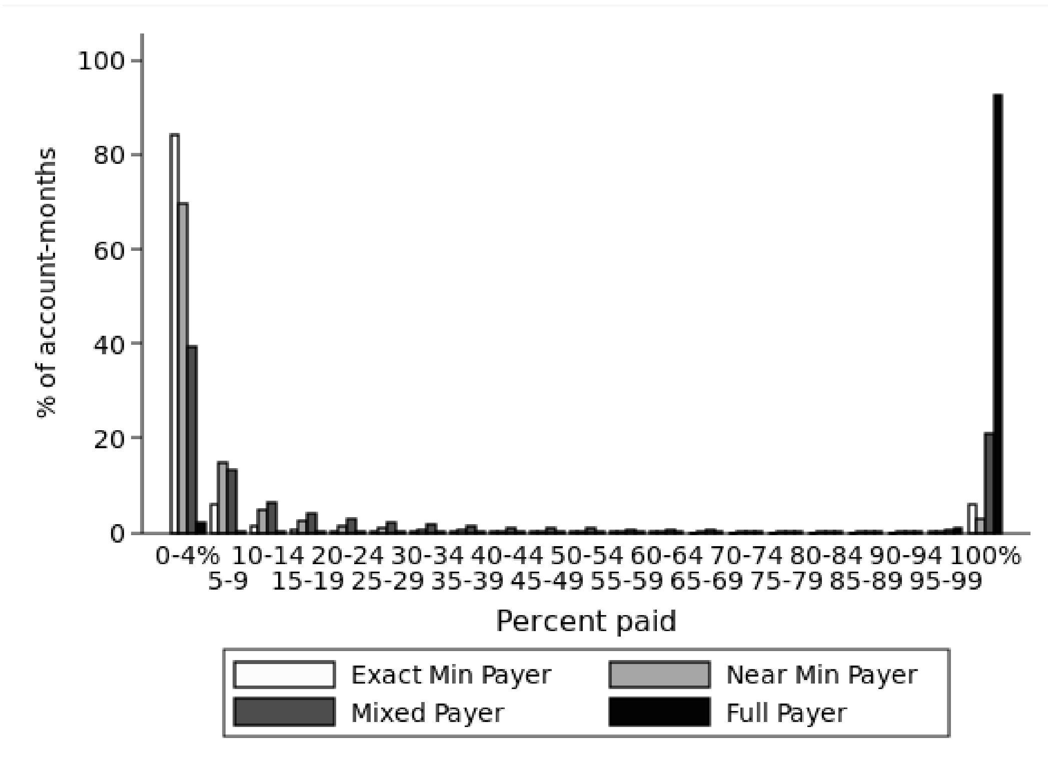


Panel B: Consistency of Payments Within Payer Type



Note: Panel A shows the distribution of accounts by payer type, and Panel B shows the composition of payments for positive-balance months within each payer type. Each account is classified into a payer type based on whether the account was paid in full or paid at or near the minimum amount in at least 50% of months. Accounts that did not pay any of these three amounts in 50% of months are classified as mixed payers. Payments are defined as "near" the minimum if they are strictly greater than but within \$50 of the minimum.

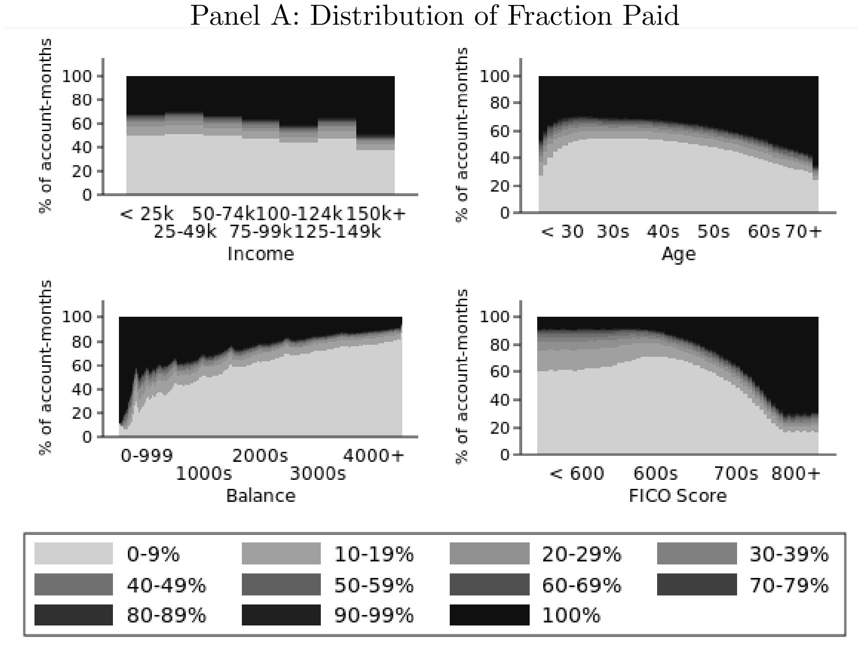
Figure 3: **Distribution of Payments as a Fraction of Balance**



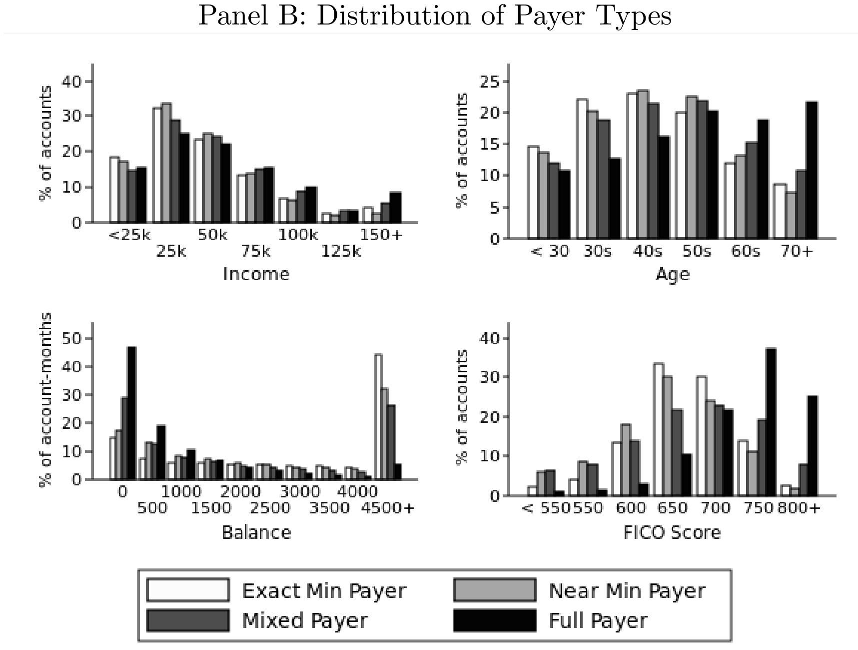
Note: The figure shows the distribution of payments as a fraction of the balance in 5% bins by payer type. Each account is classified into a payer type based on whether the account was paid in full or paid at or near the minimum amount in at least 50% of months. Accounts that did not pay any of these three amounts in 50% of months are classified as mixed payers. Payments are defined as "near" the minimum if they are strictly greater than but within $50 of the minimum.

Figure 4: **Relationship Between Payments and Borrower Characteristics**

Panel A: Distribution of Fraction Paid



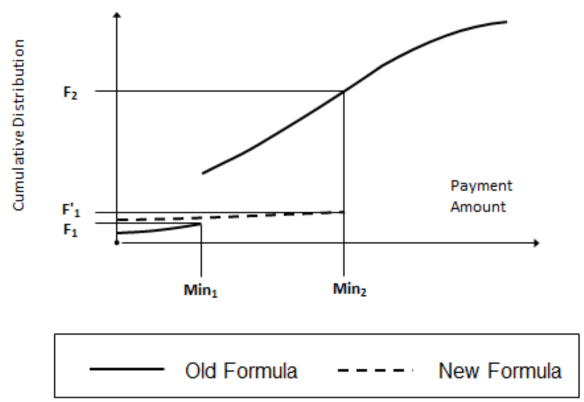
Panel B: Distribution of Payer Types



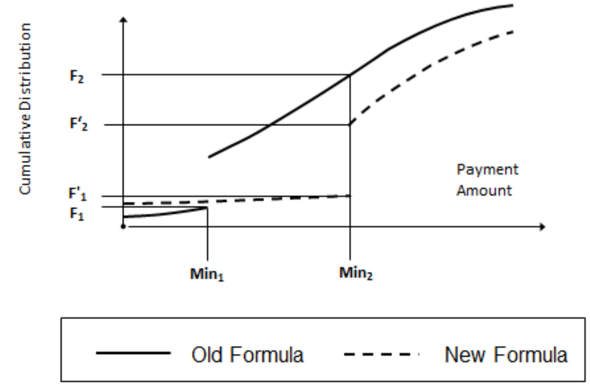
Note: Panel A shows the relationship between the distribution of payments as a fraction of balance and borrower income, borrower age, account balance, and FICO at origination. The darkest area represents full payments, the lightest area represents payments below 10% of the balance, and the gray band represents payments between 10% and 99% of the outstanding balance. Panel B shows the distributions of payer types by the same borrower characteristics. Each account is classified into a payer type based on whether the account was paid in full or paid at or near the minimum amount in at least 50% of months. Accounts that did not pay any of these three amounts in 50% of months are classified as mixed payers. Payments are defined as "near" the minimum if they are strictly greater than but within $50 of the minimum.

Figure 5: **Changes In Payment Distribution Due to Formula Changes: Liquidity Constraints vs. Anchoring**

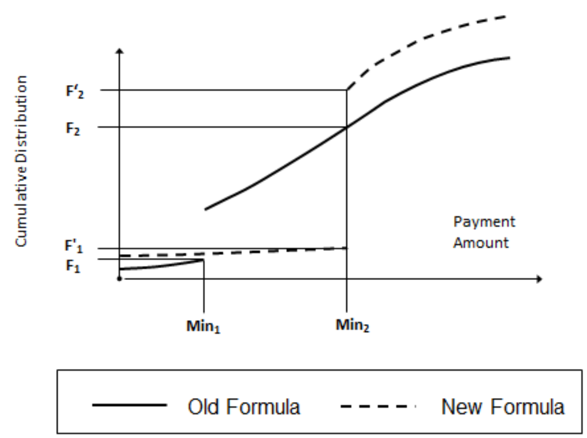
(a) Expected Bunching With Liquidity Constraints Only



(b) Expected Bunching With Anchoring



(c) Excessive Bunching

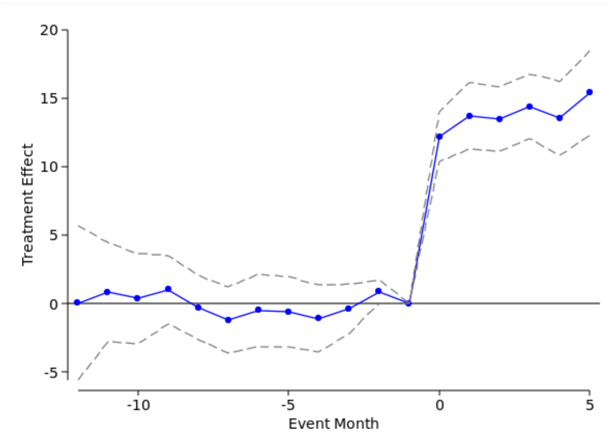


Note: The figure depicts three potential ways the distribution of payments could respond to an increase in the minimum payment from Min_1 under an old formula to Min_2 under a new formula. In each panel, the solid and dashed lines show the payment distributions under the old and new formulas, respectively. All three panels show a potential increase in the share of delinquencies from F_1 to F_1'. In figure (a), all accounts paying between Min_1 and Min_2 under the old formula bunch at Min_2 under the new formula, except those that become delinquent. The distribution of payments above Min_2 is unchanged in this case. In figure (b), some accounts paying between Min_1 and Min_2 under the old formula move to payments higher than Min_2 under the new formula. In figure (c) some accounts paying more than Min_2 under the old formula decrease payments to Min_2 or less.

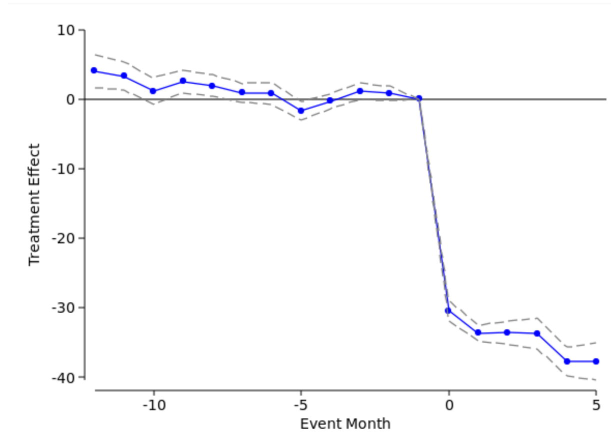
Figure 6: **Difference-in-Differences Regressions Around Issuer Formula Changes**

Panel A: Average Change in Minimum Payments

(a) Minimum Formula Increase

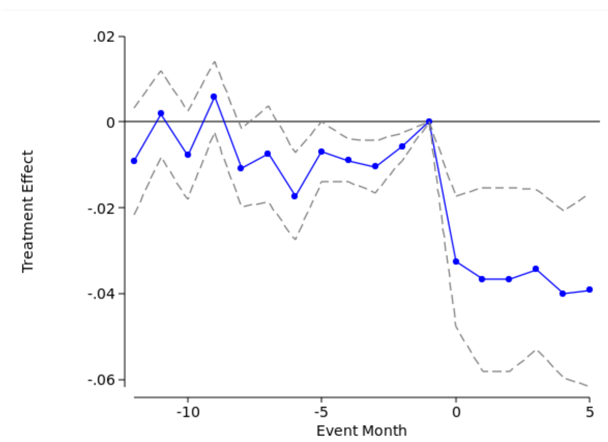


(b) Minimum Formula Decrease

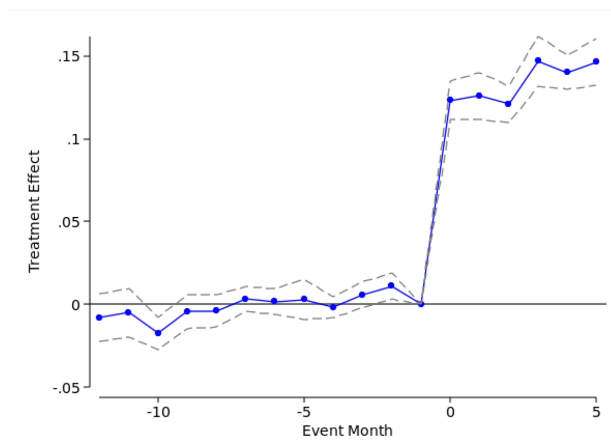


Panel B: Average Change in Probability of Paying $\leq$ Higher Minimum

(c) Minimum Formula Increase



(d) Minimum Formula Decrease



Note: The figure shows estimates from difference-in-differences regressions of the effects of minimum payment formula changes. Panel A shows the effects on average minimum payments. Panel B shows the effects on P, an indicator variable for payments that are less than or equal to the higher of the two minimum payment formulas. Figures (a) and (c) show the pooled effect for four formula changes that increased the minimum payment, and figures (b) and (d) show the effect for one formula change that decreased the minimum payment. The solid lines show point estimates, and the dashed lines show 95% confidence intervals using standard errors that cluster by issuer formula type interacted with FICO decile. All regressions include control issuers that did not change their formula and controls for time-varying account characteristics and fixed effects for issuer formula type interacted with FICO decile. See text for details.

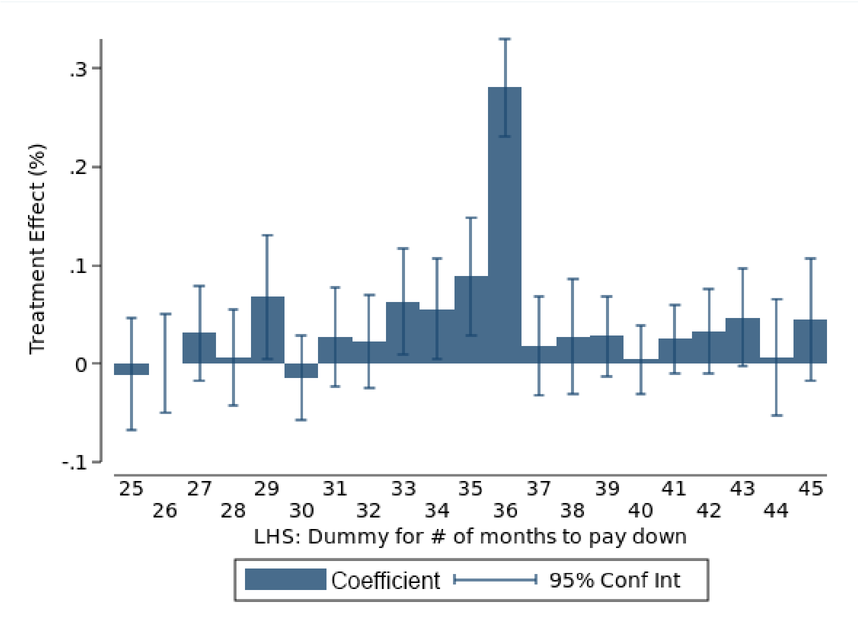
Figure 7: **Example of Three-Year Repayment Disclosure Mandated by the CARD Act**

If you make no additional charges using this card and each month you pay. . .	**You will pay off the balance shown on this statement in about. . .**	**And you will end up paying an estimated total of. . .**
Only the minimum payment	11 years	$4,745
$103	3 years	$3,712 (Savings = $1,033)

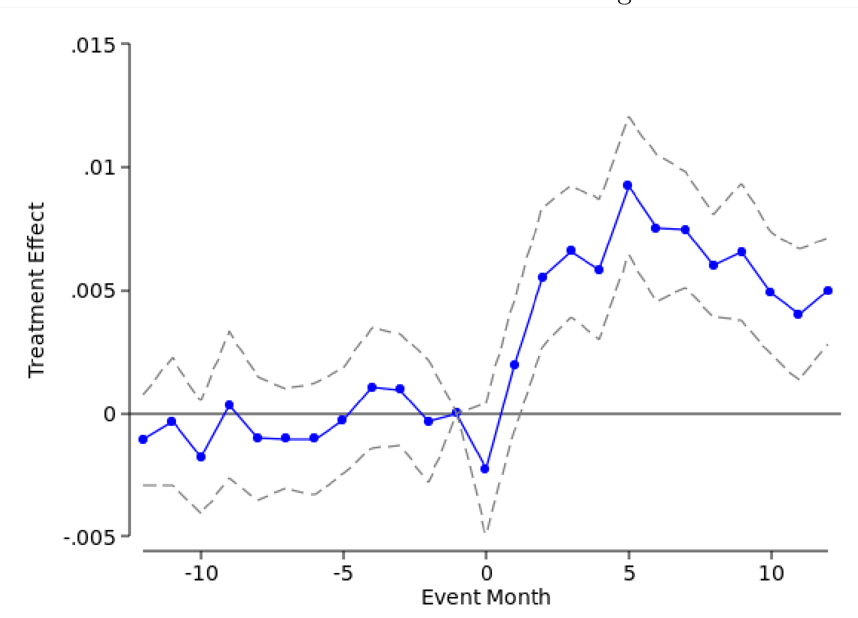
Source: Federal Reserve Board:
`http://www.federalreserve.gov/consumerinfo/wyntk_creditcardrules.htm`. Accessed February, 2013.

Figure 8: **Effect of CARD Act Disclosures on Payments**

Panel A. Cross-Sectional Regressions



Panel B: Difference-in-Differences Regression



Note: Panel A presents difference-in-differences estimates for the effects of the three-year repayment disclosure mandated by the CARD Act. The sample includes statements between December 2009 and May 2010, spanning three months before and three months after the effective date of the disclosure requirements. Each solid bar represents the results of a separate regression with dependent variable equal to an indicator for a payment duration between 25 and 45 months, rounded to the nearest month. Error bars represent 95% confidence intervals. Panel B shows the results of a difference-in-differences regression with a dependent variable equal to an indicator for payment duration between 30 and 36 months when rounded to the nearest month. The coefficients correspond to the results shown in column (4) of Table 4A. The solid line represents point estimates from the regression, and the dashed lines represent 95% confidence intervals. All regressions include controls for time-varying account characteristics and fixed effects for issuer interacted with FICO decile, and standard errors are clustered by issuer interacted with FICO decile.

Table 1: **Summary Statistics**

	Mean	Std. Dev.	p25	p50	p75
Card and account					
Income	$65,583	$49,300	$32,400	$55,000	$87,499
FICO at origination	701	76	656	707	758
Account age (years)	9.14	7.90	3	7	14
Age of primary account-holder	51.68	16.10	39	51	63
Credit limit	$9,767	$8,842	$3,000	$8,100	$13,760
Retail APR	16.14	8.10	12	15.24	19.99
Joint account	8%				
Has annual fee	12%				
All Card Accounts					
# of open cards	3.02	2.30	1	2	4
Total balance	$10,677	$16,859	$1,227	$4,541	$13,751
Total credit limit	$38,928	$35,779	$14,500	$29,600	$52,900
# of new cards in last 3 months	0.06	0	0	0	0
# of cards 60+ days past due	0.03	0	0	0	0
Purchases and Balances					
Utilization	45%	40%	6%	35%	87%
Balance	$3,187	$4,607	$384	$1,359	$4,187
Promotional	$545	$2,129	$0	$0	$0
Cash advance	$168	$988	$0	$0	$0
Penalty	$398	$1,940	$0	$0	$0
Purchase volume	$501	$1,497	$0	$62	$445
Purchase volume > 0	63%				
Payment and Delinquency Behavior					
Fraction paid	42%	50%	3%	11%	100%
Minimum payment	$82	$210	$20	$39	$88
Actual payment	$570	$1,651	$50	$150	$451
Payment:					
< Minimum	9%				
Exact minimum	15%				
Near minimum	20%				
Intermediate	23%				
Full	33%				
Charged fees:					
Late	9%				
Overlimit	1%				
NSF	0.2%				
Had past due	8%				

Note: The table provides summary statistics from our sample. The sample consists of a 1% sample of active general-purpose credit card accounts from several large issuers from 2008-2013, with approximately 40 million monthly account-level observations.

Table 2: **Estimates of Anchoring From Minimum Payment Formula Changes**

	Regression estimates			Anchoring estimates		
	Minimum Due	Delinq.	P	θ	θ*	LC*
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Positive Formula Changes, No Time-Varying Controls						
Δ (t=-1 to t=0)	14.0	0.016	- 0.013	0.07	0.03	0.39
	(0.7)	(0.002)	(0.007)	(0.04)	(0.02)	(0.02)
	[0.0]	[0.000]	[0.056]			
Δ (t=-1 to t=3)	14.3	0.002	- 0.031	0.17	0.07	0.35
	(0.6)	(0.003)	(0.006)	(0.04)	(0.01)	(0.01)
	[0.0]	[0.380]	[0.000]			
Δ (t=-1 to t=5)	14.5	0.002	- 0.037	0.21	0.09	0.33
	(0.7)	(0.003)	(0.008)	(0.04)	(0.02)	(0.02)
	[0.0]	[0.400]	[0.000]			
Panel B: Positive Formula Changes, Full Controls						
Δ (t=-1 to t=0)	12.2	0.004	- 0.033	0.18	0.08	0.34
	(0.9)	(0.003)	(0.008)	(0.04)	(0.02)	(0.02)
	[0.0]	[0.210]	[0.000]			
Δ (t=-1 to t=3)	14.4	0.000	- 0.034	0.19	0.08	0.34
	(1.2)	(0.002)	(0.009)	(0.05)	(0.02)	(0.02)
	[0.0]	[0.900]	[0.000]			
Δ (t=-1 to t=5)	15.4	- 0.002	- 0.039	0.22	0.09	0.33
	(1.6)	(0.004)	(0.011)	(0.06)	(0.03)	(0.03)
	[0.0]	[0.580]	[0.001]			
Panel C: Negative Formula Change, Full Controls						
Δ (t=-1 to t=0)	- 30.5	0.005	0.120	0.31	0.16	0.35
	(0.7)	(0.003)	(0.006)	(0.02)	(0.01)	(0.01)
	[0.0]	[0.071]	[0.000]			
Δ (t=-1 to t=3)	- 33.7	0.007	0.150	0.38	0.20	0.31
	(1.1)	(0.002)	(0.008)	(0.02)	(0.01)	(0.01)
	[0.0]	[0.003]	[0.000]			
Δ (t=-1 to t=5)	- 37.8	0.002	0.150	0.38	0.20	0.31
	(1.3)	(0.003)	(0.007)	(0.02)	(0.01)	(0.01)
	[0.0]	[0.390]	[0.000]			

Note: The table shows difference-in-differences regression estimates for the effect of issuer formula changes on payments. Panels A and B report pooled estimates for four formula changes that increased the minimum payment, and Panel C reports estimates for one formula change that decreased the minimum payment. Standard errors clustered by issuer formula type interacted with FICO decile are shown in parentheses, and p-values are shown in brackets. Columns (1) and (2) show the average dollar change in minimum payments and the share of delinquent accounts, respectively. Column (3) presents the change in P, the share of accounts paying less than or equal to the higher of the two minimum payment formulas. Columns (4) and (5) present estimates of θ and θ^*, the fraction of anchoring accounts among those directly affected by the formula changes and among all accounts, respectively. Column (6) presents estimates of the share of accounts that pay close to the minimum payment due to liquidity constraints. See text for details. The regressions in Panel A include only time fixed effects and fixed effects for issuer formula type interacted with FICO decile as independent variables, and includes only potentially treated accounts in the analysis sample. Panels B and C include all accounts from control and treated issuers and a full set of account-level controls and fixed effects for issuer formula type interacted with FICO decile.

Table 3: **Heterogeneity in Anchoring Estimates**

	P	θ*	LC*	P	θ*	LC*	P	θ*	LC*	P	θ*	LC*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Stratified by FICO Band												
Sample:	Deep Subprime			Core Subprime			Prime			Super-prime		
FICO range:	< 620			620 - 660			660 - 720			> 720		
Δ (t=-1 to t=5)	- 0.072	0.13	0.59	- 0.080	0.15	0.52	- 0.066	0.15	0.38	- 0.020	0.06	0.15
	(0.008)	(0.01)	(0.01)	(0.010)	(0.02)	(0.02)	(0.015)	(0.03)	(0.03)	(0.010)	(0.03)	(0.03)
	[0.000]			[0.000]			[0.000]			[0.049]		
Panel B: Stratified by Payer Type												
Sample:	Exact Min Payer			Near Min Payer			Mixed Payer			Full Payer		
Δ (t=-1 to t=5)	- 0.097	0.11	0.83	- 0.160	0.32	0.53	- 0.036	0.08	0.21	0.004	0.00	0.02
	(0.013)	(0.01)	(0.01)	(0.016)	(0.03)	(0.03)	(0.007)	(0.02)	(0.02)	(0.002)	(0.00)	(0.00)
	[0.000]			[0.000]			[0.000]			[0.048]		
Panel C: Stratified by Income Quartile												
Sample:	Lowest			Second			Third			Highest		
Δ (t=-1 to t=5)	- 0.046	0.10	0.36	- 0.045	0.10	0.36	- 0.036	0.08	0.32	- 0.033	0.07	0.29
	(0.013)	(0.03)	(0.03)	(0.013)	(0.03)	(0.03)	(0.012)	(0.03)	(0.03)	(0.011)	(0.02)	(0.02)
	[0.000]			[0.001]			[0.005]			[0.004]		
Panel D: Stratified by Age Quartile												
Sample:	Lowest			Second			Third			Highest		
Δ (t=-1 to t=5)	- 0.064	0.13	0.35	- 0.045	0.10	0.39	- 0.041	0.11	0.31	- 0.024	0.08	0.24
	(0.015)	(0.03)	(0.03)	(0.010)	(0.02)	(0.02)	(0.012)	(0.03)	(0.03)	(0.009)	(0.03)	(0.03)
	[0.000]			[0.000]			[0.003]			[0.009]		

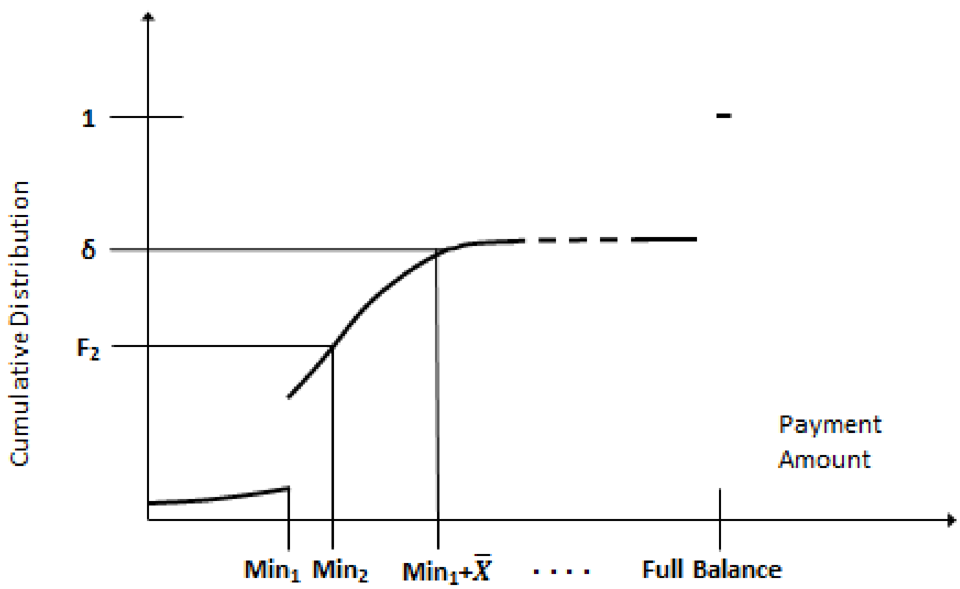
Note: The table shows heterogeneity in estimates of anchoring from difference-in-differences regressions stratified by borrower characteristics. The first column in each group presents the estimate for the change in P, the share of accounts paying less than or equal to the higher of the two minimum payment formulas. The second column presents estimates of θ^*, the fraction of all accounts that anchor to the minimum payment. The third column presents estimates of the share of accounts that pay close to the minimum payment due to liquidity constraints. Standard errors clustered by issuer formula type interacted with FICO decile are shown in parentheses, and p-values are shown in brackets. Panel A stratifies the results by FICO at origination, Panel B stratifies by payer type, Panel C stratifies by income, and Panel D stratifies by borrower age. All regressions include both treated and control issuers and controls for time-varying account characteristics and fixed effects for issuer formula type interacted with FICO decile.

Table 4: **Effects of the CARD Act Disclosures on Payments**

	(1)	(2)	(3)	(4)
Panel A: Full Sample				
Outcome:	Paid 36-month	Paid 35-36-month	Paid 34-36-month	Paid 30-36-month
Δ (t=-1 to t=3)	0.002	0.003	0.004	0.007
	(0.001)	(0.001)	(0.001)	(0.001)
	[0.000]	[0.000]	[0.000]	[0.000]
Δ (t=-1 to t=6)	0.003	0.004	0.005	0.008
	(0.001)	(0.001)	(0.001)	(0.002)
	[0.000]	[0.000]	[0.000]	[0.000]
Δ (t=-1 to 12+)	0.001	0.002	0.002	0.005
	(0.000)	(0.001)	(0.001)	(0.001)
	[0.026]	[0.017]	[0.019]	[0.000]
Panel B: Stratified by FICO Band				
Outcome:	Paid 30-36 month amount			
Sample:	Deep Subprime	Core Subprime	Prime	Super-prime
FICO Range:	< 620	620 - 660	660 - 720	> 720
Δ (t=-1 to 12+)	0.020	0.017	0.004	0.003
	(0.001)	(0.003)	(0.002)	(0.001)
	[0.000]	[0.001]	[0.140]	[0.007]
Panel C: Stratified by Payer Type				
Outcome:	Paid 30-36 month amount			
Sample:	Exact Min Payers	Near Min Payers	Mixed Payers	Full Payers
Δ (t=-1 to 12+)	0.050	0.018	- 0.002	- 0.004
	(0.005)	(0.003)	(0.003)	(0.005)
	[0.000]	[0.000]	[0.490]	[0.330]

Source: The table shows difference-in-differences regression estimates for the effect of the three-year repayment disclosure mandated by the CARD Act. Panel A presents coefficient estimates for the full sample. The columns refer to different dependent variables defined as indicators for repayment durations between 30 to 36 months. Panel B stratifies the results for 30-36-month repayment durations by FICO score, and Panel C stratifies by payer type. All regressions include controls for time-varying account characteristics and fixed effects for issuer interacted with FICO decile. Standard errors clustered by issuer interacted with FICO decile are shown in parentheses, and p-values are shown in brackets.

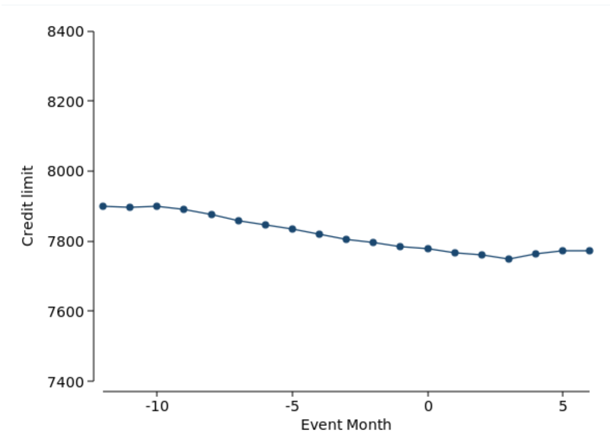
Figure A-1: **Illustration of Stylized CDF for Anchoring Calculations**



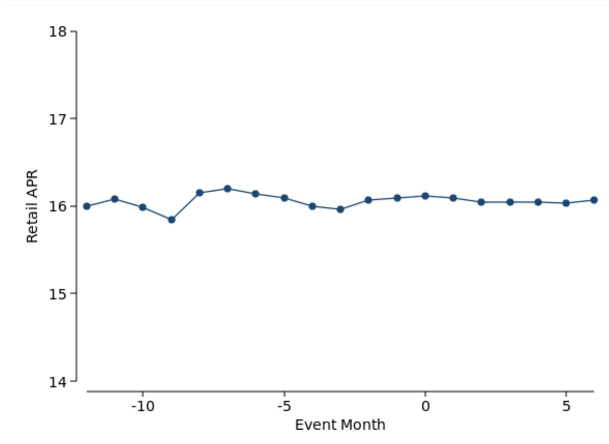
Note: The figure shows the CDF of payments when the minimum payment is equal to Min_1. F_2 denotes the fraction of payments less than or equal to a potential higher minimum payment Min_2, and δ denotes the fraction of payments less than or equal to $Min_1 + \bar{X}$, for some $\bar{X} > 0$. The cumulative distribution has discontinuities at Min_1 and the full balance, where consumers bunch at making exactly the minimum payment and paying their balances in full.

Figure A-2: **Account Characteristics Before and After Formula Changes**

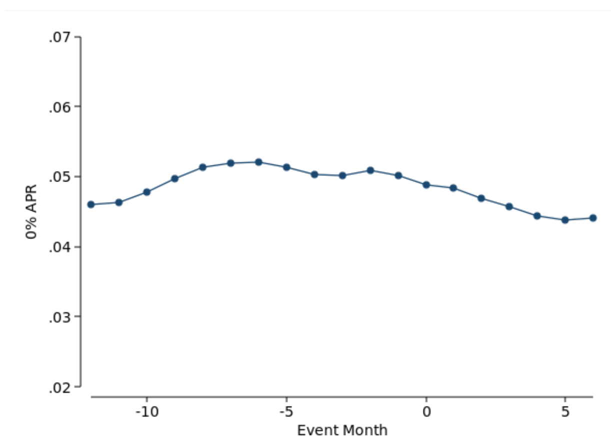
(a) Credit Limit



(b) APR



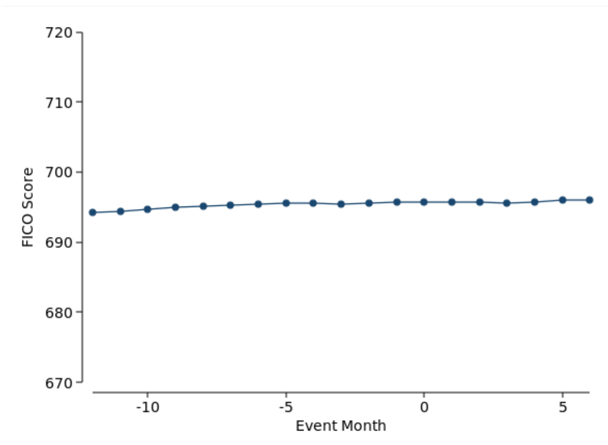
(c) Share with Zero APR



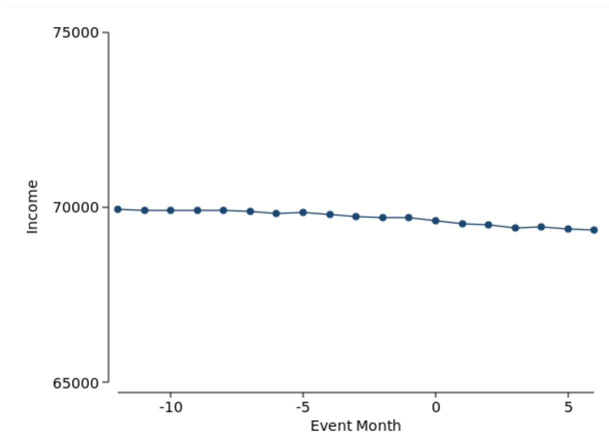
Note: The figures show mean account characteristics for each month before and after minimum payment formula changes.

Figure A-3: **Borrower Characteristics Before and After Formula Changes**

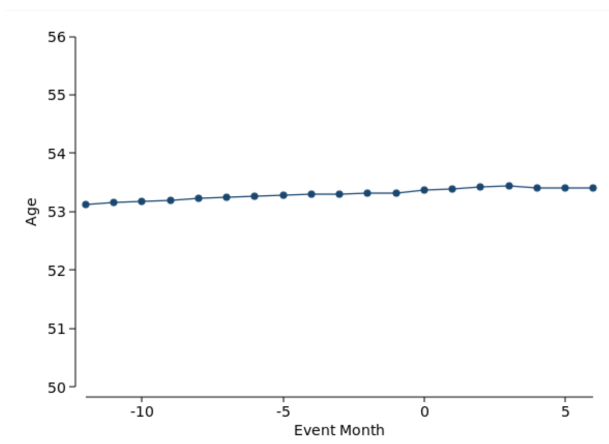
(a) FICO at Origination



(b) Borrower Income



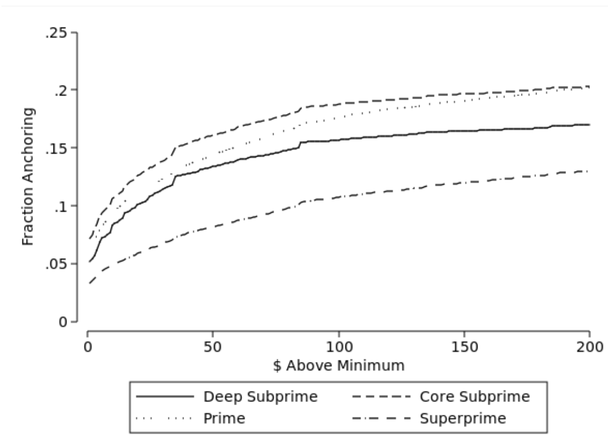
(c) Borrower Age



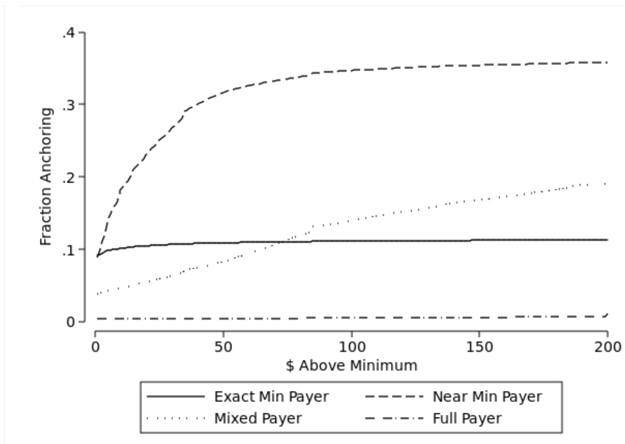
Note: The figures show mean borrower characteristics for each month before and after minimum payment formula changes.

Figure A-4: **Sensitivity of Anchoring Estimates**

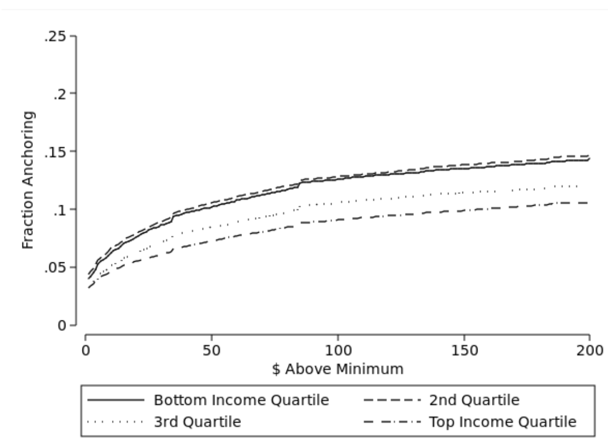
(a) By FICO Band



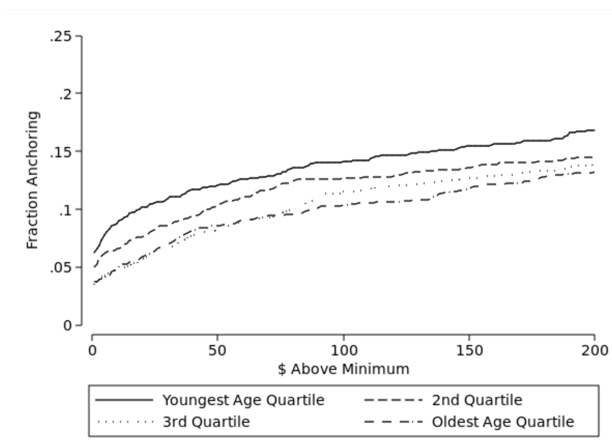
(b) By Payer Type



(c) By Income Quartile



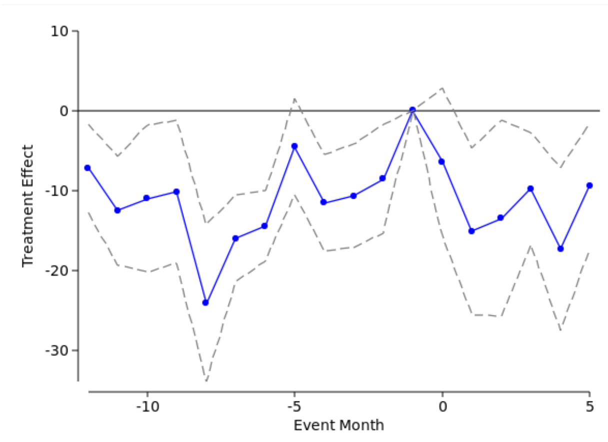
(d) By Age Quartile



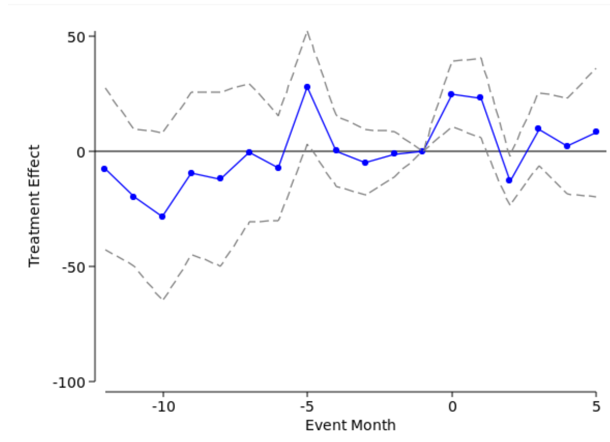
Note: The figures show the sensitivity of estimates of θ^*, the fraction of all accounts that anchor to the minimum payment, to assumptions about the set of accounts potentially susceptible to anchoring. Each graph shows the estimate of the share of anchoring accounts as a function of whether payments within a given band ($\bar{X}$ in the text) of the minimum varying between \$1 and \$200 are assumed to be susceptible to anchoring. The graphs show sensitivity estimates for the stratified regressions shown in Table 3.

Figure A-5: **Spillover Effects of Formula Changes**

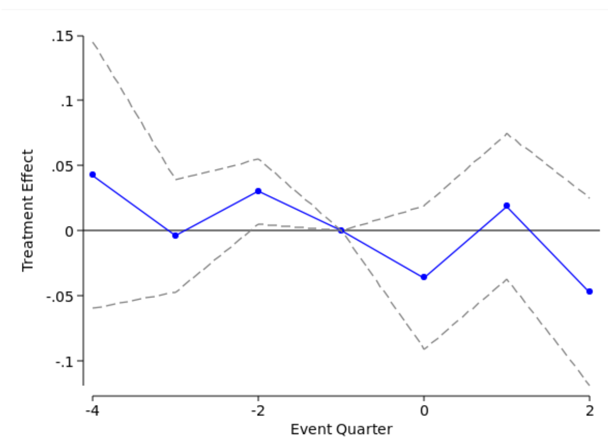
(a) Purchases on Affected Card



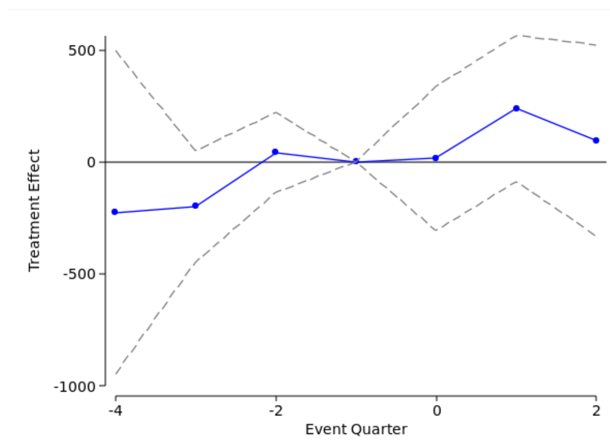
(b) Total Balance on Affected Card



(c) Total Number of Open Cards



(d) Total Balance on All Open Cards



Note: The figures show difference-in-differences regression estimates for the effects of minimum payment changes on purchases, balances, and number of open cards. The sample includes accounts that were potentially treated with one of four formula changes that increased the minimum payment. The regressions include only time fixed effects and fixed effects for issuer formula type interacted with FICO decile as independent variables. The solid lines show point estimates, and the dashed lines show 95% confidence intervals using standard errors that cluster by issuer formula type interacted with FICO decile.

Table A-1: **Summary Statistics By Payer Type**

	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.
	A. Min payer			B. Near Min Payer			C. Mixed payer			D. Full payer		
Card and account												
Income	$58,325	$47,499	$44,926	$56,579	$48,000	$39,900	$66,097	$57,499	$48,723	$74,117	$62,000	$56,259
FICO at origination	692	693	58	671	678	71	693	701	77	762	772	53
Account age (years)	8.93	6.65	8	7.09	4.84	7	8.01	5.39	8	12.72	12.09	8
Age of primary account-holder	48.57	47	15	48.66	48	15	49.95	50	15	56.60	57	17
Credit limit	$7,490	$6,000	$6,448	$7,048	$4,800	$7,069	$9,307	$7,500	$8,520	$13,402	$11,900	$10,033
Retail APR	15.03	16.00	10	16.98	16.99	9	16.75	15.99	9	14.82	14.00	5
Joint account	6%			4%			6%			16%		
Has annual fee	7%			15%			12%			12%		
All Card Accounts												
# of open cards	3.79	3.00	3	4.07	3.00	3	3.07	3.00	2	2.19	2.00	1
Total balance	$17,837	$12,117	$19,182	$17,533	$11,996	$18,173	$12,030	$6,322	$16,889	$3,412	$1,467	$12,029
Total credit limit	$34,974	$25,400	$33,542	$36,156	$26,700	$33,647	$40,802	$30,900	$37,433	$38,932	$30,400	$35,040
# of new cards in last 3 months	0.05	0	0	0.06	0	0	0.07	0	0	0.05	0	0
# of cards 60+ days past due	0.06	0	0	0.05	0	0	0.04	0	0	0.00	0	0
Purchases and Balances												
Utilization	73%	89%	30%	68%	80%	30%	48%	45%	40%	11%	6%	20%
Balance	$5,045	$3,787	$5,000	$4,062	$2,416	$4,638	$3,558	$1,555	$5,122	$1,258	$566	$2,355
Promotional	$737	$0	$2,527	$815	$0	$2,449	$675	$0	$2,392	$52	$0	$660
Cash advance	$383	$0	$1,512	$308	$0	$1,273	$157	$0	$970	$6	$0	$200
Penalty	$362	$0	$1,793	$388	$0	$1,764	$607	$0	$2,465	$65	$0	$611
Purchase volume	$83	$0	$371	$103	$0	$351	$335	$31	$1,009	$1,230	$581	$2,428
Purchase volume > 0	30%			42%			58%			99%		
Payment and Delinquency Behavior												
Fraction paid	9%	2%	20%	9%	3%	20%	31%	9%	40%	95%	100%	20%
Minimum payment	$88	$45	$177	$97	$57	$140	$102	$40	$284	$35	$22	$55
Actual payment	$139	$45	$628	$171	$80	$613	$438	$150	$1,297	$1,247	$573	$2,533
Payment:												
< Minimum	6%			7%			15%			2%		
Exact minimum	77%			18%			9%			3%		
Near minimum	10%			58%			16%			0%		
Intermediate	6%			15%			42%			5%		
Full	2%			2%			19%			90%		
Charged fees:												
Late	7%			9%			13%			3%		
Overlimit	1%			1%			2%			0%		
NSF	0.2%			0.2%			0.3%			0.1%		
Had past due	6%			7%			14%			1%		

Note: The table provides summary statistics for accounts in each payer type. Each account is classified into a payer type based on whether the account was paid in full or paid at or near the minimum amount in at least 50% of months. Accounts that did not pay any of these three amounts in 50% of months are classified as mixed payers. The sample definition is the same as that in Table 1.

Table A-2: **Robustness of Anchoring Estimates**

	Regression estimates			Anchoring estimates		
	Minimum Due	Delinq.	P	θ	θ*	LC*
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Treatment Intensity Specification						
Δ (t=-1 to t=5)	1.230	0.0004	- 0.0019	0.13	0.10	0.36
	(0.130)	(0.0002)	(0.0006)	(0.04)	(0.03)	(0.02)
	[0.000]	[0.0510]	[0.0019]			
Panel B: Exclude Promotions						
Δ (t=-1 to t=5)	16.3	0.001	- 0.029	0.19	0.08	0.31
	(1.3)	(0.003)	(0.010)	(0.07)	(0.03)	(0.03)
	[0.0]	[0.640]	[0.007]			
Panel C: Single Cardholders Only						
Δ (t=-1 to t=5)	17.0	- 0.011	- 0.041	0.34	0.09	0.17
	(4.7)	(0.007)	(0.011)	(0.09)	(0.02)	(0.02)
	[0.0]	[0.110]	[0.001]			
Panel D: Multiple Cardholders Only						
Δ (t=-1 to t=5)	22.2	0.006	- 0.044	0.25	0.11	0.34
	(2.8)	(0.005)	(0.012)	(0.07)	(0.03)	(0.03)
	[0.0]	[0.230]	[0.001]			

Note: The table shows difference-in-differences regression estimates for the effects of issuer formula changes on payments in four variations of our main specification. Panel A uses the difference in the minimum payments between the old and new formulas as the treatment variable. Panel B excludes any cards with a promotional interest rate offer. Panels C and D use subsamples of single cardholders and multiple cardholders, respectively. Columns (1) and (2) show the average dollar change in minimum payments and the share of delinquent accounts. Column (3) presents the change in P, the share of accounts paying less than or equal to the higher of the two minimum payment formulas. Columns (4) and (5) present estimates of θ and θ^*, the fraction of anchoring accounts among those directly affected by the formula changes and among all accounts, respectively. Column (6) presents estimates of the share of accounts that pay close to the minimum payment due to liquidity constraints. All regressions include both treated and control issuers and controls for time-varying account characteristics and fixed effects for issuer formula type interacted with FICO decile. Standard errors clustered by issuer formula type interacted with FICO decile are shown in parentheses, and p-values are shown in brackets.

Table A-3: **Microdata Regressions with Account Fixed Effects**

	Regression estimates			Anchoring estimates		
	Minimum Due	Delinq.	P	θ	θ*	LC*
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Positive Formula Changes, No Time-Varying Controls						
Δ (t=-1 to t=0)	13.7	0.018	- 0.013	0.07	0.03	0.39
	(0.7)	(0.002)	(0.007)	(0.04)	(0.02)	(0.02)
	[0.0]	[0.000]	[0.057]			
Δ (t=-1 to t=3)	14.0	0.009	- 0.027	0.15	0.06	0.35
	(0.6)	(0.003)	(0.007)	(0.04)	(0.02)	(0.02)
	[0.0]	[0.004]	[0.000]			
Δ (t=-1 to t=5)	14.1	0.011	- 0.031	0.17	0.07	0.35
	(0.6)	(0.002)	(0.007)	(0.04)	(0.02)	(0.02)
	[0.0]	[0.000]	[0.000]			
Panel B: Positive Formula Changes, Full Controls						
Δ (t=-1 to t=0)	11.8	0.005	- 0.031	0.17	0.07	0.35
	(0.9)	(0.003)	(0.008)	(0.04)	(0.02)	(0.02)
	[0.0]	[0.150]	[0.000]			
Δ (t=-1 to t=3)	12.0	0.001	- 0.035	0.19	0.08	0.34
	(1.3)	(0.002)	(0.009)	(0.05)	(0.02)	(0.02)
	[0.0]	[0.500]	[0.000]			
Δ (t=-1 to t=5)	12.2	0.000	- 0.040	0.22	0.09	0.32
	(1.4)	(0.002)	(0.010)	(0.06)	(0.02)	(0.02)
	[0.0]	[0.940]	[0.000]			
Panel C: Negative Formula Change, Full Controls						
Δ (t=-1 to t=0)	- 30.9	0.004	0.120	0.31	0.16	0.35
	(0.6)	(0.003)	(0.007)	(0.02)	(0.01)	(0.01)
	[0.0]	[0.160]	[0.000]			
Δ (t=-1 to t=3)	- 32.2	0.006	0.130	0.34	0.17	0.34
	(0.7)	(0.002)	(0.007)	(0.02)	(0.01)	(0.01)
	[0.0]	[0.007]	[0.000]			
Δ (t=-1 to t=5)	- 35.0	0.000	0.120	0.31	0.16	0.35
	(1.2)	(0.002)	(0.006)	(0.02)	(0.01)	(0.01)
	[0.0]	[0.980]	[0.000]			

Note: The table shows difference-in-differences regression estimates for the effect of issuer formula changes on payments using micro data (rather than the collapsed data shown in Table 2). Panels A and B report pooled estimates for four formula changes that increased the minimum payment, and Panel C reports estimates for one formula change that decreased the minimum payment. Standard errors clustered by issuer formula type interacted with FICO decile are shown in parentheses, and p-values are shown in brackets. Columns (1) and (2) show the average dollar change in minimum payments and the share of delinquent accounts, respectively. Column (3) presents the change in P, the share of accounts paying less than or equal to the higher of the two minimum payment formulas. Columns (4) and (5) present estimates of θ and θ^*, the fraction of anchoring accounts among those directly affected by the formula changes and among all accounts, respectively. Column (6) presents estimates of the share of accounts that pay close to the minimum payment due to liquidity constraints. See text for details. The regressions in Panel A include only time and account fixed effects as independent variables, and includes only treated accounts in the analysis sample. Panels B and C include all accounts from control and treated issuers and a full set of account-level controls and account fixed effects.