The Semblance of Success in Nudging Consumers to Pay Down Credit Card Debt

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We test a nudge in a field experiment on credit cards. The nudge shrouds the Autopay enrollment option for cardholders to automatically pay exactly the credit card minimum payment each month. After six months, the nudge decreases the fraction of cardholders who only pay exactly the minimum by 23%. However, the nudge does not significantly reduce credit card debt. Nudged cardholders often choose Autopay amounts that are only slightly higher than the minimum payment. The nudge reduces Autopay enrollment, which increases missed payments. The nudge reduces manual payments by Autopay enrollees. Cardholders frequently lacking liquid cash best explains our results.

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Policymakers often make decisions based on observing the effects of a potential policy on short-run choices that act as proxies for longer-run outcomes (e.g., Athey et al., 2024). Our paper provides an example of how one "nudge" (Thaler and Sunstein, 2008) policy changes enrollment choices and *proximate* outcomes without changing the more challenging *distal* economic outcome of ultimate importance to policymakers.

We study this topic in the domain of credit card policymaking. Credit card payments are often at or near the minimum due: 25% of payments in the UK (Financial Conduct Authority, 2016a) and 29% in the US (Keys and Wang, 2019). A potential explanation for such payment choices is that a credit card's minimum payment "can serve as an anchor, and as a nudge that this minimum payment is an appropriate amount" (Thaler and Sunstein, 2008) that acts as a psychological default (Sakaguchi et al., 2022) or focal point.[1] There is empirical support for this explanation (e.g., Stewart, 2009; Keys and Wang, 2019; Medina and Negrin, 2022; Sakaguchi et al., 2022).

We test whether one previously untested nudge, that reduces the salience of an option to automatically only pay the minimum payment, can cause consumers to pay more than the minimum and to reduce their credit card debt. We conduct a pre-registered field experiment on 40,708 UK credit cardholders. Consistent with the minimum payment acting as a focal point, the nudge is effective in shifting payment choices away from the minimum, a *proximate* outcome. However, the nudge is ultimately ineffective in changing the amount of credit card debt accumulated, a *distal* outcome. We find that credit cardholder responses to the nudge make it ineffective. These results are consistent with these consumers lacking liquid cash to reduce their debt, and we show further evidence of this using linked bank account data.

A mechanism facilitating low credit card payments is the FinTech feature called "Autopay" in the US, known as "Direct Debit" in the UK. Autopay is a common payment mechanism used across non-financial (e.g., cell phones) and financial (e.g., auto loans, mortgages) products. For credit cards, enrolling in Autopay is an opt-in choice. Cardholders choosing to enroll in Autopay are presented with three options: automatically paying exactly the minimum amount due each month ("Autopay Min"), automatically paying a fixed amount each month ("Autopay Fix") where the automatic payment is the maximum of a fixed amount and the minimum due that month, and automatically paying the full balance due on the statement each month ("Autopay Full"). These three Autopay options are standard in the UK and US.[2] Autopay is used by 42% of UK cards (Financial Conduct Authority, 2016a) and 20% to 38% of US cards (Consumer Financial Protection Bureau, 2021), with growing use over time. Cardholders enrolled in Autopay can also make supplemental, non-Autopay ("manual") payments either online or by phone.

Consumers may enroll in Autopay for convenience: providing insurance against forget-

[1] Recent research (Bartels et al., 2024; Schwartz, 2024) reveals the prevalence of credit card payments exactly at or just above the minimum is more accurately described as "targeting" behavior, where consumers exert effort to meet a threshold, rather than as "anchoring" behavior (Tversky and Kahneman, 1974), partially because there is not a mass of payments just below the minimum, which would be predicted under anchoring but not under targeting.

[2] The largest US credit card lenders (e.g., American Express, Chase, Citi, Capital One, Discover, US Bank, and Wells Fargo) offer these Autopay options.

ting to pay a bill and also providing flexibility on how much to pay given uncertainty over their liquid cash. Yet, Autopay means that credit cardholders no longer need to actively decide each month how much to pay and may become inattentive to their debt (Sakaguchi et al., 2022) and procrastinate on paying it down, resulting in them paying high credit card interest costs that strain their liquid cash reserves, rather than increasing their savings or consumption. Consistent with this, persistent minimum payments and high credit card interest costs are concentrated among cardholders enrolled in Autopay Min. 75% of consumers in "persistent credit card debt"—using a regulatory definition of making nine or more minimum payments in a year on interest-bearing cards—are enrolled in Autopay Min (Financial Conduct Authority, 2016a). Consumers who switch into Autopay Min pay 20% more in total credit card interest and fees than if they had not switched, this is despite being more likely to incur late fees without Autopay (Sakaguchi et al., 2022). The 20% of UK credit cards enrolled in Autopay Min account for 43% of total interest and fees across all UK credit cards (Sakaguchi et al., 2022). Credit cardholders enrolled in Autopay Min underestimate how long it will take to pay off credit card debt if they only pay the minimum, suggesting that their payment decisions are not well informed, and policies to correct this bias are ineffective in reducing debt (e.g., Adams et al., 2022).[3]

In our field experiment's treated group, we remove the minimum payment as a visible and salient focal point for cardholders enrolling in Autopay at card opening. We nudge consumers by removing the explicit appearance of the Autopay Min option for the treated group. Autopay Fix and Autopay Full remain visible options for both the control and treatment groups. Autopay Min remains a feasible choice for consumers if they actively choose a low Autopay Fix amount that binds at the minimum. By shrouding the Autopay Min option, we increase the salience of the Autopay Fix option, which enables an active choice and, without offsetting consumer responses, would automatically amortize debt faster.

This field experiment is an ex ante test of a potential nudge that the UK consumer financial protection regulator, the Financial Conduct Authority (FCA), was considering implementing, given regulatory concerns about substantial amounts of UK credit card debt (Financial Conduct Authority, 2014, 2016b).[4] The field experiment is conducted on cardholders who have self-selected to reach the Autopay enrollment web page. We measure outcomes in administrative credit card data and consumer credit reporting data. Among consumers enrolled in Autopay Min in the control group of our experiment, 69% only pay exactly the minimum amount, indicating a large potential scope for the nudge to increase

[3]Adams et al. (2022) find 96% of survey respondents, from a sample of UK consumers enrolled in Autopay Min, underestimate the time it would take to fully pay a debt if the cardholder only paid the minimum each month. More generally, approximately half of UK credit cardholders in one survey incorrectly thought the minimum payment is the amount most people paid, when in fact only a quarter do (Financial Conduct Authority, 2016b). Studies across countries show that cardholders significantly overestimate the speed with which debt is cleared (and, by implication, underestimating the interest costs) if they only pay the minimum (e.g., Lusardi and Tufano, 2015; Seira et al., 2017; Adams et al., 2022).

[4]See Guttman-Kenney et al. (2018) and Adams et al. (2022) for other nudges the FCA tested. There are practical limits on how many potential policies regulators can test through field experiments, especially in this domain, where estimating effects on credit card debt requires large samples and observing outcomes for several months.

payments.

The nudge initially appears effective. It reduces initial Autopay Min enrollment from 36.9 percent of the control group to 9.6 percent in the nudged treatment group, a 74% decline, and increases Autopay Fix enrollment by 73%. These initial changes in Autopay enrollment are persistent over time. The nudge successfully decreases the probability of cardholders only paying exactly the minimum by seven percentage points or 23% after seven completed cycles, spanning six months. We also conduct a field experiment of the same nudge with a second lender but after observing similarly large initial effects on Autopay enrollment this second lender withdrew before fieldwork was complete, which prevents us from evaluating its distal effects.

The nudge does *not* change credit card debt accumulated after six months. We observe null effects, on average, on credit card debt as well as spending, total payments, and borrowing costs on the specific card in the trial and across a consumer's entire portfolio of credit cards, and consumers are no more likely to pay the full balance. Such null results are critical policy inputs (Abadie, 2020) especially when the null effects on real outcomes contrast with the large effects on Autopay enrollment outcomes.

We investigate the mechanisms that cause the enrollment effects of the nudge to be undone so that the effects on economic outcomes are not statistically significant. We find that three factors explain why the nudge is ineffective. First, nudged cardholders set up fixed Autopay amounts that are only modestly higher than the minimum payment due, and, in the long-run, essentially no higher than the minimum payment because the minimum payment rises mechanically as card balances rise over time. Second, nudged cardholders are less likely to enroll in Autopay, causing more missed payments relative to the cardholders who are not nudged. Third, nudged cardholders enrolled in Autopay substitute higher automatic payments for lower manual payments, which is consistent with having limited liquid cash available to pay more overall.

Limited liquid cash balances can best explain why consumers do not reduce their credit card debt. For a selected subsample of our field experiment, we observe daily liquid cash balances from bank account data linked to our credit card data. We use these linked data to construct a new dynamic measure of liquid cash balances: the *minimum* liquid cash balance in the ninety days before card opening. This dynamic liquid cash measure reveals that half of consumers reach effectively zero liquid cash balances and 84% have £500 or less; this is much higher than the 13% that a traditional point-in-time measure of liquid cash balances would indicate. Our new measure strongly predicts credit card payment decisions six months later. After six months, consumers with small positive minimum liquid cash balances before card opening held approximately 20 percentage points less credit card debt, as a percentage of the statement balance, than those with zero or small negative minimum liquid cash balances before card opening. Consistent with limited liquid cash balances preventing consumers from reducing their debt, heterogeneity analysis shows that low liquidity consumers appear even less responsive to the nudge than high liquidity consumers. Heterogeneity analysis does not find robust evidence that the nudge reduces debt for low liquidity or high liquidity consumers; the latter group may be the subgroup of consumers most expected to be making behavioral mistakes that the nudge could debias. This is important given that Allcott et al. (2024) show that the welfare effects of nudges depend on the heterogeneity of their impacts, and List et al. (2023) show that nudges' efficiency depends on their ability to debias consumers.

Our first contribution is to the literature on credit card policymaking. We show a previously untested nudge is ineffective at reducing debt, and reveal that consumers enrolled in Autopay are not as inert as they may initially appear. A challenge for consumer protection regulators is how to reduce high cost borrowing, such as on credit cards. Around the world, informational disclosures or nudges are ineffective at reducing credit card debt (e.g., Agarwal et al., 2015; Seira et al., 2017; Adams et al., 2022). While there is a large body of research testing a range of choice architectures attempting to increase retirement savings (see reviews by Beshears et al., 2018 and Gomes et al., 2021), there are fewer studies testing ways to reduce credit card debt and they tend to be information-based interventions, such as letters, emails, and text alerts (e.g. Agarwal et al., 2015; Medina, 2021; Seira et al., 2017; Adams et al., 2022), rather than more forceful changes in choice architecture, such as the nudge we test (an exception being the small pilot of Karlan and Zinman, 2012).[5]

Our second contribution is to the literature on the drivers of credit card indebtedness. Credit card debt is a well-established puzzle (e.g., Zinman, 2015; Gomes et al., 2021). Our research helps to understand some of the factors that contribute to this. Our findings show that "anchoring" to minimum payments in credit cards appears less economically important than previously thought. While the headline results for Keys and Wang (2019) and Medina and Negrin (2022) both show that changes in minimum payments cause changes to payments, consistent with anchoring, neither finds that this causes significant changes in debt.[6] It is still possible for anchoring to be important for manual credit card payment choices, given lab evidence (e.g. Stewart, 2009; Navarro-Martinez et al., 2011; Guttman-Kenney et al., 2018; Sakaguchi et al., 2022). However, our research shows that anchoring does not appear to be the reason why consumers enrolled in Autopay do not pay more of their credit card debt. Instead, these consumers' payments are constrained by frequently lacking liquid cash balances.

Our third contribution is to the literature on nudging. Our study is an example of how important it is for policymakers to evaluate nudges on how they impact distal outcomes. Our experiment shows that policymakers should not assume that changes in enrollment choices lead to changes in economic outcomes. For example, if a policymaker only observes the effects of the nudge on the composition of Autopay enrollments, it may appear effective: we estimate that it would reduce debt by approximately 4.5%. However, examining the effects of the nudge on actual debt reveals that the nudge is ultimately ineffective. We show even when a nudge not only changes enrollment but also successfully changes *proximate* outcomes (e.g., only paying the minimum), the same nudge may still not change the more

[5]This is understandable given there is an incentive for firms to conduct field experiments to find ways to increase retirement contributions because higher assets generate higher revenues. However, it is not in the incentives of credit card lenders to test or publicize ways to reduce credit card debt, as lower debt generates lower interest revenue.

[6]Neither of these studies observe Autopay enrollment or liquid cash balances, and the minimum payment also remains salient in both studies.

distal outcomes (e.g., debt), and therefore it is critical to measure effects on the latter. Without ex ante tests that measure distal outcomes, policies that sound appealing may be introduced that are costly and ineffective at changing distal outcomes, for example, as discovered ex post with the US CARD Act disclosures (Agarwal et al., 2015; Keys and Wang, 2019). Across financial domains, nudges can shift enrollments, but consumers may also subtly counteract these effects. For example, Choukmane (2024) finds the long-run effects of automatic enrollment defaults on savings are smaller than short-run contribution increases found in the earlier academic literature (e.g., Madrian and Shea, 2001; Thaler and Benartzi, 2004). Some nudges are still highly effective even when potential countervailing effects are measured. For example, Chetty et al. (2014) show automatic enrollment increases retirement savings. Other nudges may be effective in changing the targeted behavior, however, they may have unintended side effects. For example, Medina (2021) shows credit card reminders help consumers to avoid credit card late fees, but unintentionally lead them to incur more in overdraft fees. Our study contributes to the broader debate on the effectiveness of nudges (e.g., Thaler, 2017; Laibson, 2020). DellaVigna and Linos (2022)'s meta-study documents the heterogeneous effects of nudges and provides evidence for publication bias.[7] Recent meta-studies (e.g., Beshears and Kosowsky, 2020; Saccardo et al., 2023) show very few studies examine the long-term effects of nudges, as we do, or measure broader outcomes that could offset effects, and, when these are observed, nudges are less effective.[8] Our nudge's contrasting proximate and distal effects are an important example to consider when designing and evaluating policies.

The paper proceeds as follows. Section I explains our field experiment: the design of the nudge, and how the field experiment is implemented. Section II describes the data we use and our empirical methodology. We present our experimental results in Section III. Section IV studies the mechanisms that explain our experimental results, including using linked bank data to study liquid cash balances. Finally, Section V concludes. Additional results are contained in the Online Appendix, this paper's code and data depository (Guttman-Kenney et al., 2024), and in our earlier working paper (Guttman-Kenney et al., 2023).

I. Field Experiment

A. Nudge Design

Credit cardholders have broad discretion in how much to pay on their credit card each month; paying any amount between the minimum due and the full balance fulfills their contractual obligations. The minimum payment due is typically calculated by

[7] DellaVigna and Linos (2022) show the average effect among academic published studies of nudges is 8.7 percentage points, a 33.4% increase, whereas the average effects from the population of studies from Behavioral Insights Teams are smaller: 1.4 (8% increase). In this meta-study, the average effect is compiled from a mixture of short-run and long-run outcomes based on the outcomes observed in the original studies.

[8] Beshears and Kosowsky (2020) review 174 nudge papers and find only 17 examine long-term effects and only 12 study effects on outcomes that could offset the nudge's effectiveness. Saccardo et al. (2023) show effects of Behavioral Insights Teams' nudges are smaller when the outcomes are more broadly defined or measured over longer time horizons.

$max\{£5,\ 1\%$ statement balance $+$ interest $+$ fees$\}$. This formula means that the minimum payment amount will typically decrease as balances decrease. If a cardholder is only paying the minimum, then (i) their payment is effectively only servicing debt interest payments, with interest rates near 20% typical, and (ii) debt reduction only happens at all if new spending is less than 1% of the statement balance. Even with *no* new spending, debt paydown is only 1% of the statement balance per month if a cardholder only pays the minimum.

In our field experiment, we vary how Autopay enrollment options are presented to UK consumers who have opened a new credit card account. We nudge Autopay enrollment at card origination because these initial Autopay decisions are highly persistent (e.g., Sakaguchi et al., 2022; Adams et al., 2022; Wang, 2024). When a consumer opens a new credit card online, they are typically presented with the option to enroll in Autopay. If a consumer decides to opt-in, they are normally presented with three Autopay options: Autopay Full, Autopay Fix, and Autopay Min. All of these Autopay options are shown to our control group. At this stage, consumers can still decide against enrolling in any type of Autopay by not completing the enrollment process. They could also return and complete the Autopay enrollment later. The treatment is a previously untested nudge that shrouds the option to automatically make only the minimum payment each month. This is done by removing the explicit appearance of the Autopay Min option. The nudge makes it difficult for inattentive consumers to default into automatically only paying exactly the minimum each month. Removing the Autopay Min option increases the salience of the alternative Autopay Fix and Autopay Full options. Online Appendix Figure A1 shows the designs of the control and treatment.

While Autopay Min is a common payment option, cardholders also have the option to enroll in an alternative Autopay option that would pay down debt faster: "Autopay Fix". Autopay Fix is calculated by: $max\{$Autopay Fix £, Minimum Payment Due$\}$. If a consumer is enrolled in Autopay Min, their Autopay Min amount will decrease when balances decrease due to the minimum payment formula described above.[9] Consider a typical credit card balance of £1,000, assuming 18.9% APR and no further card spending. This would take 18 years and 6 months to pay off if only exactly the minimum is paid each month, such as through Autopay Min. It takes a long time for this debt to be paid off because as balances decrease, the minimum payment amount, and therefore the Autopay Min amount, will also decrease from around £25 and to £5 over time. However, by fixing the monthly payment to £25 each month, the debt pay-off horizon falls to 5 years and 1 month, saving over £750 in interest costs. If a consumer chooses a slightly higher fixed monthly payment amount, this would further reduce the time of pay off and borrowing costs. For example, with a fixed payment of £50 each month, the debt pay-off time decreases to 2 years and the interest costs become only £191, compared to £509 if paying a fixed amount of £25 each month.

We want consumers to make active choices (e.g., Carroll et al., 2009; Keller et al., 2011)

[9]This issue would also occur if Autopay options to pay a percentage of the statement balance were provided. The effect of offering such options is not tested in our experiment and is left for future research.

about how much they want to pay each month using the Autopay Fix option, or to target the Autopay Full option. Because few consumers can pay their credit card debt in full each month, the nudge is primarily designed to work by increasing Autopay Fix enrollment which, relative to Autopay Min, is expected to increase automatic payments, which would then be expected to reduce debt and interest costs. A further possible effect could be to increase consumer spending via debt paydown increasing credit limit availability (e.g., Gross and Souleles, 2002; Agarwal et al., 2017).

We purposefully do not include an alternative recommended Autopay Fix amount in the treatment because we do not want to replace the Autopay Min as a focal point with another focal point (other than the Autopay Full option) distorting consumers' payment choices. This design choice is motivated by US studies (e.g., Agarwal et al., 2015; Hershfield and Roese, 2015; Keys and Wang, 2019) that find that providing consumers with credit card payment scenarios unintentionally reduces payments for some consumers.

While there is no longer an explicit Autopay Min option in the treatment arm, cardholders can choose an operationally equivalent option by setting an Autopay Fix of £5 (or less). These two options are equivalent as the minimum payment is calculated as $max\{£5,\ 1\%\ \text{statement balance} + \text{interest} + \text{fees}\}$ and so is greater than or equal to £5 by construction. This means that when the minimum payment due in a particular month is more than £5, the Autopay attempted to be taken will adjust accordingly, regardless of whether a consumer has an Autopay Fix amount of £5 or an Autopay Min. This equivalence is not highlighted to consumers, and we do not expect them to be aware of this or work this out. We explain this to show that the treatment does not restrict consumer choice of an Autopay option to pay the minimum, and therefore the treatment is a nudge rather than a restriction (the Autopay Min option is no longer explicitly labelled on the website).

B. *Experiment Implementation*

We test the nudge through a randomized controlled trial (RCT) conducted in the field on UK credit cardholders. The FCA invited all UK credit card lenders to voluntarily participate in a field trial. Two lenders were willing and technically able to participate within the timelines necessary to inform FCA policymaking.

When a consumer is applying for a new credit card online and has been accepted by a lender they have the option to set up Autopay on this new card. If a consumer selects the option confirming that they want to enroll in Autopay, they are included in the experiment. At this point consumers are randomly assigned to either control or treatment (the nudge). Once allocated to control or treatment the consumer would view the same assigned screen if they returned to the Autopay landing page within thirty days. If a consumer in either the control or treatment group phones the lender's call center they could still enroll in an explicit Autopay Min if they ask to do so. Thirty days after card opening, cardholders in both the control and treatment groups have identical screens containing explicit Autopay Min enrollment options. This is relevant if a cardholder comes back to the Autopay launch page to change their Autopay enrollment status. Inclusion in the experiment is irrespective of whether the Autopay enrollment process is completed after reaching the Autopay enrollment screen. We carried out qualitative consumer testing to ensure consumers would understand how to navigate the treatment, the experiment was reviewed by the FCA's Institutional Review Board's governance and by both lenders' governance, and we also sought feedback from all UK credit card providers and large consumer organizations. Lenders did not report any consumer complaints regarding the trial, or the lack of an explicit Autopay Min option in the treatment.

Our field experiment is conducted on two UK lenders. The main lender is a large UK firm, and our experiment included 40,708 credit cards that are newly issued between February and May 2017. We wanted at least 20,000 cards in each of control and treatment groups to ensure we have sufficient statistical power to estimate effects on debt. The final achieved number is slightly higher as for logistical reasons new cards were included until the end of May 2017. We also conducted the experiment with a second lender. The second lender stopped the experiment after one week of fieldwork due to the lender's concern over the large treatment effects on Autopay enrollments. The second lender's experiment was not restarted, and the pre-agreed target sample size was not reached. The second lender's experiment's achieved sample size of 1,531 cards is insufficiently powered to distinguish between null results and imprecisely estimated non-null effects. Had we known this second lender would stop fieldwork prematurely, we would not have started the experiment with this lender. For completeness, results from the second lender are in Online Appendix B. The rest of this paper is based on the field experiment with the main lender unless explicitly stated otherwise.

II. Data and Methodology

A. Data

Our data is gathered by the FCA using its statutory powers (Financial Conduct Authority, 2018). All analysis is conducted on anonymized data (Guttman-Kenney et al., 2024).

Credit Card Data. — We collect detailed administrative data for every credit card in the experiment. We observe data recorded at card origination (e.g., opening date, interest rates, initial credit limit) and across all statements (e.g., statement balances, spending) to December 2017. A completed statement cycle is one where the payment due date for a credit card statement has passed. For the main lender, we observe seven completed cycles for effectively all cards (99.9%) and up to eleven for the cards opened at the start of the experiment's fieldwork. For the second lender, we observe twelve completed cycles. Each individual payment made against these statements is observed including the date, amount, and whether the payment is made via Autopay or manually.

Consumer Credit Reporting Data. — For consumers in the experiment, we gather consumer credit reporting data (see Gibbs et al., 2024, for a review of these data), which enables us to observe effects across the consumer's debt portfolio. Consumer credit reporting data provide monthly tradeline-level data showing credit limits, balances, payments, and arrears, for each account, from card opening to the end of 2017. We observe statement balances (i.e., before payments), payments, balances after payments (i.e., debt), and indicators for whether a card only paid the minimum. UK credit reporting data contain payments data for all credit cards, something that does not occur in US credit reporting data, (Guttman-Kenney and Shahidinejad, 2024). We observe credit risk scores and income estimates (where available) at two points in time: the month before the card was opened and nine months afterwards. These data mean that if the treatment caused a large increase in payments to credit cards in the experiment that caused financial distress elsewhere in their portfolio, we could observe it. Credit card administrative data and credit reporting data are linked using an anonymous key created for this project.

Bank Account Data. — We also observe bank account data, checking/current accounts and savings accounts, for the subset of cardholders who hold these with the main credit card lender in our experiment. The bank account data report end-of-day balances each day up to a year before the experiment started (or when the account was opened) and up to June 2017 – a month after the last card is enrolled in our experiment. After restricting these data to cardholders who appear to be actively using this bank as their primary bank account, we observe 3,753 cardholders or 9.2% of our field experiment. Additional details are provided in Online Appendix E.

Summary Statistics. — As the experiment is conducted on newly opened cards, we describe summary statistics for the control group after seven cycles. We observe a diversity of credit cardholders in our data with a wide range of interest rates, credit scores, credit card credit limits, ages, and incomes. The mean credit card statement balance after cycle seven is £2,164 and £1,963 after payments. Cardholders often hold other credit cards in their portfolio: Their mean credit card portfolio statement balances, aggregated across cards held in consumer credit reporting data, are £3,917 and £3,432 after payments. Credit card portfolio balances both before and after payments are higher than consumers' mean income of £2,437. In line with the motivation for our experiment, the cardholders in our control group are often only paying exactly the minimum, *especially* those enrolled in Autopay Min. 30% only pay the minimum payment in the seventh cycle, and 19% only pay the minimum six or more times in the first seven cycles. 18% had paid in full six or more times. Among consumers enrolled in Autopay Min, 69% only pay exactly the minimum amount and only 20% are pay more than ten percentage points in excess of the minimum. For more details, see summary statistics in Online Appendix Table A1 and Figure A6.

B. *Empirical Methodology*

Before analyzing data, we pre-registered our methodology. Our pre-registration designates primary outcomes, regression specifications, and thresholds for statistical significance (Guttman-Kenney et al., 2022). We structure our analysis in three parts: primary, secondary, and tertiary analyses. Conducting secondary analysis depends on the primary analysis's results. We design and implement tertiary analysis after examining the data. This structure limits the potential for data mining or p-hacking. The primary analysis focuses on ten primary, real economic outcomes upon which the nudge's effectiveness is evaluated.

The first six primary outcomes (1 to 6) measure the impact on the credit card in the experiment ("target card") - constructed from microdata collected from the lender. All these primary outcomes are bounded between zero and one. Outcomes 1, 2, and 3 are binary: (1) any minimum payment, (2) any full payment, (3) any missed payment. Outcome (4) is a measure of credit card (revolving) debt: statement balance net of payments (% statement balance). We examine multiple moments because credit card payments have a non-normal, bimodal distribution (e.g., Keys and Wang, 2019) with the tails being economically important. Outcome (5) is a measure of borrowing costs (combining interest and fees): Costs (% statement balance). Outcome (6) is a measure of consumption: Spending (% statement balance). Our measures of debt, consumption, and costs are all normalized by dividing by statement balances, denoted by (% statement balances), to deal with fat-tailed credit card balances. Normalizing our measures of debt by credit card statement balance is not ideal as it means our outcome is a ratio of two endogenous components. To address this our secondary analysis also shows the numerator and denominator in levels (£) separately (and having completed the analysis we find the results are consistent). Primary outcomes 7 to 10 are analogous to primary outcomes 1 to 4 but constructed using consumer credit reporting data to assess the impact across a consumer's portfolio of credit cards. These primary outcomes are: (7) Share of credit card portfolio only paying minimum, (8) Share of credit card portfolio making full payment, (9) Share of credit card portfolio missing payment, (10) Credit card portfolio balances net of payments (% statement balances). See Online Appendix A for more details on primary outcome definitions.

Following Benjamin et al. (2018), we regard a p-value of 0.005 as the threshold for statistical significance but also highlight where results are "suggestively significant" at the 0.01 and 0.05 levels. A 0.005 significance aligns with 14+ Bayes factors: often considered substantial evidence for a hypothesis. This approach is analogous to applying Bonferroni or familywise error corrections to ten outcomes evaluated at the 0.05 significance level.

The pre-registered secondary analysis considers a broader set of outcomes and empirical approaches to understand our results and their robustness. This secondary analysis measures the effects of the nudge on Autopay enrollment and uses pounds (£) amounts of credit card debt and payments as robustness checks of our primary outcomes.

We can causally identify the effects of the treatment on consumers in our field experiment through our randomization of a consumer to the control or the treatment.[10] Equation 1 shows the OLS regression specification used to derive average treatment effects. To estimate this, we construct an unbalanced panel with one observation for each consumer's (i) credit card statement cycle (t) observed. This panel is unbalanced as some cards are opened earlier than others. In this specification, δ_τ are the coefficients on the interaction terms between treatment indicator and statement cycle indicators. Therefore, δ_τ shows the average treatment effect for $\tau \in \{1, 2, ..., T\}$ cycles since the beginning of the experiment. Our regression includes a constant (α), a vector of time-invariant control variables (X_i') constructed using information on the new credit card opened and cardholder data from before the start of the experiment (all controls are listed in footnote).[11] We also include time fixed effects: we control for both the statement cycle (γ_t) and year-month ($\gamma_{m(i,t)}$) because statement cycles do not perfectly align with calendar months and new credit cards have different opening dates. Standard errors are clustered at the consumer level.

$$Y_{i,t} = \alpha + \sum_{\tau=1}^{T} \delta_\tau \left(TREATMENT_i \times CYCLE_\tau \right) + X_i'\beta + \gamma_{m(i,t)} + \gamma_t + \varepsilon_{i,t} \tag{1}$$

For our primary analysis, we focus on the outcomes at the seventh completed statement cycle (δ_7) as this is the last cycle where the panel is "balanced", i.e., where we observe a completed payment cycle for all cards. The seventh cycle is complete when its due date for payment has passed: a mean of 195 and a median of 196 days from card opening with a range of 175 to 245 days. Seven cycles are six genuine cycles over six months as a new card's first statement is typically less than a month—in our data, the first statement is issued a mean of 12 and a median of 11 days from card opening—to onboard the card onto a particular billing cycle and this first statement has a zero payment due that makes it uninteresting, but we show for completeness. A consumer's first full cycle is statement two—the second statement is issued at a mean of 43 and a median of 42 days from card opening—when the cardholder has at least one month to view the control or treatment screens and to use their card (and, if used, has a non-zero payment due).

In tertiary analysis, we pool data across all cycles to provide more statistical power. We

[10] Online Appendix Table A3 shows that allocation to the treatment group is balanced, on average, across measures. However, we observe the probability of being in the treatment group slightly varies with credit card limit. Investigating this revealed that the "live" randomization code used by the lender was not completely random: 526 more consumers (0.65%) are allocated to control than to treatment. As consumers applying for credit cards were unaware of (and unable to manipulate) their probability of being allocated treatment, we can recover balance between treatment and control through conditioning on covariates. Conditioning on observables using our preregistered controls does not change our results; see our earlier working paper (Guttman-Kenney et al., 2023).

[11] The controls (X_i') are Gender, Age, Age squared, Log Estimated Income, Credit Score, Unsecured Debt-to-Income (DTI) Ratio, Any Mortgage Debt, Log Credit Card Credit Limit, Credit Card Purchases Rate, Subprime Credit Card, Any Credit Card Promotional Rate, Any Credit Card Balance Transfer, Credit Card Open Date, Credit Card Statement Day, Any Credit Card Secondary Cardholder. These are all from the time of card origination except for the variables constructed from consumer credit reporting data (Credit Score, DTI Ratio, and Any Mortgage Debt), which are from the month preceding card origination. For outcomes constructed from consumer credit reporting data, up to eleven dummies for lags of outcomes are included as controls (X_i') for months preceding the start of the experiment.

modify Equation 1 replacing the dynamic $TREATMENT_i \times CYCLE_\tau$ with the static $TREATMENT_i$ shown in Equation 2 where our single static parameter of interest is δ. When interpreting δ, it is important to note that this may provide a misleading view of the longer-term impacts of the nudge if the effect sizes change over time.

$$Y_{i,t} = \alpha + \delta TREATMENT_i + X_i'\beta + \gamma_{m(i,t)} + \gamma_t + \varepsilon_{i,t} \tag{2}$$

III. Experimental Results

A. Effects on Autopay Enrollment

The first effect we examine is the mechanism through which the treatment is designed to work through: changing Autopay enrollment choices by the time of the second credit card statement. Autopay enrollments are secondary outcomes. Figure 1 Panel A shows that the treatment causes large, significant initial effects in Autopay enrollment choices. The treatment increases the fraction of cardholders who enroll in Autopay Fix by 20.9 percentage points: a 72% increase in the mean of the control group. For comparison, Figure 1 Panel B shows that these enrollment effects are even greater for the second lender who stopped the field experiment early: increasing the enrollment of Autopay Fix by 40 percentage points, a 216% increase on the control mean. The subsequent results are all based on the main lender. Almost all the mass of increased Autopay Fix enrollment is redistributed from cardholders who enroll in Autopay Min in the control group. The treatment reduces the fraction of cardholders enrolling in Autopay Min by 27.3 percentage points: a 74% decrease on the mean of the control group. Autopay Min is not eliminated as it is possible for consumers in the treatment group to sign up for this through other ways (e.g., telephoning the call center). The treatment causes an increase in Autopay Full enrollment of 1.2 percentage points relative to the control mean of 14.5%. The treatment also causes a decline in any Autopay enrollment (i.e., Autopay Full, Autopay Fix, or Autopay Min) of 5.1 percentage points from the control mean of 80.2.

The Autopay Fix amounts consumers initially choose are frequently round numbers. 62% of Autopay Fix amounts are for £100, £50, £200, £150, £20, £30, and £25, in descending order of frequency. Very few consumers select Autopay Fix amounts of £5 or less that are mechanically identical to Autopay Min: 2.4% of the treatment group set an Autopay Fix of £5 or less, and effectively no cardholders who enroll in an Autopay Fix set this exactly equal to £5 in either control (0.06%) or treatment (0.07%). These are statistically significant increases relative to 0.5% in the control group that we interpret as being economically small. Consumers' initial choices of Autopay Fix amounts are persistent over time. 88.3% of those in the treatment group who are enrolled in Autopay Fix at their second credit card statement remain enrolled in Autopay Fix at their seventh statement. Of these, 97% have it set for the same Autopay Fix amount, and, on average, the difference in amount is trivial: £0.78. Of the remainder, 7.0% are not enrolled in any Autopay, 4.4% in Autopay Min, and 0.3% in Autopay Full. Among all cardholders in the treatment group enrolled in

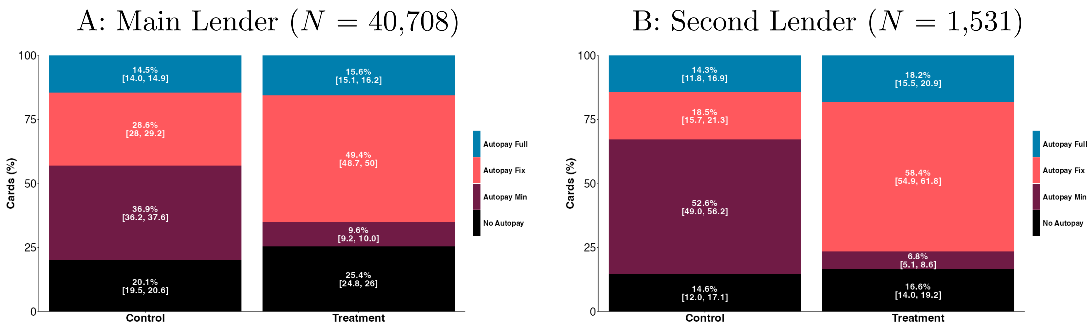

Figure 1. Autopay enrollment for control and treatment groups after two statements, split by lender

Notes: Numbers display percentage of cards enrolled in each type of Autopay by the second statement cycle. 95% confidence intervals in [ ].

Autopay Fix at cycle two, the mean Autopay amount is £96.85 (median £80) compared to £104.60 (median £100) at cycle seven: this indicates that cardholders who enroll in Autopay Fix later on are choosing slightly higher Autopay Fix amounts than the initial group.

Table 1 shows statistically significant effects of the treatment on Autopay enrollment using our pre-registered regression specification. The regression coefficients after seven cycles, δ_7 in Equation 1, are consistent with the initial changes in enrollment. Autopay Min enrollment significantly decreases by 21.7 percentage points, Autopay Fix enrollment significantly increases by 16.7 percentage points, Autopay Full increases by 0.6 percentage points which is significant at the 5% but not at the 0.5% level, and any Autopay enrollment significantly declines by 4.4 percentage points. The purple coefficients in Panel A of Figure 2 show the dynamic effects on Autopay Fix enrollment, δ_τ in Equation 1. The initial effect increasing Autopay Full enrollment attenuates over time and becomes statistically insignificant from zero. The effects on Autopay Fix and Autopay Min enrollments also attenuate over time, but these effects remain large. As the initial Autopay choices in the treatment group are highly persistent, this attenuation is primarily driven by the control group "catching up" by naturally switching from Autopay Min towards Autopay Fix or Autopay Full. The observed changes in Autopay enrollments—the nudge making consumers more likely to choose full, less likely to choose minimum, and changing the distribution of Autopay amounts—are consistent with lab evidence studying the manual payment environment (e.g., Stewart, 2009; Navarro-Martinez et al., 2011; Sakaguchi et al., 2022; Guttman-Kenney, 2024) that finds that the salience of the minimum payment amount distorts the control group's choices.

Which types of consumers stop enrolling in any Autopay due to the nudge? We segment consumers into three groups following the methodology in Marbach and Hangartner (2020). This methodology requires the monotonicity assumption that the nudge does not make

Table 1—Average treatment effects for automatic payment enrollment outcomes after seven statement cycles

Outcome	Estimate, p.p. (s.e.)	95% C.I.	P value	Control mean
Any autopay	-0.0437 (0.0041)	[-0.0517, -0.0356]	0.0000	0.7811
Autopay full	0.0065 (0.0028)	[0.0009, 0.0120]	0.0217	0.1309
Autopay fix	0.1670 (0.0045)	[0.1583, 0.1757]	0.0000	0.2955
Autopay min	-0.2172 (0.0041)	[-0.2251, -0.2092]	0.0000	0.3547
Autopay fix exceeding minimum payment amount	0.0859 (0.0043)	[0.0774, 0.0943]	0.0000	0.2523

Notes: Table shows average treatment effects after seven statement cycles. Each row of the table shows estimates from separate regressions with different outcomes. Estimated treatment effects are from coefficient (δ_7) on interaction terms between treatment indicator and the seventh statement cycle indicator in the OLS regression specified in Equation 1. Regressions also include: interactions between treatment indicator and other statement cycles, statement cycle fixed effects, year-month fixed effects, and the following controls: Gender, Age, Age squared, Log Estimated Income, Credit Score, Unsecured Debt-to-Income (DTI) Ratio, Any Mortgage Debt, Log Credit Card Credit Limit, Credit Card Purchases Rate, Subprime Credit Card, Any Credit Card Promotional Rate, Any Credit Card Balance Transfer, Credit Card Open Date, Credit Card Statement Day, Any Credit Card Secondary Cardholder. These are all from the time of card origination except for the variables constructed from consumer credit reporting data (Credit Score, DTI Ratio and Any Mortgage Debt), which are from the month preceding card origination. Standard errors are clustered at the consumer-level. There are 40,708 credit cards with 368,162 observations.

consumers more likely to enroll in any Autopay. We estimate that 4.2% of the sample are "Compliers", who would have enrolled in Autopay but did not do so due to the nudge, 21.9% are not enrolled in Autopay regardless of the nudge ("Always Takers"), and 73.9% are enrolled in Autopay regardless of the nudge ("Never Takers"). On average, compliers, compared to the other groups, have lower credit scores, lower estimated incomes, lower unsecured debt-to-income (DTI) ratios, smaller credit limits, fewer credit cards, lower debt, and are also more likely to be younger and male. See Online Appendix Table A7 for details.

B. Effects on Long-Term Real Economic Outcomes

Table 2 shows the effects on our ten primary outcomes. These estimates use our pre-registered regression specification and show our treatment estimates seven cycles after card opening, the δ_7 coefficient in Equation 1.

Only Paying The Minimum. — We find a large and persistent effect of the nudge, making cardholders significantly less likely to only pay exactly the minimum. Table 2 shows that the nudge causes a significant decrease in the probability of only paying exactly the minimum after seven cycles of 7.1 percentage points, with a 95% confidence interval of -6.2 to -7.9 percentage points. This is a 23% decrease relative to the control group mean. Figure 2

A: Autopay Fix enrollment (purple) and Autopay Fix > minimum payment (pink)

B: Only paying the minimum

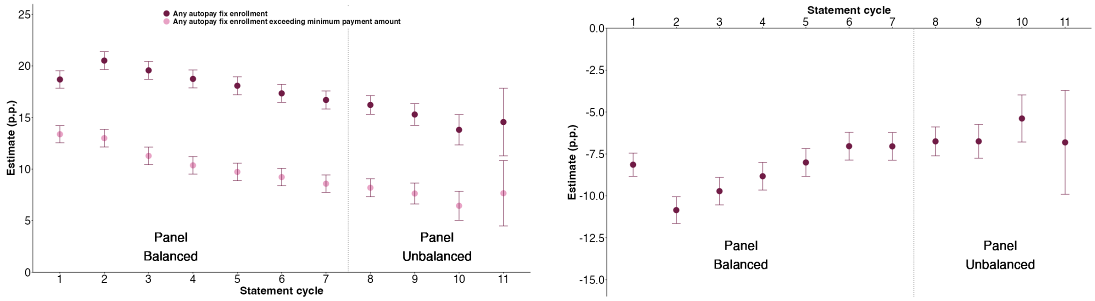

Figure 2. Average treatment effects on A. Autopay Fix enrollment, and B., only paying the minimum, across 1-11 statement cycles

Notes: Treatment effects from coefficients (δ_τ) on interaction terms between treatment indicator and statement cycle indicators in the OLS regression specified in Equation 1. Regression outcomes in Panel A are any automatic fixed payment enrollment (pink), and any automatic fixed payment enrollment where the fix amount is not binding at minimum payment amount (purple), and outcome in Panel B outcome is only paying exactly the minimum payment. Regressions also include statement cycle fixed effects, year-month fixed effects, and the following controls: Gender, Age, Age squared, Log Estimated Income, Credit Score, Unsecured Debt-to-Income (DTI) Ratio, Any Mortgage Debt, Log Credit Card Credit Limit, Credit Card Purchases Rate, Subprime Credit Card, Any Credit Card Promotional Rate, Any Credit Card Balance Transfer, Credit Card Open Date, Credit Card Statement Day, Any Credit Card Secondary Cardholder. These are all from the time of card origination except for the variables constructed from consumer credit reporting data (Credit Score, DTI Ratio and Any Mortgage Debt), which are from the month preceding card origination. Error bars are 95% confidence intervals. Standard errors are clustered at the consumer-level. There are 40,708 credit cards with 368,162 observations.

Panel B shows the effect is −10.9 percentage points in the second cycle and stabilizes near −7 by the sixth cycle. The effect of the nudge on only paying the minimum is smaller than the effect size on Autopay Min enrollment shown in the previous subsection. This is because cardholders enrolled in Autopay Min can also make additional manual payments to pay more than the minimum. Also, as some cards have no balance due and therefore no minimum payment and no payments taken–we classify these as full payments. The average treatment effect on the share of a cardholder's credit card portfolio that only pay the minimum, constructed from consumer credit reporting data, is a third of the size for the card for which the treatment is targeted. This smaller overall effect across the credit card portfolio is due to consumers holding multiple cards—only one of which is directly affected by the nudge.

We profile consumers who the nudge makes less likely to only pay exactly the minimum, again following the methodology in Marbach and Hangartner (2020) used in the previous subsection, but now with the monotonicity assumption that the nudge does not make consumers more likely to only pay exactly the minimum. 6.9% of the sample are "Compliers", who would have only paid the minimum but did not do so because of the nudge, 69.9% do not pay only the minimum regardless of the nudge ("Always Takers"), and 23.2% only pay the minimum irrespective of the nudge ("Never Takers"). Compliers, on average, have similar characteristics to other groups. See Online Appendix Table A8 for details.

Table 2—Average treatment effects for primary outcomes after seven statement cycles

Outcome	Estimate, p.p. (s.e.)	95% C.I.	P value	Control mean
Any minimum payment	-0.0705 (0.0042)	[-0.0787, -0.0622]	0.0000	0.3012
Any full payment	0.0040 (0.0037)	[-0.0032, 0.0112]	0.2747	0.2397
Any missed payment	0.0038 (0.0019)	[0.0002, 0.0075]	0.0409	0.0369
Statement balance net of payments (% statement balance)	-0.0051 (0.0035)	[-0.0119, 0.0017]	0.1428	0.6936
Costs (% statement balance)	-0.0003 (0.0006)	[-0.0015, 0.0010]	0.6782	0.0111
Spending (% statement balance)	0.0025 (0.0031)	[-0.0036, 0.0087]	0.4199	0.2007
Share of credit card portfolio only paying minimum	-0.0264 (0.0027)	[-0.0317, -0.0210]	0.0000	0.2012
Share of credit card portfolio making full payment	0.0011 (0.0033)	[-0.0054, 0.0076]	0.7340	0.4414
Share of credit card portfolio missing payment	-0.0000 (0.0013)	[-0.0025, 0.0024]	0.9701	0.0236
Credit card portfolio balances net of payments (% statement balances)	-0.0053 (0.0031)	[-0.0115, 0.0008]	0.0896	0.6954

Notes: Table shows average treatment effects after seven statement cycles. Each row of the table shows estimates from separate regressions with different outcomes. Estimated treatment effects from the coefficient (δ_7) on interaction terms between treatment indicator and the seventh statement cycle indicator in the OLS regression specified in Equation 1. Regressions also include: interactions between treatment indicator and other statement cycles, statement cycle fixed effects, year-month fixed effects, and the following controls: Gender, Age, Age squared, Log Estimated Income, Credit Score, Unsecured Debt-to-Income (DTI) Ratio, Any Mortgage Debt, Log Credit Card Credit Limit, Credit Card Purchases Rate, Subprime Credit Card, Any Credit Card Promotional Rate, Any Credit Card Balance Transfer, Credit Card Open Date, Credit Card Statement Day, Any Credit Card Secondary Cardholder. These are all from the time of card origination except for the variables constructed from consumer credit reporting data (Credit Score, DTI Ratio and Any Mortgage Debt), which are from the month preceding card origination. For outcomes constructed from consumer credit reporting data up to eleven dummies for lags of outcomes are included as controls (X_i') for months preceding the start of the experiment. Standard errors are clustered at the consumer-level. There are 40,708 credit cards with 368,162 observations.

Debt. — Figure 3 Panel A shows that our treatment does not significantly reduce credit card debt at or before the seventh cycle. Table 2 shows the mean effect of the treatment on debt is an insignificant -0.5 percentage points, with a 95% confidence interval of -1.2 to 0.2 percentage points. As a robustness check as part of our secondary analysis, we look at debt in pounds in Figure 3 Panel B and find precise zero effects. Table 3 shows that after seven cycles the treatment insignificantly changes debt by £4, with a 95% confidence interval of −£30 to £38. Examining the full distribution of debt reveals little discernible difference between these two measures, see Online Appendix Figure A7 for details. Given that there is no significant reduction in debt, it is unsurprising that we also find no significant reduction in borrowing costs by our primary measure in Table 3 or other measures in Table 3. Tables 2 and 3 show that we do not find a significant effect of the nudge to reduce the portfolio of credit card debt held, when measured in percentages or pounds.

As the cycle-by-cycle estimates on our primary measure of credit card debt are stable over time but persistently, slightly, but statistically insignificantly, below zero, we check the robustness of this result by pooling across all cycles to provide more statistical power (Equation 2). The average effect on debt on the target card is, *at most*, a 1.1 percentage points reduction, based on the maximum of the 95% Confidence Interval, and insignificantly different from zero at our 0.5% threshold. Even with this pooling, there is no statistically significant effect on credit card debt across the portfolio of cards held: at most a 0.79 percentage points reduction, also based on the maximum of the 95% Confidence Interval. See Online Appendix Table A5 for details.

Full Payment. — We find no effect of the treatment on increasing the probability of full payment on the target card. Table 2 shows the average effect after seven cycles is 0.4 percentage points, and this is not significantly different from zero, with a 95% confidence interval of −0.3 to 1.1. This finding is robust to pooling across all cycles where the 95% Confidence Interval is −0.2 to 1.0 percentage points, with a point estimate of 0.4 percentage points, see Online Appendix A5. This null result is also robust to measuring the effects on the cumulative number of full payments, as shown in Online Appendix Table A4.

Spending. — One potential explanation for the nudge's ineffectiveness in reducing debt would be if consumers responded by spending more. Our results rule out this explanation. Figure 3 Panel C and Table 3 show that we find null effects over time for new spending (% statement balances), with a 95% confidence interval of −0.4 to 0.9 percentage points after seven cycles. Table 3 also shows that there is a null effect on statement balances (i.e., before payments, which reflects the combination of revolving debt and new spending). Figure 3 Panel D shows that there is a slight decrease in spending measured in pounds of £9.84 (95% confidence interval −£19.61,−£0.07), however, this is not significant at our 0.5% threshold, and is insignificant when we study cumulative spending, shown in Table 3.

Missed Payments. — We find an increase in the probability of missed payments on the target card of 0.38 percentage points with a 95% confidence interval of 0.02 to 0.75 percentage points, in Table 2, that is statistically significant at the 5% level but not at our 0.5% threshold. Although this increase is not statistically significant at our 0.5% significance threshold when examining a cycle, it is clearly significant when conducting a joint significance test pooling data across all cycles, while still clustering at the consumer level. We

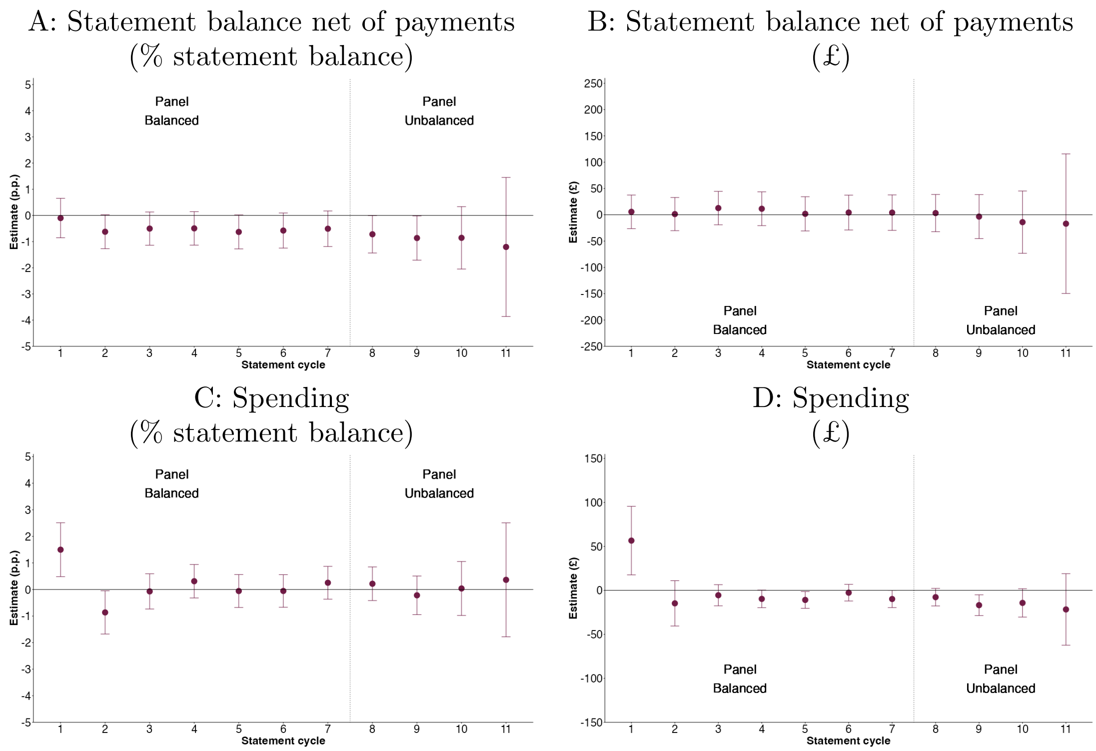

Figure 3. Average treatment effects on credit card debt and spending, across 1-11 statement cycles

Notes: Treatment effects from coefficients (δ_τ) on interaction terms between treatment indicator and statement cycle indicators in the OLS regression specified in Equation 1. Regression outcome in Panel A is statement balance net of payments (% statement balance), in Panel B is statement balance net of payments (£), in Panel C is spending (% statement balance), and in Panel D is spending (£). Regressions also include statement cycle fixed effects, year-month fixed effects, and the following controls: Gender, Age, Age squared, Log Estimated Income, Credit Score, Unsecured Debt-to-Income (DTI) Ratio, Any Mortgage Debt, Log Credit Card Credit Limit, Credit Card Purchases Rate, Subprime Credit Card, Any Credit Card Promotional Rate, Any Credit Card Balance Transfer, Credit Card Open Date, Credit Card Statement Day, Any Credit Card Secondary Cardholder. These are all from the time of card origination except for the variables constructed from consumer credit reporting data (Credit Score, DTI Ratio and Any Mortgage Debt), which are from the month preceding card origination. Error bars are 95% confidence intervals. Standard errors are clustered at the consumer-level. There are 40,708 credit cards with 368,162 observations.

find that the nudge increases the probability of missed payments by 0.4 percentage points with a 95% confidence interval of 0.19 to 0.62. The effect on missed payments is solely that of being one payment behind. The nudge does not lead to consumers being in more severe arrears, which the industry defines as being at least two or three payments behind.

These are all null results even when pooling observations across cycles to increase power to account for the low incidence of such severe arrears. Only more severe arrears are reported in their credit report (that is, missing a payment by one day would not be reported, but by 31 days would be reported). This explains why we do not observe increases in our Table 2 primary outcome of missed payments measured this in credit reports. Given that there is no difference in severe arrears on the card in the experiment and also no difference in severe arrears across the portfolio of cards in credit reports, we infer that severe arrears on other cards are unaffected. See Online Appendix Table A6 for estimates using different measures of arrears.

Other Portfolio Primary Outcomes. — Table 2 shows there are null effects on average treatment effects across our other consumer credit reporting outcomes: the probability of paying in full, the probability of missing payments, and outstanding debt when aggregating across the portfolio of credit cards held. There is no evidence that the treatment affects other cards held by a consumer. The results on primary outcomes are persistent over time, see Online Appendix Figures A4 and A5.

C. *Heterogeneous Effects*

We examine heterogeneity in our results by covariates that are constructed from credit reporting data from the month preceding card origination or credit card data at origination. We estimate Equation 1 separately for two quantiles of each variable, pooling data across cycles to increase power.[12] Consistent with our previous analysis, we find significant effects of the nudge to reduce Autopay Min enrollment, and also to reduce the fraction of consumers only paying exactly the minimum, across all heterogeneous groups examined, see Online Appendix Table A10 for details.

Our heterogeneity analysis does not robustly show that debt is reduced by the nudge for a subgroup of consumers. We find suggestive evidence that the nudge reduces debt, measured as a percentage of the statement balance, for consumers with lower credit scores, lower unsecured debt-to-income (DTI) ratios, younger ages, lower credit limits, fewer credit cards in portfolio with debt, lower credit card portfolio balances net of payments, and men, but no clear effects by income. However, none of these subgroups shows significant effects at the 5% significance level when debt is measured in pounds, and we also suggest that the reader applies a stricter threshold given concerns regarding multiple hypothesis testing. The largest heterogeneous effect is for low DTI consumers where the nudge reduces debt, as a percent of statement balance, by -1.4 percentage points (standard error 0.4), however, this result is not robust as the nudge insignificantly increases debt when measured in pounds by £2.74 (standard error £16.81). See Online Appendix Table A11 for details.

[12] Analysis not in this version of the paper also found consistent results when not pooling data and instead focusing on the seventh statement cycle, and also when studying quartiles.

TABLE 3—AVERAGE TREATMENT EFFECTS FOR SECONDARY OUTCOMES AFTER SEVEN STATEMENT CYCLES

Outcome	Estimate, p.p. (s.e.)	95% C.I.	P value	Control mean
Statement balance (£)	-0.33 (17.24)	[-34.11, 33.46]	0.9848	2164.49
Statement balance net of payments (£)	4.11 (17.22)	[-29.64, 37.85]	0.8115	1962.52
Costs (£)	0.11 (0.18)	[-0.24, 0.46]	0.5312	7.97
Cumulative costs (£)	1.39 (0.83)	[-0.23, 3.01]	0.0924	76.02
Spending (£)	-9.84 (4.99)	[-19.61, -0.07]	0.0485	193.24
Cumulative spending (£)	-7.23 (20.95)	[-48.29, 33.83]	0.7300	3186.19
Credit card portfolio statement balances (£)	23.65 (31.15)	[-37.42, 84.71]	0.4479	3916.96
Credit card portfolio balances net of payments (£)	12.06 (30.92)	[-48.55, 72.66]	0.6966	3431.69
Any Autopay Payment	0.0019 (0.0046)	[-0.0071, 0.0108]	0.6839	0.6171
Any Manual Payment	0.0064 (0.0045)	[-0.0024, 0.0151]	0.1537	0.3166
Total payments (£)	-4.44 (5.07)	[-14.38, 5.51]	0.3820	201.98
Automatic payments (£)	-0.6123 (2.1195)	[-4.7665, 3.5419]	0.7727	86.9490
Manual payments (£)	-3.90 (4.79)	[-13.29, 5.48]	0.4152	116.38
Total payments (% statement balance)	0.0060 (0.0032)	[-0.0002, 0.0123]	0.0579	0.2271
Automatic payments (% statement balance)	0.0072 (0.0025)	[0.0023, 0.0122]	0.0040	0.1101
Manual payments (% statement balance)	-0.0005 (0.0028)	[-0.0061, 0.0050]	0.8477	0.1212
Cumulative total payments (£)	6.68 (16.19)	[-25.06, 38.41]	0.6800	1277.27
Cumulative automatic payments (£)	27.30 (10.35)	[7.01, 47.59]	0.0084	573.79
Cumulative manual payments (£)	-18.87 (13.97)	[-46.25, 8.50]	0.1766	711.97
Cumulative payments (% cumulative spending)	0.0202 (0.0051)	[0.0101, 0.0303]	0.0001	0.4728
Cumulative automatic payments (% cumulative spending)	0.0256 (0.0048)	[0.0162, 0.0350]	0.0000	0.2135
Cumulative manual payments (% cumulative spending)	-0.0046 (0.0033)	[-0.0111, 0.0019]	0.1662	0.2644
Cumulative payments (% credit limit)	0.0130 (0.0063)	[0.0006, 0.0254]	0.0398	0.5046
Cumulative automatic payments (% credit limit)	0.0240 (0.0038)	[0.0165, 0.0315]	0.0000	0.1864
Cumulative manual payments (% credit limit)	-0.0101 (0.0057)	[-0.0212, 0.0011]	0.0760	0.3249

Notes: Table shows average treatment effects after seven statement cycles. Each row of the table shows estimates from separate regressions with different outcomes. Estimated treatment effects are from the coefficient (δ_7) on interaction terms between treatment indicator and the seventh statement cycle indicator in the OLS regression specified in Equation 1. Regressions also include: interactions between treatment indicator and other statement cycles, statement cycle fixed effects, year-month fixed effects, and the following controls: Gender, Age, Age squared, Log Estimated Income, Credit Score, Unsecured Debt-to-Income (DTI) Ratio, Any Mortgage Debt, Log Credit Card Credit Limit, Credit Card Purchases Rate, Subprime Credit Card, Any Credit Card Promotional Rate, Any Credit Card Balance Transfer, Credit Card Open Date, Credit Card Statement Day, Any Credit Card Secondary Cardholder. These are all from the time of card origination except for the variables constructed from consumer credit reporting data (Credit Score, DTI Ratio and Any Mortgage Debt), which are from the month preceding card origination. Standard errors are clustered at the consumer-level. There are 40,708 credit cards with 368,162 observations.

IV. Mechanisms

A. *Factors Explaining Nudge Ineffectiveness*

Our null average treatment effects on debt are surprising, given the nudge has seemingly large changes in Autopay enrollment and makes consumers less likely to only pay the minimum payment. Why does the treatment not, on average, reduce debt if one in five more consumers are enrolled in Autopay Fix, and it does not cause them to spend more? If the only effects of the nudge are compositional—changing Autopay enrollment but *assuming no other changes*—then the effects on Autopay enrollment may have been expected to lead to an effect of reducing debt by approximately 4.5%.[13] Indeed, the fact that the second lender withdrew after only observing effects on enrollment is evidence that our null effects on the more distal debt outcome are unexpected. We examine how three consumer responses on the target card make the nudge ineffective at reducing debt.

Autopay Fix Amounts "Too Low". — Cardholders often respond to the nudge by setting an Autopay Fix that is "too low": binding at or just above the minimum. The purple coefficients in Figure 2 Panel A show that although the treatment causes an increase of 16.7 percentage points in Autopay Fix enrollment by statement seven, the pink coefficients show how the effect on enrollment with Autopay Fix *exceeding* the minimum payment amount due is still large, but is half the size: 8.6 percentage points, which is a 34% increase on the control group mean. See Table 1 for estimates. As credit card balances accumulate over the first few months of card ownership, the minimum amount due rises, causing the minimum payment amount to exceed many of the fixed payments. After seven cycles, the proportion of consumers in the treatment group with an Autopay Fix that exceeds the minimum payment amount is 66%—noticeably lower than 78% in the second cycle, see Online Appendix Figure A9 for details.

Examining the distribution of Autopay Fix amounts chosen by the treatment group, they are often "low", that is, small amounts in excess of the minimum. Pooling across all seven cycles, we find that for 48% of Autopay Fix enrollees in the treatment group, the cumulative Autopay Fix amount is £100 or less in excess of the minimum. The cumulative Autopay Fix amount is only more than £500, for 13%, where the control mean is £1,277. We interpret that the additional payments from Autopay Fix over the minimum are typically "low" in absolute levels, however, they are large increases relative to the extremely low minimum payment due, which averages £46 per month (£320 cumulative across cycles one to seven). This is consistent with studying excess payments: the value of payments (the sum of Autopay and manual payments) in excess of the minimum, as a percentage of statement balances (also in excess of the minimum), measured after seven cycles. Excess payments for the treatment group, relative to the control group, are more likely to be one percentage point or more (56.9% in control and 60.2% in treatment); however, this

[13] Calculated using the mean debt net of payments in cycle seven for cardholders in the control group for each Autopay enrollment type and weighting these by the treatment group's Autopay enrollments' shares.

difference quickly tends toward zero as we move up the excess payments distribution: Two percentage points or more is 50.8% in control and 52.9% in treatment, three percentage points or more is 46.9% in control and 48.3% in treatment, five percentage points or more is 41.2% in control and 42.0% in treatment, and ten percentage points or more is 35.6% in control and 35.7% in treatment. The full distributions of Autopay Fix amounts and excess payments are shown, respectively, in Online Appendix Figures A8 and A6. Consumers only selecting low Autopay Fix amounts and making low payments in excess of the minimum when the Autopay Min option is shrouded appears consistent with consumers only wanting to make low automatic payments, possibly due to uncertainty in how much liquid cash they will have to smooth their payments.

Decreasing Enrollment In Any Autopay. — The nudge causes a 4.3 percentage points or 5.6% significant decline in enrollment in any type of Autopay, as shown in Table 1. This decline in enrollment explains an unintended slight average increase in the probability of missed payments, also shown in Table 1. If enrolled in Autopay, a consumer will only miss a payment if they have insufficient funds in their checking account, whereas consumers not enrolled may easily forget to make a payment. Our earlier finding that the effect is only on missing one payment and not for severe arrears repeatedly missing payments indicates not being enrolled in any Autopay means consumers forget to make a payment, which has a temporary impact, most notably incurring a late payment fee and not reducing debt, rather than causing a debt spiral or severe distress. Although reduced enrollment in Autopay is not an intended effect of the nudge, it does not increase consumer indebtedness. These results are consistent with consumers being more attentive to their debt if they do not enroll in Autopay (Gathergood et al., 2021; Sakaguchi et al., 2022).[14] This is different from other domains where reduced enrollment may be a worse economic outcome. For example, if a nudge reduces 401(k) enrollment, then consumers can be missing out on "free money" from employer-matched contributions and under-save for retirement.

Our explanation is also consistent with analysis calculating "Lee Bounds" (Lee, 2009), as used in Levy (2021). This methodology provides bounds on the treatment effects after accounting for selection in outcomes that occurs due to the nudge reducing Autopay enrollment. These bounds require the monotonicity assumption that the nudge only makes consumers less likely to enroll in any Autopay. Pooling data across all cycles, we estimate Lee Bounds that the treatment causes a -12.27 to -6.42 percentage points change in the probability of only making a minimum payment. Lee Bounds also show that the nudge causes a -0.01 to 0.41 percentage points change in any missed payments and a 0.04 to 0.09 percentage points change in missing two or more payments. The Lee Bounds also show that effects are insignificant from zero for debt, statement balances, costs, and spending, as shown in Online Appendix Table A9.

[14]This is consistent with another domain; Sexton (2015) argues that enrollment into Autopay (Full) for utility bills, reduces price salience and results in "overconsumption" of electricity.

Manual Payments Substitution. — Cardholders can make manual payments instead of or in addition to automatic payments. We find substitution between the two as another offsetting effect. Figure 4 and Table 3 show that there is a positive and significant treatment effect increasing automatic payments, however, the effect on overall payments is smaller due to a negative, but statistically insignificant, effect on manual payment. We find that the treatment causes consumers to be 1.3 percentage points more likely to make both an automatic and manual payment in the same cycle despite reduced Autopay enrollment. More details are in Online Appendix Table A4.

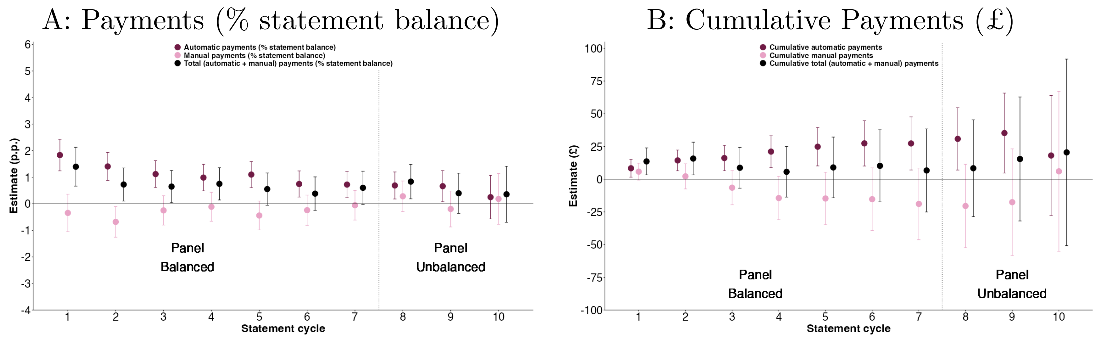

Figure 4. Average treatment effects on automatic, manual, and total (automatic + manual) payments, across 1-10 statement cycles

Notes: Treatment effects from coefficients (δ_τ) on interaction terms between treatment indicator and statement cycle indicators in the OLS regression specified in Equation 1. The regression outcome in Panel A is payments (% statement balance), and the outcome in Panel B is cumulative payments (£). Regressions also include statement cycle fixed effects, year-month fixed effects, and the following controls: Gender, Age, Age squared, Log Estimated Income, Credit Score, Unsecured Debt-to-Income (DTI) Ratio, Any Mortgage Debt, Log Credit Card Credit Limit, Credit Card Purchases Rate, Subprime Credit Card, Any Credit Card Promotional Rate, Any Credit Card Balance Transfer, Credit Card Open Date, Credit Card Statement Day, Any Credit Card Secondary Cardholder. These are all from the time of card origination except for the variables constructed from consumer credit reporting data (Credit Score, DTI Ratio and Any Mortgage Debt), which are from the month preceding card origination. Error bars are 95% confidence intervals. Standard errors are clustered at the consumer-level. Cycle 11 is excluded from this figure as, due to few cards being observed in this cycle, the confidence intervals on Panel B are extremely large such that the estimates are uninformative. There are 40,708 credit cards with 368,162 observations.

Manual payments are infrequent, but large. Only 8.5% of those enrolled in any Autopay option in the control group also made a manual payment in the seventh cycle. However, manual payments account for 45% of the total cumulative value of payments made across cycles one to seven by those in the control group enrolled in Autopay at cycle seven (and 54% for those enrolled in Autopay Fix or Min). In months where manual payments are made by those enrolled in Autopay in the control group, the mean manual payment amount is £377, with a median value of £105. By contrast, automatic payments in these months average £105 with a median of £55. We interpret this evidence as showing that consumers appear to use Autopay as insurance against forgetting to make a payment (in line with Fuentealba et al., 2021; Gathergood et al., 2021; Sakaguchi et al., 2022) as opposed to paying down debt. Survey responses presented in our earlier working papers (Adams et al., 2018a,b) align with this explanation.[15]

Comparing automatic and manual payments conflates two effects: a change in Autopay enrollment composition and a change in Autopay amount. Conditional on being enrolled in Autopay, one would expect automatic payments to be higher in the treatment than the control, since Autopay Fix is greater than or equal to Autopay Min. Automatic payments will be lower in the treatment group because fewer consumers enroll in Autopay than in the control group. Similarly, we may expect manual payments to be higher in the treatment group; however, this is ambiguous, as cardholders may forget to make any payments rather than substituting automatic for manual payments. We unravel this by decomposing Equation 1 by whether the consumer is enrolled in any Autopay (that is, Autopay Min, Fix, or Full) in Cycle seven ($AUTOPAY_{i,7}$) shown in Equation 3. This is a decomposition by an endogenous variable, and therefore the estimates are not causal and may be biased.

$$Y_{i,t} = \alpha + \sum_{\tau=1}^{T} \delta_\tau \left(TREATMENT_i \times CYCLE_\tau \right) + X_i'\beta + \gamma_{m(i,t)} + \gamma_t + \varepsilon_{i,t} \quad \text{(3)}$$
$$if\ AUTOPAY_{i,7} = g, \quad g \in \{0,1\}$$

We examine the cumulative value of payments, in total and split by automatic and manual payments, by the seventh cycle in these subgroups in Figure 5. Panel A of Figure 5 shows evidence of substitution among consumers enrolled in Autopay: the average change in automatic payments is an increase of £62, average manual payments decrease by £57, and the average overall payments are effectively unchanged with an increase of only £2. If all the increased automatic payments had passed through, without offsetting manual payments, average debt would have been reduced by approximately 2.9%. Panel B of Figure 5 shows zero estimates on automatic, manual, and total payments for those not enrolled in Autopay. This indicates the treatment's main effect on this group is likely shifting this group's size rather than changing its payment amounts differentially to what one would expect from a cardholder in the control group who is not enrolled in Autopay. These results are robust to alternative measurement approaches shown in Online Appendix Figure A11. Our manual payment substitution result is also robust to calculations using "Lee Bounds". The nudge causes an increase in automatic payments with bounds of −£2.03 to £42.10, or as a percentage of statement balances is 0.46 to 5.71 percentage points. Manual payments

[15]In Adams et al. (2018a) and Adams et al. (2018b), the most common reasons survey respondents enrolled in Autopay provide for using Autopay is to prevent incurring a late fee or to prevent a negative credit score impact, while the most common reason respondents not enrolled in Autopay provide is they prefer the control of manually adjusting payments each month.

attenuate this effect, leading to bounds on total payments of −£19.01 to £84.66, or as a percent of statement balances is −0.08 to 4.35 percentage points, see Online Appendix Table A9 for details. This substitution of higher automatic payments for lower manual payments by cardholders enrolled in Autopay shows that these consumers are less inert in their payment choices than they initially appeared. The most natural explanation for such substitution is that these consumers often lack liquid cash to pay more on their credit card. If so, once a consumer has made slightly higher automatic payments, there is less cash available for manual payments.

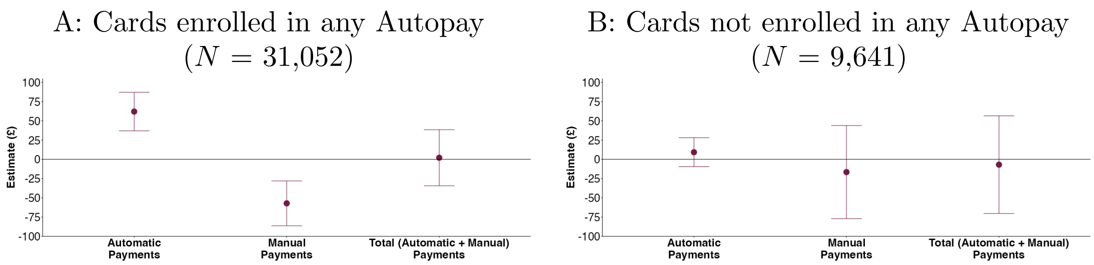

Figure 5. Non-causal decomposition of estimates on cumulative payments, by any Autopay enrollment after seven statement cycles

Notes: Each panel shows outcomes from two separate regressions where outcomes are: cumulative automatic payments, cumulative manual payments, and cumulative total (automatic + manual) payments. Regressions also include: interactions between the treatment indicator and other statement cycles, statement cycle fixed effects, year-month fixed effects, and the following controls: Gender, Age, Age squared, Log Estimated Income, Credit Score, Unsecured Debt-to-Income (DTI) Ratio, Any Mortgage Debt, Log Credit Card Credit Limit, Credit Card Purchases Rate, Subprime Credit Card, Any Credit Card Promotional Rate, Any Credit Card Balance Transfer, Credit Card Open Date, Credit Card Statement Day, Any Credit Card Secondary Cardholder. These are all from the time of card origination except for the variables constructed from consumer credit reporting data (Credit Score, DTI Ratio and Any Mortgage Debt), which are from the month preceding card origination. Error bars are 95% confidence intervals. Standard errors are clustered at the consumer-level. Panels A and B show non-causal estimates (δ_7) from the OLS regression specified in Equation 3, which have the same specification except that Panel A restricts to the subsample of 31,052 credit cards that are enrolled in any Autopay at statement cycle seven, and Panel B restricts to the subsample of 9,641 credit cards that are not enrolled in any Autopay at statement cycle seven.

B. *Liquid Cash*

Having documented the effects of the nudge and investigated the factors that explain our null result, we wanted to understand *why* consumers are not paying more on their credit card. Doing so can help to understand whether other interventions may be more effective than the one nudge we test. The most natural potential explanation is that many consumers in our study have limited liquid cash balances available, which prevents or discourages them from reducing their credit card debt. While one may term limited liquid cash balances as liquidity constraints, we caveat that limited liquid cash balances are an observable financial outcome that may arise for many reasons, including financial illiteracy (e.g., Lusardi and Tufano, 2015) and behavioral factors such as naïve present bias leading to impulsive overconsumption (e.g., Heidhues and Kőszegi, 2015), which are well-documented among credit cardholders (e.g., Meier and Sprenger, 2010; Kuchler and Pagel, 2021).

In this section, we conduct an analysis using linked bank account data for three purposes. First, we evaluate the prevalence of low liquid cash balances among the selected sample where the linked data are observed. If few consumers have liquid cash available, it means that few are likely to be able to pay more of their credit card debt, even if nudged. Second, we study whether, among this selected sample, these liquid cash balances explain credit card behaviors seven months later. If there is a relationship between measures of liquid cash balances and subsequent credit card debt, then this means these measures are informative for understanding the credit card market. Third, we examine whether the nudge heterogeneously affects consumers by their liquid cash balances, again for this selected sample. We might expect the nudge to be effective in reducing the debt of consumers who are not liquidity constrained and so could afford to pay more when the minimum is shrouded. All three purposes represent an advance on prior research on credit card anchoring where liquid cash balances, and also Autopay, are unobserved (Keys and Wang, 2019; Medina, 2021). Studies of co-holding (e.g., Vihriälä, 2022; Batista et al., 2024; Gathergood and Olafsson, 2024) have a different focus, studying the *simultaneous* holding of low-yield liquid cash while also carrying high-interest credit card or overdraft debt, whereas we study whether the *dynamics* of liquid cash *before* card opening are informative for understanding credit card debt accumulated *months later*.

Measuring Liquid Cash. — We construct measures of liquid cash before card opening from our linked bank account data. We calculate liquid cash as the end-of-day balance aggregated across across all observed checking and non-checking, instantly-accessible cash savings accounts. In the UK, checking accounts often have an overdraft line of credit facility, so liquid cash measures can have negative balances. Based on observed socio-economic characteristics, we expect the selected sample with linked bank account data to be less liquidity constrained than other consumers in our field experiment. See Online Appendix E for more details. We construct two measures to capture the dynamics of liquid cash balances.[16] For each measure, we show, in Figure 6, its CDF in Panels A and B, and its relationship with credit card payments seven cycles later in Panels C and D. Our two measures are:

[16] Online Appendix C contains additional results for a third measure based on the number of days liquid cash balances are below £100 in the 30 days before card opening.

- The **Liquid Cash Balances** of a consumer the day before credit card opening. This traditional static measure reflects a consumer's liquid cash balances at one point-in-time. Different colors in Panel A of Figure 6 show the overall distribution of this variable is stable when calculated at different points-in-time 30 to 150 days before card opening, however, it may vary for individual consumers over time. We also observe this distribution has very fat tails and so the mean is not well-estimated.

- The ***Minimum*** **Liquid Cash Balances** over the last 90 days before card opening. This is a new dynamic measure that we introduce to the literature to overcome the weakness that point-in-time measures do not reflect how some consumers may only temporarily hold high balances, potentially due to a mismatch in the timing of their incomes and expenditures. Different colors in Panel B of Figure 6 show the S-shaped distribution of this variable steepens around zero when calculated over longer time windows, up to 150 days before card opening, and flattens over shorter time windows, down to 30 days before card opening. We also note that this distribution also has very fat tails and so the mean is not well-estimated. This is a new measure, prior literature has only studied different moments: the point-in-time, mean, or median balances.

Liquid Cash Before Card Opening. — Examining our first static measure initially suggests that consumers generally have liquid cash available before opening the card. Panel A of Figure 6 shows the cumulative distribution of our liquid cash balance measure and indicates that consumers commonly have funds available: Only 13% of consumers have liquidity of a zero or negative liquid cash balance, the median has £370 available, and 30% appear relatively unconstrained with over £1,000. This measure shows a clear kink with liquid cash balance above zero being much more likely than those below. This kink may reflect the discontinuous increase in costs from becoming overdrawn on checking accounts and a precautionary rationale to keep a small amount of buffer stock savings.

It is only once we examine our second measure, minimum liquid cash balances, that captures the dynamics of liquid cash balances that we reveal that consumers frequently lack liquid cash. Figure 6 Panel B shows the cumulative distribution of this measure. There is substantial bunching of consumers just managing to keep positive, but small, liquid cash balances. Half of consumers have effectively zero minimum liquid cash balances in the 90 days before card opening (median £5). Many consumers' minimum liquid balances are only for small amounts. For example, the 75$^{\text{th}}$ percentile is only £142, 84% have £500 or less, and 89% have £1,000 or less. These reveals more consumers have limited liquid cash than the point-in-time liquid cash balance measure indicate, for example the 75$^{\text{th}}$ percentile of the point-in-time measure is £1,311. This lack of liquid cash among many consumers in our experiment helps to explain why the nudge was ineffective. See Online Appendix Table C1 for detailed summary statistics of both measures. These liquid cash measures have weak correlations with covariates typically observed by researchers without access to linked bank account data, see Online Appendix Table C2 for details.

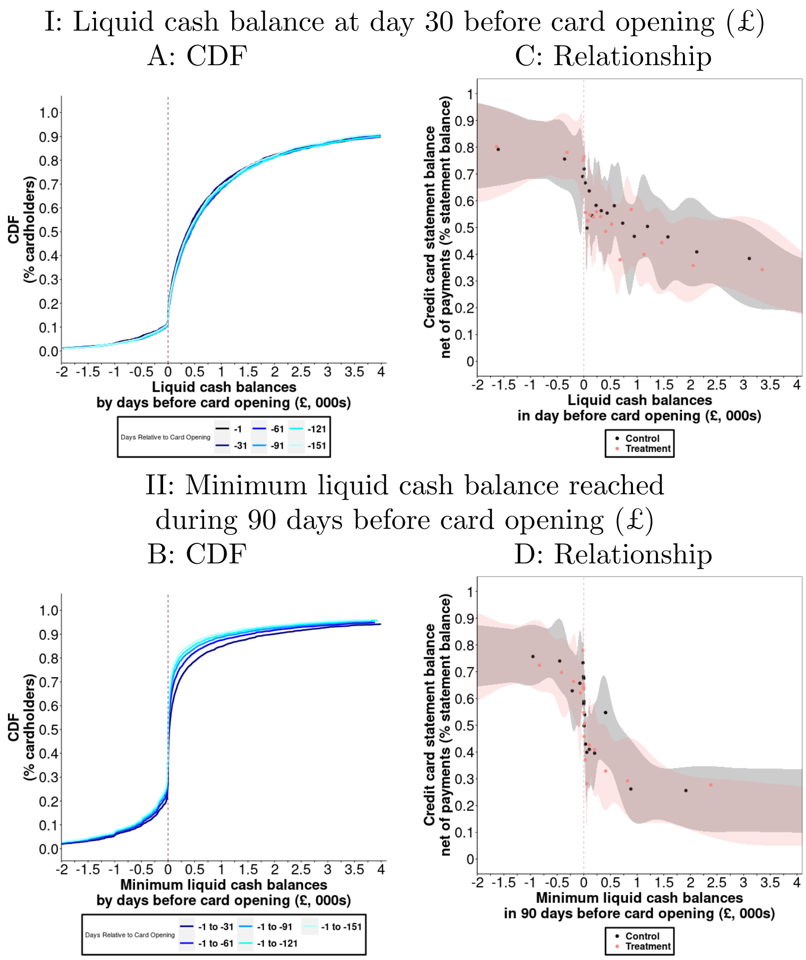

FIGURE 6. CDFs of liquid cash balances measured before card opening (Panels A and B) and their non-parametric relationships with credit card debt (statement balance net of payments as a % of statement balance) at statement cycle seven, by treatment group (Panels C and D)

Notes: N = 3,753 consumers. Liquid cash balances are measured before credit card opening. Panels A and B are CDFs. Panels C and D are binned scatterplots by quantiles of the distribution (Cattaneo et al., 2024) where error bands are 95% confidence intervals. The x-axes of all panels are censored to ease presentation given a fat tail to the distribution of these variables.

Relationship Between Liquid Cash and Credit Card Debt. — We show these measures of liquid cash before card opening explain credit card debt held seven cycles later. When examining credit card debt, we note that this is a function of both spending and payment decisions. Panels C and D of Figure 6 plot binned scatterplots, using the methodology of

Cattaneo et al. (2024), as a clean way to visualize non-linear relationships between liquid cash measures on the x-axes and credit card debt on the y-axes. Panel C of Figure 6 shows that consumers who had small positive liquid cash balances before card opening, our first measure, held less credit card debt, on average, seven cycles later than those with zero or small negative liquid cash balances. Panel D of Figure 6 shows that consumers with positive minimum liquid balances before card opening, our second measure, discontinuously hold approximately 20 percentage points less credit card debt, as a percentage of statement balance, seven cycles later than those with zero or small negative minimum liquid balances.

Given the bimodal distribution of payments, we also examine the other moments: payments at the minimum, full, and less than minimum. The discontinuity in average payments is driven by discontinuous increases in the probability of paying in full and decreases in the probability of missing a payment. Approximately 70% of the small subset of consumers with high minimum liquid cash balances (e.g., £1,000+) pay in full, and these are largely enrolled in Autopay Full, suggesting that there is limited room for the nudge to increase payments among this group. The relationship with Autopay enrollment choices is less clear except for a discontinuous increase in Autopay Full enrollment. Paying only the minimum becomes less likely among less liquidity-constrained consumers; however, there is a less clear discontinuity around zero. See Online Appendix Figure C2 for details. Our dynamic measures appear to be important to understand credit card usage and, as shown in Figure 6, there are nonlinearities in the relationship between liquid cash and credit card debt that simple correlations would not capture. Overall, this means that the high prevalence of low liquid cash among consumers in our experiment, which we show predicts low credit card debt as a percent of statement balances, potentially helps to explain the nudge's ineffectiveness. Consumers appear to be making "low" credit card payments and offsetting the nudge to not reduce their debt due to frequently holding limited liquid cash balances. Such limited liquidity may also mean other policies intended to change consumer choices around repayment may also ultimately fail to reduce credit card debt.

Heterogeneous Effects of Nudge By Liquid Cash. — As shown in the previous sections, very few consumers consistently have non-trivial amounts of liquid cash before card opening. We examine whether the nudge is effective for the small minority of consumers with high liquid cash before card opening. We pool data across all cycles to increase power and show sensitivity to alternative thresholds when defining consumers as holding high liquid cash. Across all heterogeneous groups of high and low liquid cash, we find that the nudge significantly reduces the probability of enrolling in any Autopay and also significantly reduces the probability of consumers only paying exactly the minimum, details in Online Appendix Table C3. There is very weak evidence that the nudge causes some high liquid cash consumers to reduce their debt, however, this result is not at all robust. There are declines for consumers with high liquid cash as measured by the liquid cash balance of £501+ (-3.42 percentage points, 95% confidence interval -6.35 to -0.49 percentage points) and £1,001+ (-4.48 percentage points, 95% confidence interval -7.95 to -1.00 percentage points), both significant at the 5% level, and insignificant declines for other groups of consumers (<£1, £1+, <£501, and <£1,001). By our second measure, there are very few high liquidity consumers and, therefore, we do not have power to conclude whether there is an imprecisely estimated significant effect or a null result, for example, the 95% confidence interval for the £1,001+ group is −6.57 to 3.31. No heterogeneous group of either measure shows a decrease in credit card debt measured in pounds that is close to being statistically significant, with the smallest p-value is 0.29. As in our earlier heterogeneous analysis, we also note that the reader may want to apply a stricter threshold than 0.5% to evaluate significance given concerns over multiple hypothesis testing. See Online Appendix Table C4 for details.

While we cannot precisely rule out whether effects for the small group of high liquid cash consumers are zero or not, we can test whether effects for these consumers are significantly different from those estimated for low liquid cash consumers. T tests show that this is the case; however, results are sensitive to whether the debt outcome is measured as a percent of the statement balance or in pounds (£), the liquid cash measure used, and the threshold to classify consumers as holding high liquid cash. The two robust results across outcomes and time periods are when liquid cash balances are £1,001+ or when minimum liquid cash balances are £501+, the effects of the nudge are significantly stronger, reducing debt in comparison to consumers with lower liquid cash. When liquid cash balances are £1,001+, compared to <£1,001, there is a significant differential effect of the nudge on debt: −3.3 percentage points (95% confidence interval −3.4 to −3.2 percentage points) and −£38 (95% confidence interval −£42 to −£34). The effect of the nudge on debt after seven cycles is significantly stronger when minimum liquid cash balances are £501+, compared to <£501: −1.2 percentage points (95% confidence interval −1.3 to −1.1) and −£66 (95% confidence interval −£71 to −£62), see Online Appendix Table C5 for more details. These results therefore help to understand why consumers in our experiment are less "nudge-able" than they first appeared from their Autopay choices and inert minimum payment behavior. Most consumers lack liquid cash.

V. Conclusions

We expected that successfully nudging credit cardholders away from enrolling in Autopay set to only pay exactly the minimum payment would reduce their debt. Our field experiment shows that this did not occur. We show how an active choice nudge is successful in significantly and persistently changing *proximate* outcomes: decreasing Autopay Min enrollment by 74% and decreasing the probability of only paying exactly the minimum by 23% after six months. However, the nudge is unsuccessful at significantly reducing the *distal* outcome of the amount of credit card debt accumulated after six months. This is explained by offsetting consumer responses consistent with consumers frequently holding low liquid cash balances. Our study is an example of the difficulty in changing distal consumer behaviors, and highlights the need to evaluate policies, such as nudges, on how they impact *distal* rather than *proximate* outcomes.

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Online Appendix accompanying "*The Semblance of Success in Nudging Consumers to Pay Down Credit Card Debt*"

By Benedict Guttman-Kenney (corresponding author, benedictgk@rice.edu), Paul Adams, Stefan Hunt, David Laibson, Neil Stewart, and Jesse Leary.

15 November 2024

Online Appendix Contents:

A. Additional Results for Main Lender

Definitions of Primary Outcomes

1) **Any minimum payment:** Binary outcome for target card. Defined as only paying exactly the minimum (unless that is zero or equal to the full statement balance).

2) **Any full payment:** Binary outcome for target card. Defined as paying the full statement balance (or if no payment is due because there's a zero statement balance).

3) **Any missed payment:** Binary outcome for target card. Defined as paying zero or less than the minimum.

4) **Statement balance net of payments (% statement balance):** Continuous outcome for target card as a measure of credit card debt. Defined as the value of statement balance net of payments as a percent of the value of statement balance. This is the fraction of credit card debt remaining after payments.

5) **Costs (% statement balance):** Continuous outcome for target card. A measure of the costs of borrowing. Defined as the sum of credit card interest and fees as a percentage of statement balance.

6) **Spending (% statement balance):** Continuous outcome for target card. A measure of consumption. Defined as the sum of the value of new credit card transactions that statement cycle as a percentage of statement balance.

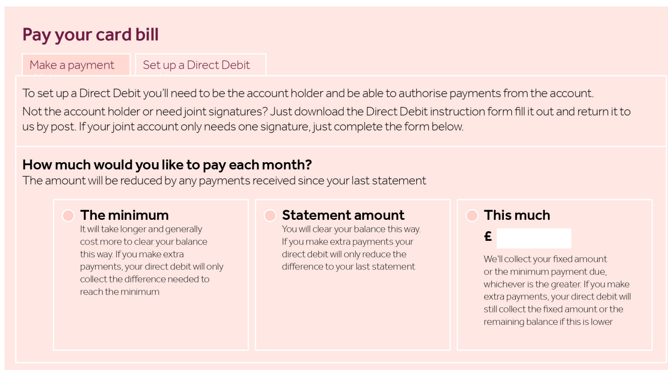
7) **Share of credit card portfolio only paying minimum:** Outcome ranging from zero to one. Defined as the proportion of credit cards paying exactly the minimum (unless that is zero or equal to the full balance).

8) **Share of credit card portfolio making full payment:** Outcome ranging from zero to one. Defined as the proportion of credit cards paying the full statement balance (or if no payment is due because there's a zero statement balance).

9) **Share of credit card portfolio missing payment:** Outcome ranging from zero to one. Defined as the proportion of credit cards paying zero or less than the minimum.

10) **Credit card portfolio balances net of payments (% statement balances):** Continuous outcome for credit card portfolio. Defined as the aggregated value of statement balances net of payments across the credit card portfolio as a percent of the aggregated value of statement balances across credit card portfolio. This is the fraction of credit card debt portfolio remaining after payments.

A: Control



B: Treatment

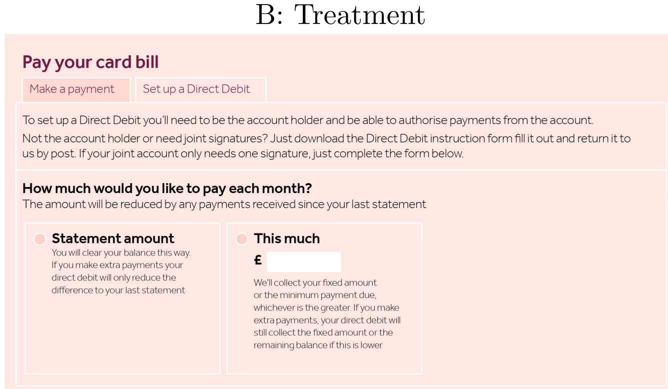


Figure A1. Autopay enrollment choice architecture presented to control (panel A) and treatment (panel B) groups

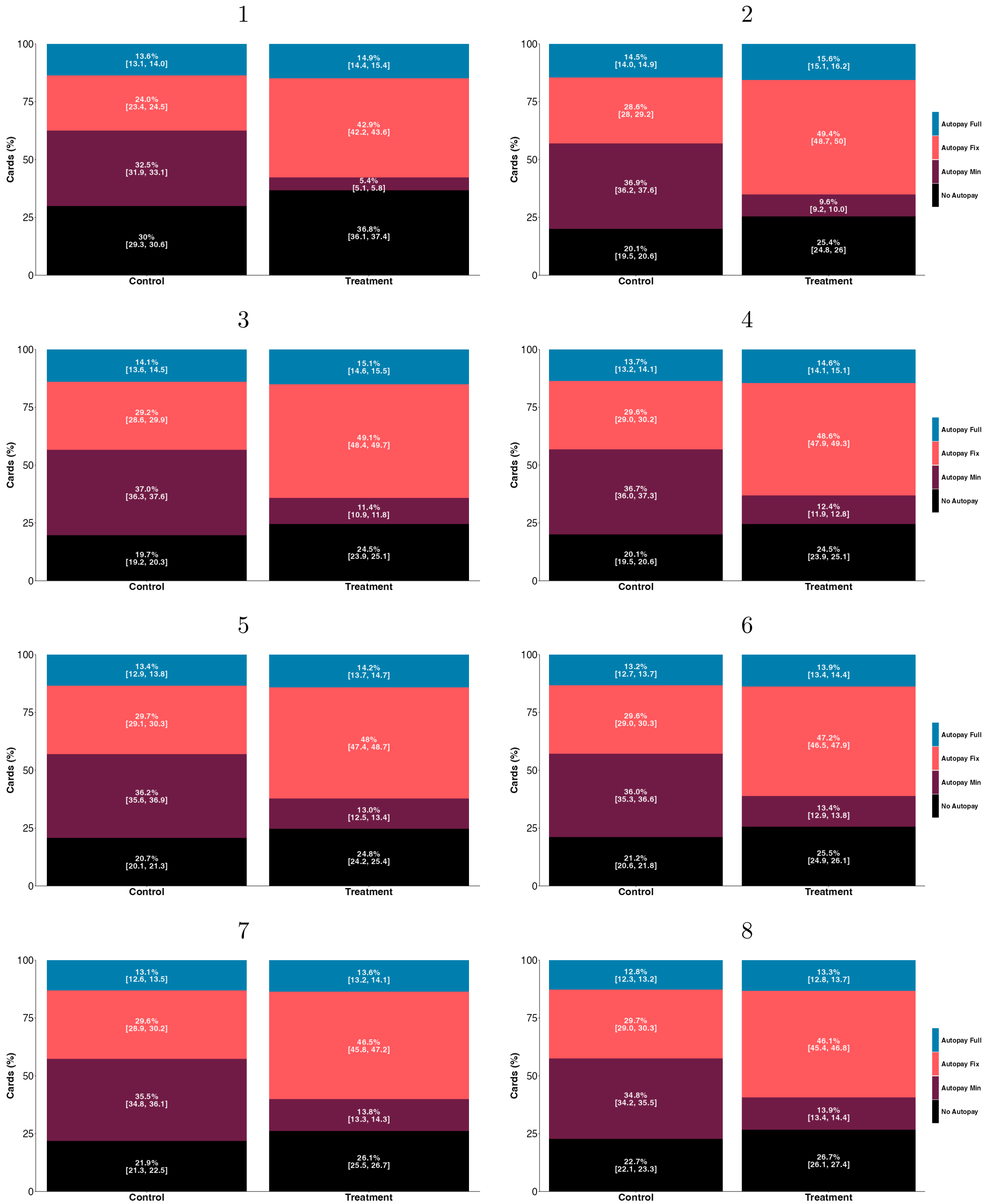


FIGURE A2. AUTOPAY ENROLLMENT FOR CONTROL AND TREATMENT GROUPS, BY STATEMENT CYCLES ONE TO EIGHT

Notes: Numbers display percentage of cards enrolled in each type of Autopay. 95% confidence intervals in [ ]. Cycle 1 is before all treated cards have had 30 days to experience the treatment. Not all cards are observed in cycle 8.

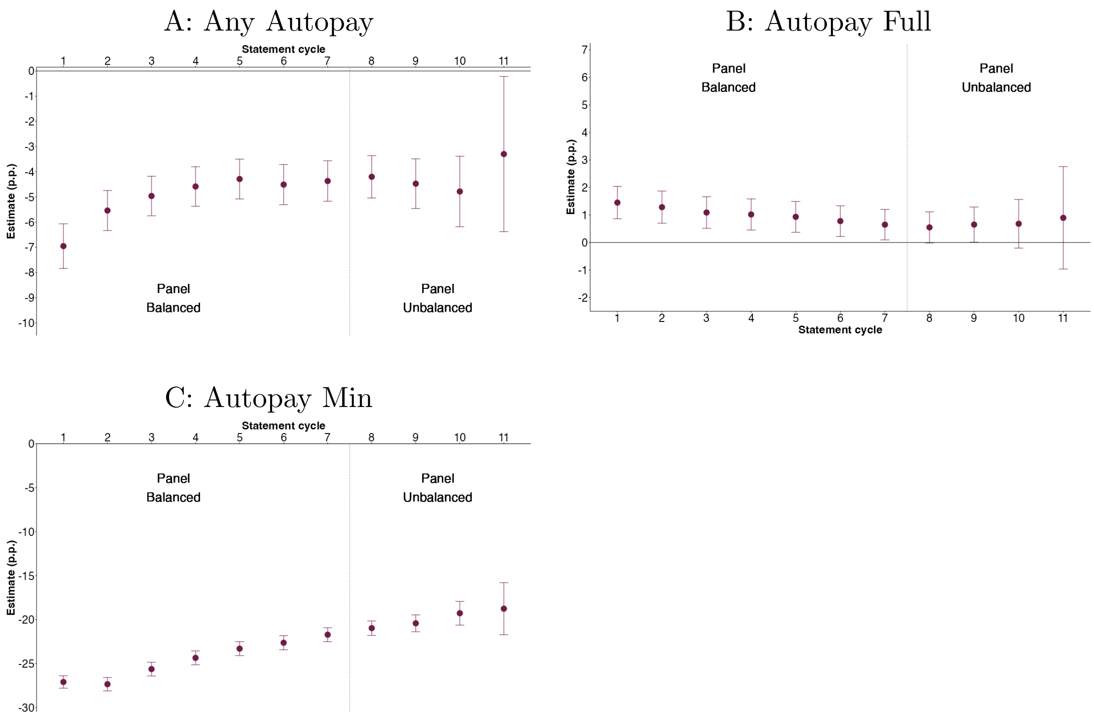


Figure A3. Average treatment effects on Autopay enrollments, across 1-11 statement cycles

Notes: Treatment effects from the coefficients (δ_τ) on interaction terms between treatment indicator and statement cycle indicators in the OLS regression specified in Equation 1. The regression outcome in Panel A is any automatic payment enrollment, the outcome in Panel B is any automatic full payment enrollment, and the outcome in Panel C is any automatic minimum payment enrollment. Regressions also include statement cycle fixed effects, year-month fixed effects, and the following controls: Gender, Age, Age squared, Log Estimated Income, Credit Score, Unsecured Debt-to-Income (DTI) Ratio, Any Mortgage Debt, Log Credit Card Credit Limit, Credit Card Purchases Rate, Subprime Credit Card, Any Credit Card Promotional Rate, Any Credit Card Balance Transfer, Credit Card Open Date, Credit Card Statement Day, Any Credit Card Secondary Cardholder. These are all from the time of card origination except for the variables constructed from consumer credit reporting data (Credit Score, DTI Ratio and Any Mortgage Debt), which are from the month preceding card origination. Error bars are 95% confidence intervals. Standard errors are clustered at consumer-level. There are 40,708 credit cards with 368,162 observations.

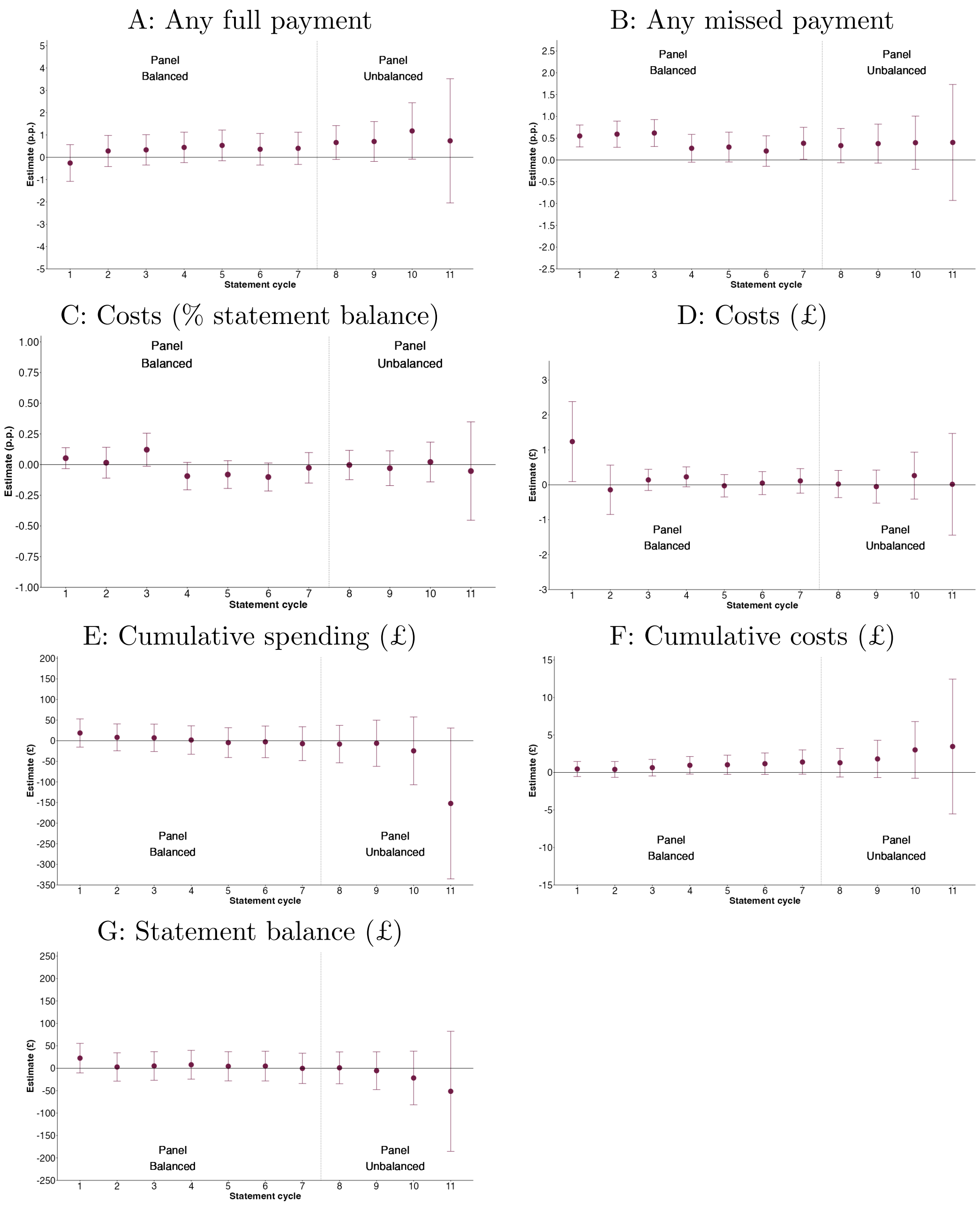


FIGURE A4. AVERAGE TREATMENT EFFECTS ON OUTCOMES ON TARGET CARD, ACROSS 1-11 STATEMENT CYCLES

Notes: Treatment effects from the coefficients (δ_τ) on interaction terms between treatment indicator and statement cycle indicators in the OLS regression specified in Equation 1. The regression outcome in Panel A is pay full balance, outcome in Panel B is pay less than the minimum, the outcome in Panel C is the sum of interest and fees (% statement balance), the outcome in Panel D is the sum of interest and fees (£), the outcome in Panel E is cumulative spending (£), the outcome in Panel E is cumulative costs (£), and the outcome in Panel F is statement balance (£, this is before payments). Regressions also include statement cycle fixed effects, year-month fixed effects, and the following controls: Gender, Age, Age squared, Log Estimated Income, Credit Score, Unsecured Debt-to-Income (DTI) Ratio, Any Mortgage Debt, Log Credit Card Credit Limit, Credit Card Purchases Rate, Subprime Credit Card, Any Credit Card Promotional Rate, Any Credit Card Balance Transfer, Credit Card Open Date, Credit Card Statement Day, Any Credit Card Secondary Cardholder. These are all from the time of card origination except for the variables constructed from consumer credit reporting data (Credit Score, DTI Ratio and Any Mortgage Debt), which are from the month preceding card origination. Error bars are 95% confidence intervals. Standard errors are clustered at consumer-level. There are 40,708 credit cards with 368,162 observations.

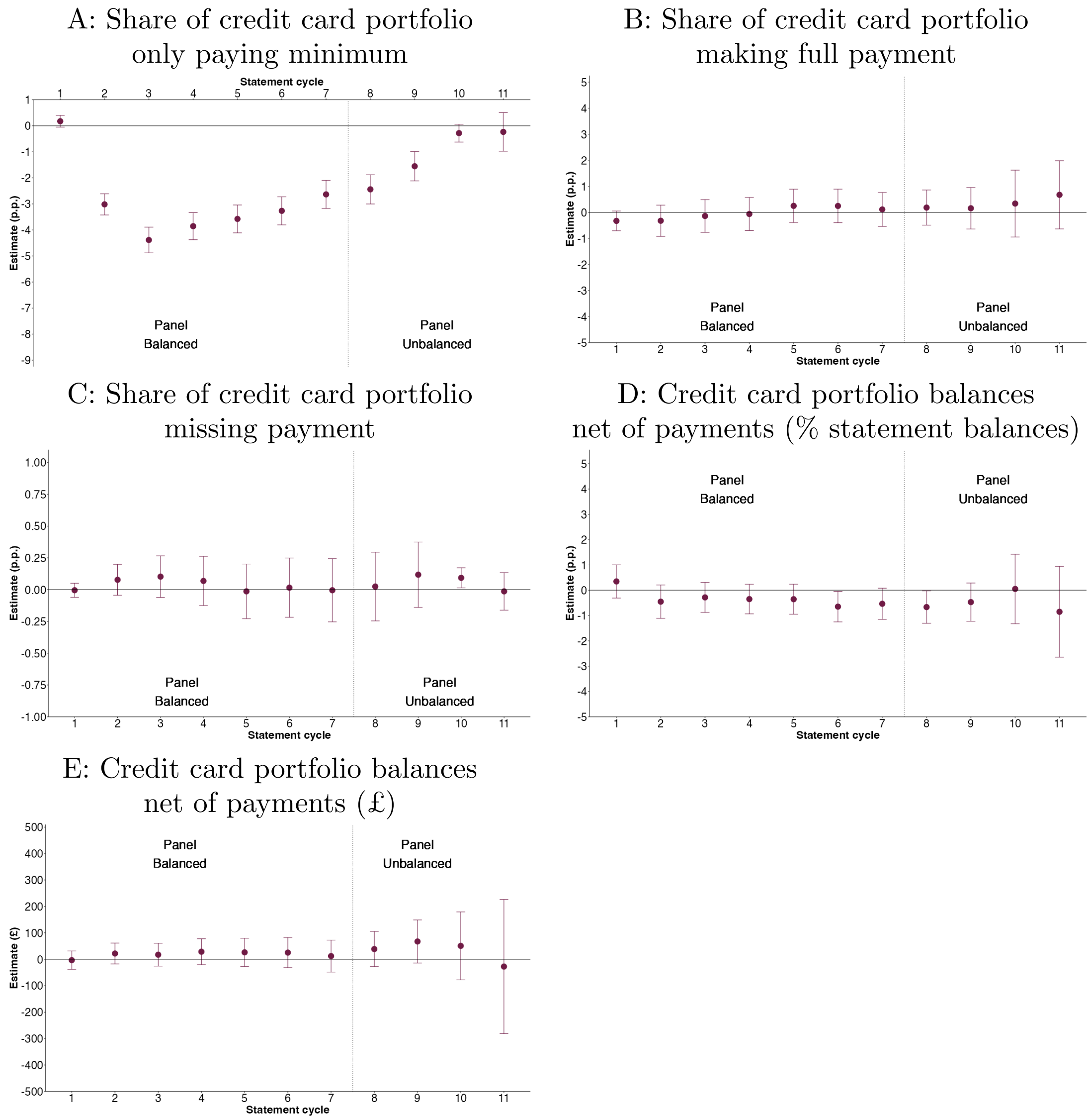


FIGURE A5. AVERAGE TREATMENT EFFECTS ON CREDIT CARD PORTFOLIO OUTCOMES, ACROSS 1-11 STATEMENT CYCLES

Notes: Treatment effects from the coefficients (δ_τ) on interaction terms between treatment indicator and statement cycle indicators in the OLS regression specified in Equation 1. The regression outcome in Panel A is share of credit cards paying the minimum, the outcome in Panel B is share of credit cards paying the full balance, the outcome in Panel C is share of credit cards paying less than the minimum, the outcome in Panel D is credit card portfolio balances net of payments as a percent of statement balances, and the outcome in Panel E is credit card balances net of payments (£). Regressions also include statement cycle fixed effects, year-month fixed effects, and the following controls: Gender, Age, Age squared, Log Estimated Income, Credit Score, Unsecured Debt-to-Income (DTI) Ratio, Any Mortgage Debt, Log Credit Card Credit Limit, Credit Card Purchases Rate, Subprime Credit Card, Any Credit Card Promotional Rate, Any Credit Card Balance Transfer, Credit Card Open Date, Credit Card Statement Day, Any Credit Card Secondary Cardholder. These are all from the time of card origination except for the variables constructed from consumer credit reporting data (Credit Score, DTI Ratio and Any Mortgage Debt), which are from the month preceding card origination. For outcomes constructed from consumer credit reporting data up to eleven dummies for lags of outcomes are included as controls (X_i') for months preceding the start of the experiment. Error bars are 95% confidence intervals. Standard errors are clustered at consumer-level. There are 40,708 credit cards with 368,162 observations.

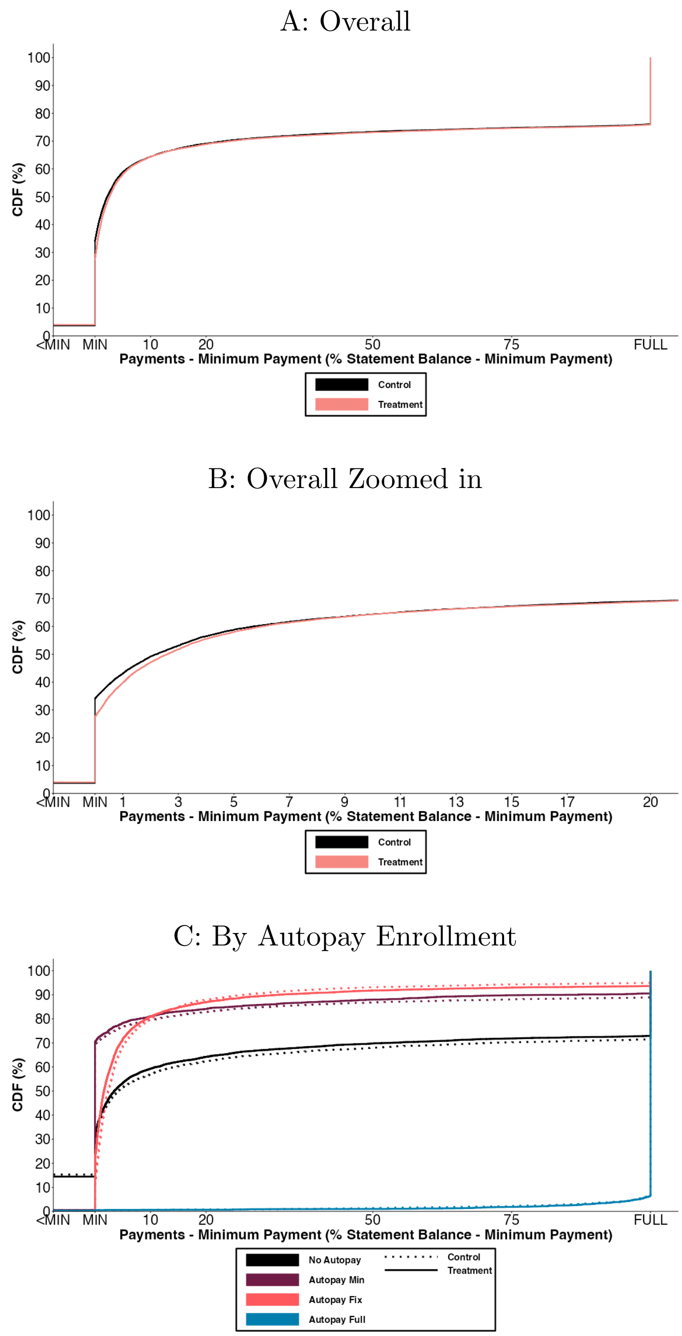


Figure A6. CDF of excess payments (payments − minimum payment, as a % of statement balance − minimum payment) after seven statement cycles

Notes: Figure shows CDFs of payments − minimum payment (% statement balance − minimum payment) measured at the seventh statement cycle. In this outcome, MIN shows cases where payments equal the minimum payment, cases where payments are less than the minimum are assigned to the $< MIN$ group, cases where payments greater than the statement balance are assigned to the $FULL$ group. The CDFs show the cumulative fraction of cards within each group. Panel A shows the CDF split by treatment and control groups. Panel B shows the CDF split by treatment and control groups (as in Panel A), but zoomed in to focus on the part of the distribution where the outcome is from $< MIN$ to 20%. Panel C shows the CDF split by combinations of treatment status groups and Autopay enrollment groups at the seventh statement cycle. When interpreting Panel C, it is important to note that the sample sizes of cards in each Autopay enrollment status dramatically change as a result of the treatment, as shown in Figure A2. All panels use data on 40,693 credit cards with one observation per card.

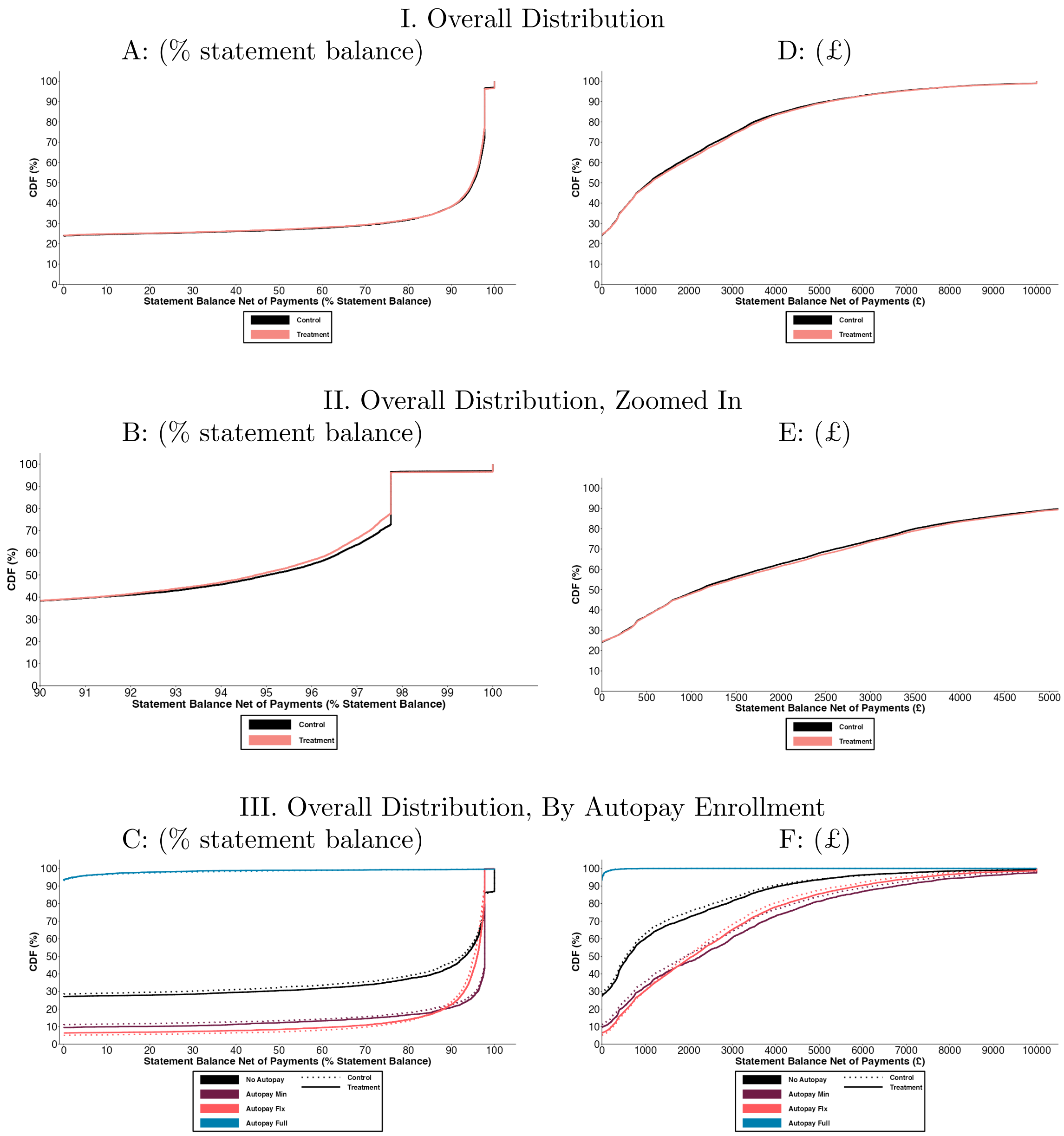
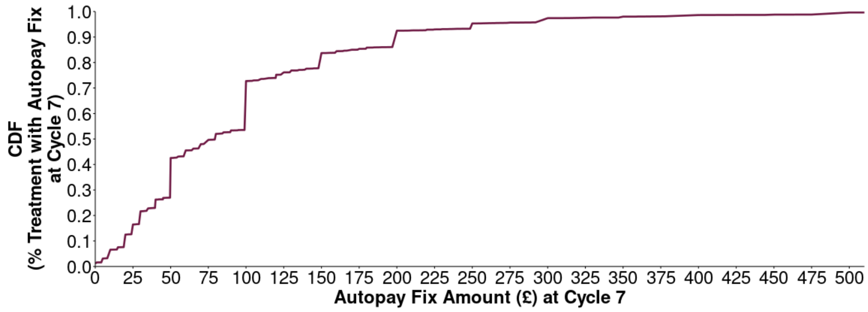


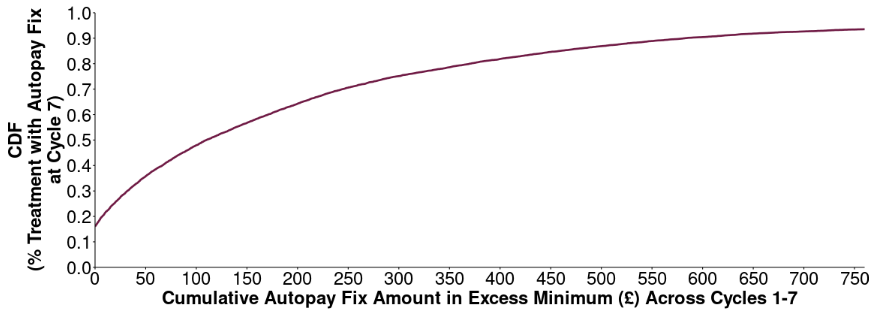
FIGURE A7. CDF OF STATEMENT BALANCE NET OF PAYMENTS AFTER SEVEN STATEMENT CYCLES

Notes: Figure shows CDFs of statement balance net of payments (% statement balance) measured at the seventh statement cycle. The CDFs show the cumulative fraction of cards within each group. Panel A shows the CDF split by treatment and control groups. Panel B shows the CDF split by treatment and control groups (as in Panel A), but zoomed in to focus on the part of the distribution where the outcome is from 90% to 100%. Panel C shows the CDF split by combinations of treatment status groups and Autopay enrollment groups at the seventh statement cycle. Panel D shows CDF split by treatment and control groups. Panel E shows CDF split by treatment and control groups (as in Panel D), but zoomed in to focus on the part of the distribution where the outcome is from £0 to £5,000. Panel F shows the CDF split by combinations of treatment status groups and Autopay enrollment groups at the seventh statement cycle. When interpreting Panels C and F, it is important to note that the sample sizes of cards in each Autopay enrollment status dramatically change as a result of the treatment, as shown in Figure A2. All panels use data on 40,693 credit cards with one observation per card.

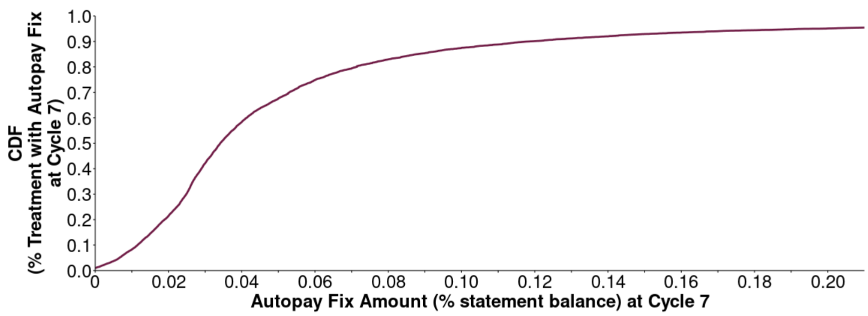
A: Autopay fix amount (£) at cycle 7



B: Cumulative autopay fix amount in excess of minimum (£) across cycles 1-7



C: Autopay fix amount (% statement balance) at cycle 7



D: Autopay fix amount in excess of minimum (% statement balance) at cycle 7

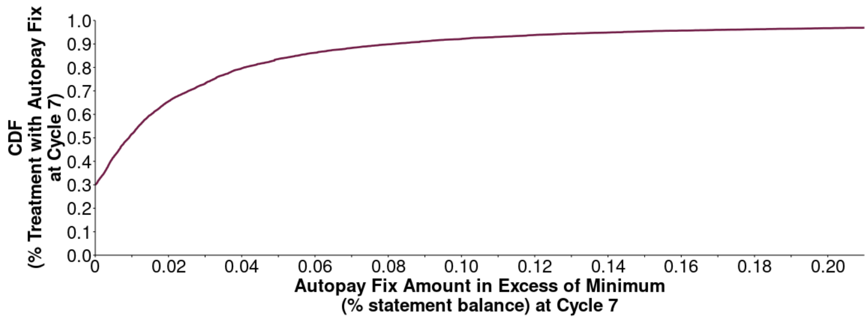


Figure A8. CDF of Autopay Fix payment amounts for those enrolled in Autopay Fix in the treatment group after seven statements

Notes: The x-axes of CDFs are right-censored to ease presentation. The CDFs are calculated for the 9,337 credit cards that are in treatment group and enrolled in Autopay Fix at cycle 7.

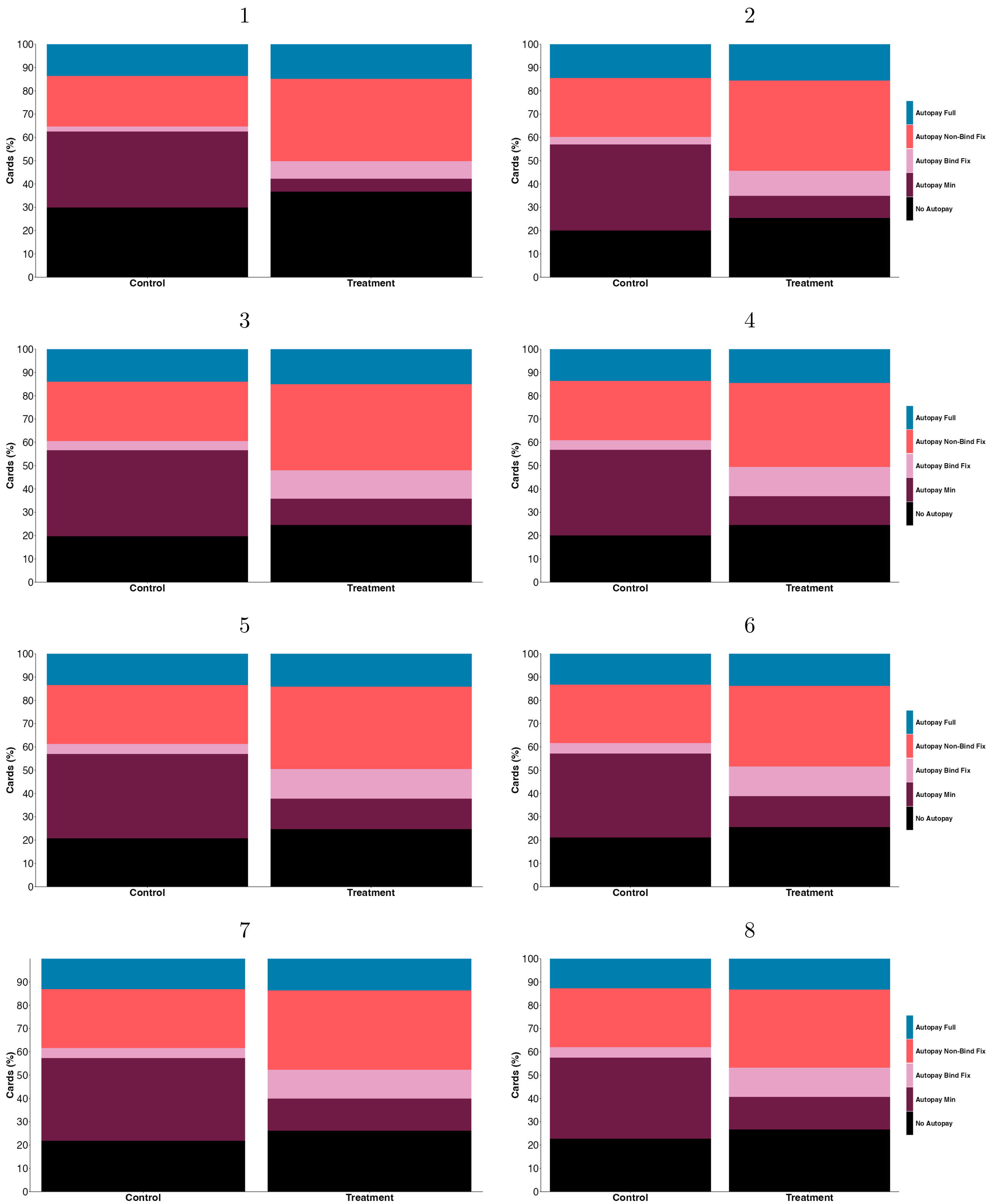


Figure A9. Autopay enrollment - splitting out automatic fixed payments into those that do and do not bind at the minimum payment amount - for control and treatment groups split by statement cycles one to eight

Notes: The numbers display percentage of cards enrolled in each type of Autopay. 95% confidence intervals in [ ].

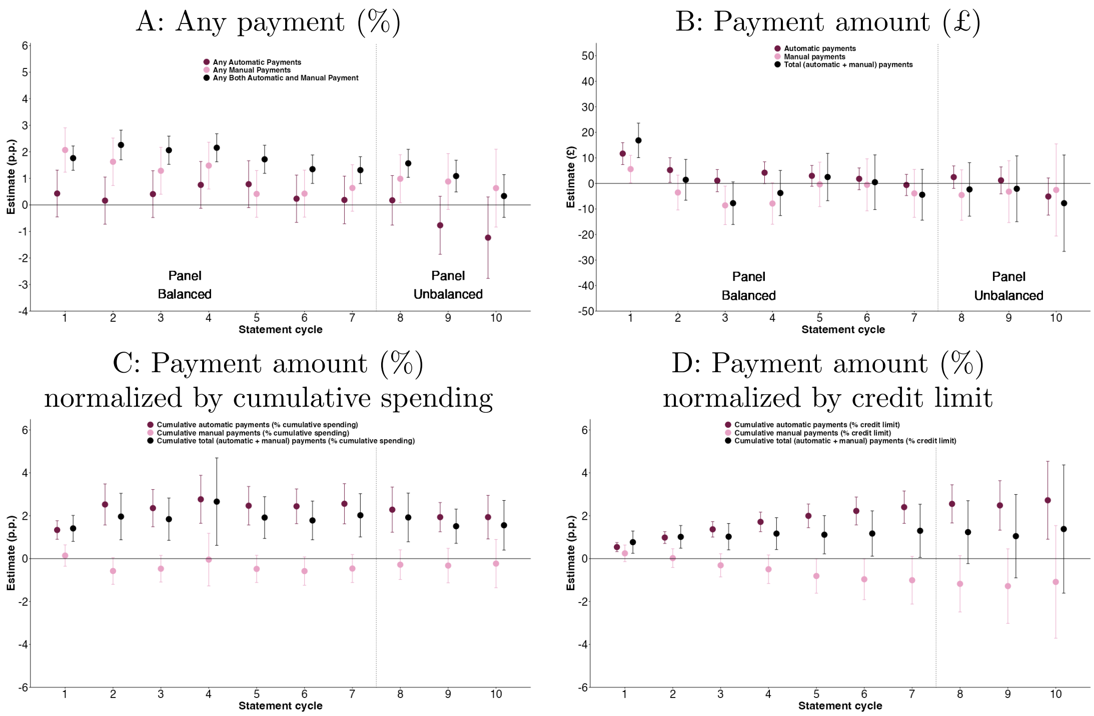


Figure A10. Average treatment effects on payments, across 1-10 statement cycles

Notes: Treatment effects from the coefficients (δ_τ) on interaction terms between treatment indicator and statement cycle indicators in the OLS regression specified in Equation 1. Regressions also include statement cycle fixed effects, year-month fixed effects, and the following controls: Gender, Age, Age squared, Log Estimated Income, Credit Score, Unsecured Debt-to-Income (DTI) Ratio, Any Mortgage Debt, Log Credit Card Credit Limit, Credit Card Purchases Rate, Subprime Credit Card, Any Credit Card Promotional Rate, Any Credit Card Balance Transfer, Credit Card Open Date, Credit Card Statement Day, Any Credit Card Secondary Cardholder. These are all from the time of card origination except for the variables constructed from consumer credit reporting data (Credit Score, DTI Ratio and Any Mortgage Debt), which are from the month preceding card origination. Error bars are 95% confidence intervals. Standard errors are clustered at consumer-level. There are 40,708 credit cards with 368,162 observations. Cycle 11 is excluded from figure as, due to few cards being observed in this cycle, the confidence intervals are extremely large such that estimates are uninformative.

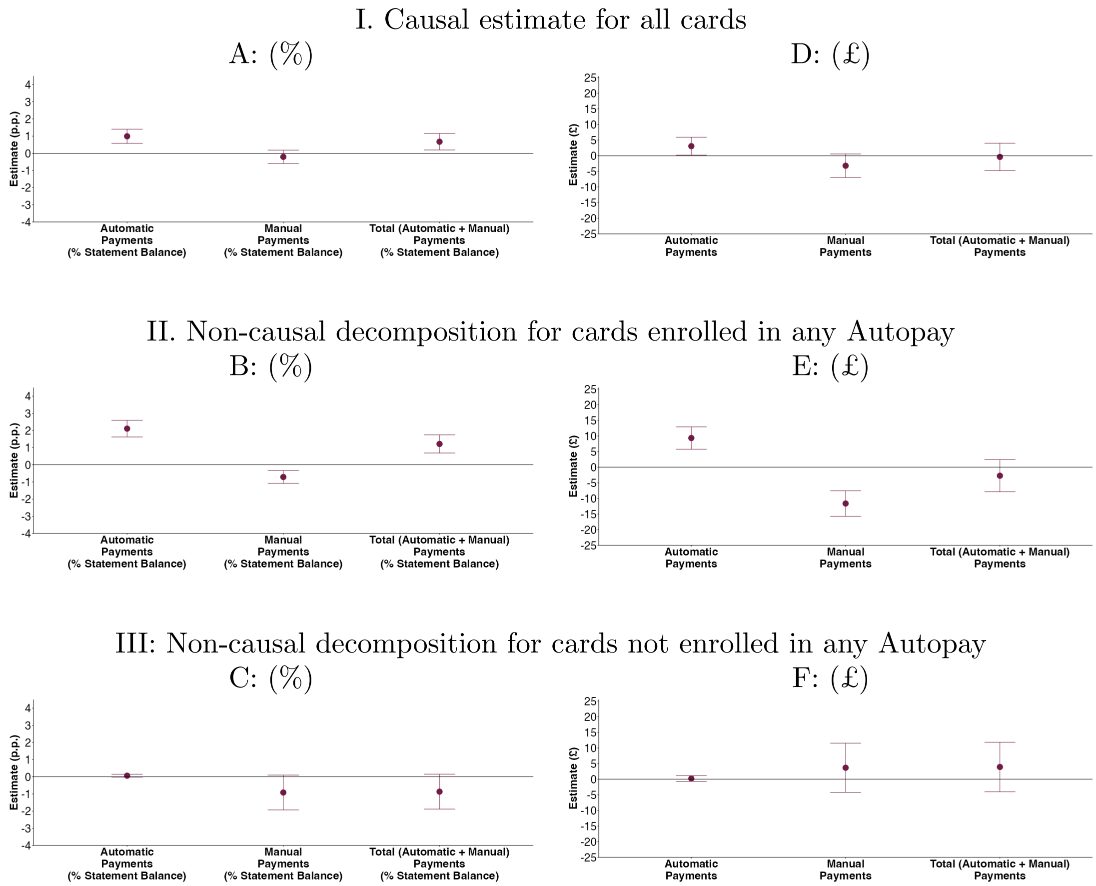


Figure A11. Estimates on payments pooled across all statement cycles, decomposed by any Autopay enrollment after seven statement cycles

Notes: Panels A and D are the causal estimated treatment effects from the coefficient (δ) on the treatment indicator in the OLS regression specified in Equation 2. Each panel (A to F) show the outcomes from three separate regressions where outcomes are: automatic payments, manual payments, and total (automatic +) manual) payments. In Panels A, B, and C these outcomes are all measured as % statement balance. In Panels D, E, and F these outcomes are all measured in £. Regressions also include: statement cycle fixed effects, year-month fixed effects, and the following controls: Gender, Age, Age squared, Log Estimated Income, Credit Score, Unsecured Debt-to-Income (DTI) Ratio, Any Mortgage Debt, Log Credit Card Credit Limit, Credit Card Purchases Rate, Subprime Credit Card, Any Credit Card Promotional Rate, Any Credit Card Balance Transfer, Credit Card Open Date, Credit Card Statement Day, Any Credit Card Secondary Cardholder. These are all from the time of card origination except for the variables constructed from consumer credit reporting data (Credit Score, DTI Ratio and Any Mortgage Debt), which are from the month preceding card origination. Error bars are 95% confidence intervals. Standard errors are clustered at consumer-level. Panels A and D contain 40,708 credit cards with 368,162 observations. Panels B, C, E, and F show the non-causal estimates (δ) from the OLS regression specificed in Equation 3, this has the same specification as explained above except Panels B and E restrict to the subsample of 31,052 credit cards that are enrolled in any Autopay at statement cycle 7, and Panels C and F restrict to the subsample of 9,641 credit cards that are not enrolled in any Autopay at statement cycle 7.

Table A1—Summary statistics

Outcome	Mean	S.D.	P10	P25	P50	P75	P90
Age (years)	36.46	12.44	23	27	34	45	54
Female (% cards)	0.46	0.50	0	0	0	1	1
Credit limit (£)	4356.81	3366.08	660	1,400	3,800	6,300	9,000
Any credit score	0.99	0.12	1	1	1	1	1
Credit score (0-100)	0.65	0.07	0.560	0.610	0.660	0.700	0.740
Purchases rate (%)	22.85	6.11	18.900	18.900	18.900	29.900	34.900
Any estimated income	0.97	0.18	1	1	1	1	1
Estimated income (£)	2437.38	2155.20	899	1,321	1,880	2,816	4,336
Any autopay	0.78	0.41	0	1	1	1	1
Autopay full	0.13	0.34	0	0	0	0	1
Autopay fix	0.30	0.46	0	0	0	1	1
Autopay min	0.35	0.48	0	0	0	1	1
Statement balance (£)	2164.49	2416.30	0	373	1,290	3,274	5,437
Statement balance net of payments (£)	1962.52	2369.65	0	41	1,086	3,070	5,162
Statement balance net of payments (% statement balance)	0.69	0.41	0	0.180	0.950	0.980	0.980
Utilization	0.52	0.37	0	0.200	0.530	0.840	0.980
Any minimum payment	0.30	0.46	0	0	0	1	1
Any full payment	0.24	0.43	0	0	0	0	1
Any missed payment	0.04	0.19	0	0	0	0	0
Cumulative number times paid minimum	2.04	2.63	0	0	0	4	7
Cumulative number times paid in full	1.90	2.56	0	0	1	3	7
Cumulative number times paid less than minimum	0.19	0.76	0	0	0	0	0
6+ times paid minimum	0.19	0.39	0	0	0	0	1
6+ times paid in full	0.18	0.38	0	0	0	0	1
6+ times paid less than minimum	0.01	0.07	0	0	0	0	0
Number of credit cards	2.80	1.90	1	1	2	4	5
Number of credit cards with debt	1.52	1.36	0	1	1	2	3
Credit card portfolio statement balances (£)	3916.96	5142.72	90	626	2,284	5,143	9,734
Credit card portfolio balances net of payments (£)	3431.69	4849.58	0	255	1,851	4,597	8,830

Notes: Summary statistics are calculated for control group (N = 20,609 credit cards) after seventh statement cycle.

Table A2—Minimum Detectable Effect (MDE) sizes at cycle 7 across significance levels 0.005, 0.01, and 0.05 (all assuming 80% power)

Outcome	0.005	0.01	0.05
Any minimum payment	0.0160	0.0150	0.0123
Any full payment	0.0155	0.0145	0.0119
Any missed payment	0.0070	0.0065	0.0053
Statement balance net of payments (% statement balance)	0.0149	0.0140	0.0114
Costs (% statement balance)	0.0023	0.0022	0.0018
Spending (% statement balance)	0.0127	0.0119	0.0098
Share of credit card portfolio only paying minimum	0.0108	0.0101	0.0083
Share of credit card portfolio making full payment	0.0136	0.0127	0.0104
Share of credit card portfolio missing payment	0.0048	0.0045	0.0037
Credit card portfolio balances net of payments (% statement balances)	0.0141	0.0132	0.0108
Any autopay	0.0154	0.0145	0.0119
Autopay full	0.0123	0.0115	0.0095
Autopay fix	0.0176	0.0164	0.0135
Autopay min	0.0156	0.0146	0.0120
Autopay fix exceeding minimum payment amount	0.0165	0.0155	0.0127
Cumulative total payments (£)	63.24	59.23	48.56
Cumulative automatic payments (£)	40.68	38.10	31.24
Cumulative manual payments (£)	52.03	48.73	39.95
Total payments (% statement balance)	0.0130	0.0121	0.0099
Automatic payments (% statement balance)	0.0098	0.0092	0.0075
Manual payments (% statement balance)	0.0103	0.0097	0.0079
Made both automatic and manual payment	0.0094	0.0088	0.0072
Statement balance (£)	87.94	82.36	67.52
Statement balance net of payments (£)	86.26	80.80	66.24
Cumulative spending (£)	106.30	99.56	81.62
Cumulative costs (£)	3.52	3.30	2.71
Spending (£)	17.18	16.09	13.19
Total payments (£)	18.88	17.68	14.50
Automatic payments (£)	8.08	7.57	6.21
Manual payments (£)	17.59	16.47	13.50
Credit card portfolio repayments (£)	40.19	37.64	30.86
Credit card portfolio repayments (% statement balances)	0.01	0.01	0.01
Credit card portfolio statement balances (£)	187.77	175.87	144.18
Credit card portfolio balances net of payments (£)	176.31	165.14	135.38

Table A3—Balance comparison

Outcome	Control	Treatment	Difference (p.p.)	95% C.I.
Age (years)	36.46	36.61	0.14	[-0.10, 0.39]
Female (% cards)	0.4606	0.4612	0.0006	[-0.0091, 0.0103]
Any estimated income	0.9660	0.9630	-0.0030	[-0.0066, 0.0006]
Estimated income (£)	2437.38	2457.50	20.13	[-21.93, 62.19]
Credit limit (£)	4356.81	4429.03	72.22	[6.36, 138.08]
Any credit score	0.9856	0.9834	-0.0023	[-0.0047, 0.0001]
Credit score (0-100)	0.6526	0.6538	0.0012	[-0.0003, 0.0026]
Purchases rate (%)	22.85	22.82	-0.03	[-0.15, 0.09]
Any balance transfer offered	0.2900	0.2976	0.0076	[-0.0013, 0.0164]
Number of credit cards	2.18	2.19	0.02	[-0.02, 0.05]
Number of credit cards with debt	0.90	0.91	0.01	[-0.01, 0.04]
Credit card portfolio statement balances (£)	2364.92	2439.09	74.16	[-0.79, 149.12]
Credit card portfolio balances net of payments (£)	2001.35	2072.53	71.18	[2.59, 139.77]

Notes: N (control) = 20,617 and N (treatment) = 20,091 cards.

TABLE A4—AVERAGE TREATMENT EFFECTS FOR SECONDARY OUTCOMES AFTER SEVEN STATEMENT CYCLES

Outcome	Estimate, p.p. (s.e.)	95% C.I.	P value	Control mean
Cumulative number times paid in full	0.0192 (0.0201)	[-0.0203, 0.0586]	0.3405	1.9020
Cumulative number times paid minimum	-0.5939 (0.0232)	[-0.6393, -0.5485]	0.0000	2.0444
Cumulative number times paid less than minimum	0.0276 (0.0075)	[0.0129, 0.0424]	0.0002	0.1892
Cumulative total payments (£)	6.68 (16.19)	[-25.06, 38.41]	0.6800	1277.27
Cumulative automatic payments (£)	27.30 (10.35)	[7.01, 47.59]	0.0084	573.79
Cumulative manual payments (£)	-18.87 (13.97)	[-46.25, 8.50]	0.1766	711.97
Total payments (% statement balance)	0.0060 (0.0032)	[-0.0002, 0.0123]	0.0579	0.2271
Automatic payments (% statement balance)	0.0072 (0.0025)	[0.0023, 0.0122]	0.0040	0.1101
Manual payments (% statement balance)	-0.0005 (0.0028)	[-0.0061, 0.0050]	0.8477	0.1212
Made both automatic and manual payment	0.0131 (0.0026)	[0.0080, 0.0182]	0.0000	0.0672
Statement balance (£)	-0.33 (17.24)	[-34.11, 33.46]	0.9848	2164.49
Statement balance net of payments (£)	4.11 (17.22)	[-29.64, 37.85]	0.8115	1962.52
Utilization	0.0002 (0.0032)	[-0.0061, 0.0064]	0.9604	0.5223
Cumulative spending (£)	-7.23 (20.95)	[-48.29, 33.83]	0.7300	3186.19
Cumulative costs (£)	1.39 (0.83)	[-0.23, 3.01]	0.0924	76.02
Spending (£)	-9.84 (4.99)	[-19.61, -0.07]	0.0485	193.24
Total payments (£)	-4.44 (5.07)	[-14.38, 5.51]	0.3820	201.98
Automatic payments (£)	-0.6123 (2.1195)	[-4.7665, 3.5419]	0.7727	86.9490
Manual payments (£)	-3.90 (4.79)	[-13.29, 5.48]	0.4152	116.38
Credit card portfolio repayments (£)	9.11 (9.39)	[-9.29, 27.51]	0.3318	485.70
Credit card portfolio repayments (% statement balances)	0.00 (0.00)	[-0.00, 0.01]	0.5730	0.26
Credit card portfolio statement balances (£)	23.65 (31.15)	[-37.42, 84.71]	0.4479	3916.96
Credit card portfolio balances net of payments (£)	12.06 (30.92)	[-48.55, 72.66]	0.6966	3431.69

Notes: Table shows average treatment effects after seven statement cycles. Each row of table shows estimates from separate regressions with different outcomes. Estimated treatment effects from the coefficient (δ_7) on interaction terms between treatment indicator and the seventh statement cycle indicator in the OLS regression specified in Equation 1. Regressions also include: interactions between treatment indicator and other statement cycles, statement cycle fixed effects, year-month fixed effects, and the following controls: Gender, Age, Age squared, Log Estimated Income, Credit Score, Unsecured Debt-to-Income (DTI) Ratio, Any Mortgage Debt, Log Credit Card Credit Limit, Credit Card Purchases Rate, Subprime Credit Card, Any Credit Card Promotional Rate, Any Credit Card Balance Transfer, Credit Card Open Date, Credit Card Statement Day, Any Credit Card Secondary Cardholder. These are all from the time of card origination except for the variables constructed from consumer credit reporting data (Credit Score, DTI Ratio and Any Mortgage Debt), which are from the month preceding card origination. For outcomes constructed from consumer credit reporting data up to eleven dummies for lags of outcomes are included as controls (X_i') for months preceding the start of the experiment. Standard errors are clustered at consumer-level. There are 40,708 credit cards with 368,162 observations.

Table A5—Average treatment effects for outcomes pooled across all statement cycles

Outcome	Estimate, p.p. (s.e.)	95% C.I.	P value	Control mean
Any minimum payment	-0.0807 (0.0033)	[-0.0871, -0.0742]	0.0000	0.2943
Any full payment	0.0041 (0.0028)	[-0.0015, 0.0096]	0.1489	0.2658
Any missed payment	0.0040 (0.0011)	[0.0019, 0.0062]	0.0002	0.0297
Statement balance net of payments (% statement balance)	-0.0056 (0.0027)	[-0.0109, -0.0003]	0.0380	0.6692
Costs (% statement balance)	-0.0001 (0.0002)	[-0.0006, 0.0003]	0.5166	0.0109
Spending (% statement balance)	0.0012 (0.0020)	[-0.0027, 0.0052]	0.5430	0.2918
Share of credit card portfolio only paying minimum	-0.0266 (0.0017)	[-0.0298, -0.0233]	0.0000	0.1631
Share of credit card portfolio making full payment	0.0002 (0.0023)	[-0.0043, 0.0048]	0.9190	0.5150
Share of credit card portfolio missing payment	0.0004 (0.0007)	[-0.0009, 0.0017]	0.5400	0.0144
Credit card portfolio balances net of payments (% statement balances)	-0.0036 (0.0022)	[-0.0079, 0.0006]	0.0967	0.6245
Statement balance (£)	3.59 14.94	[-25.70, 32.87]	0.8103	2049.8420
Statement balance net of payments (£)	3.98 14.92	[-25.26, 33.21]	0.7897	1862.3909
Spending (£)	-2.46 2.65	[-7.66, 2.74]	0.3544	395.5314
Costs (£)	0.19 0.12	[-0.04, 0.42]	0.1146	10.6055
Total payments (£)	-0.39 2.24	[-4.78, 4.00]	0.8611	187.4512
Automatic payments (£)	3.0544 (1.4627)	[0.1874, 5.9214]	0.0368	82.6856
Manual payments (£)	-3.21 1.93	[-6.99, 0.57]	0.0962	105.9518
Any Manual Payment	0.0107 (0.0034)	[0.0041, 0.0173]	0.0015	0.3146
Total payments (% statement balance)	0.0067 (0.0025)	[0.0019, 0.0115]	0.0061	0.2346
Automatic payments (% statement balance)	0.0099 (0.0021)	[0.0058, 0.0140]	0.0000	0.1121
Manual payments (% statement balance)	-0.0021 (0.0020)	[-0.0060, 0.0018]	0.2922	0.1268
Credit card portfolio statement balances (£)	30.60 22.28	[-13.06, 74.26]	0.1696	3506.8973
Credit card portfolio balances net of payments (£)	24.99 22.03	[-18.19, 68.17]	0.2567	2961.2714
Credit card portfolio repayments (£)	4.07 4.33	[-4.42, 12.55]	0.3474	545.7112

Notes: Table shows average treatment effects pooled across statement cycles. Each row of table shows estimates from separate regressions with different outcomes. Estimated treatment effects from the coefficient (δ) on the treatment indicator in the OLS regression specified in Equation 2. Regressions also include: statement cycle fixed effects, year-month fixed effects, and the following controls: Gender, Age, Age squared, Log Estimated Income, Credit Score, Unsecured Debt-to-Income (DTI) Ratio, Any Mortgage Debt, Log Credit Card Credit Limit, Credit Card Purchases Rate, Subprime Credit Card, Any Credit Card Promotional Rate, Any Credit Card Balance Transfer, Credit Card Open Date, Credit Card Statement Day, Any Credit Card Secondary Cardholder. These are all from the time of card origination except for the variables constructed from consumer credit reporting data (Credit Score, DTI Ratio and Any Mortgage Debt), which are from the month preceding card origination. Standard errors are clustered at consumer-level. There are 40,708 credit cards with 368,162 observations.

Table A6—Average treatment effects for tertiary arrears outcomes pooled across all statement cycles

Outcome	Estimate, p.p. (s.e.)	95% C.I.	P value	Control mean
Any missed payment	0.0040 (0.0011)	[0.0019, 0.0062]	0.0002	0.0297
Arrears 1+ payments behind	0.0031 (0.0010)	[0.0011, 0.0051]	0.0024	0.0267
Arrears 2+ payments behind	0.0004 (0.0007)	[-0.0009, 0.0018]	0.5476	0.0110
Arrears 3+ payments behind	0.0002 (0.0005)	[-0.0009, 0.0012]	0.7677	0.0071
Share of credit card portfolio missing payment	0.0004 (0.0007)	[-0.0009, 0.0017]	0.5400	0.0144

Notes: Table shows average treatment effects pooled across statement cycles. Each row of table shows estimates from separate regressions with different outcomes. The first row is our 3rd primary outcome: defined as paying zero or less than the minimum due (on the "target" card in the experiment). The last row is our ninth primary outcome: defined as the proportion of credit cards paying zero or less than the minimum due (constructed from consumer credit reporting data containing the portfolio of credit card held). All other rows show effects for non-primary outcomes for the card in the experiment: standard industry point-in-time measures for the number of payments in arrears was when payments became due. Estimated treatment effects from the coefficient (δ) on the treatment indicator in the OLS regression specified in Equation 2. Regressions also include: statement cycle fixed effects, year-month fixed effects, and the following controls: Gender, Age, Age squared, Log Estimated Income, Credit Score, Unsecured Debt-to-Income (DTI) Ratio, Any Mortgage Debt, Log Credit Card Credit Limit, Credit Card Purchases Rate, Subprime Credit Card, Any Credit Card Promotional Rate, Any Credit Card Balance Transfer, Credit Card Open Date, Credit Card Statement Day, Any Credit Card Secondary Cardholder. These are all from the time of card origination except for the variables constructed from consumer credit reporting data (Credit Score, DTI Ratio and Any Mortgage Debt), which are from the month preceding card origination. For outcomes constructed from consumer credit reporting data up to eleven dummies for lags of outcomes are included as controls (X_i') for months preceding the start of the experiment. Standard errors are clustered at consumer-level. There are 40,708 credit cards with 368,162 observations.

Table A7—Describing compliers (no autopay)

Outcome	Group	Share	Mean	S.E.
Credit score (0-100)	All	1	0.6431	0.0006
Credit score (0-100)	Always Takers (No Autopay)	0.2189	0.6249	0.0015
Credit score (0-100)	Compliers (Autopay to No Autopay)	0.0418	0.6028	0.0135
Credit score (0-100)	Never Takers (Autopay)	0.7393	0.6507	0.0009
Estimated income (£)	All	1	2434.08	10.79
Estimated income (£)	Always Takers (No Autopay)	0.2189	2035.87	26.97
Estimated income (£)	Compliers (Autopay to No Autopay)	0.0418	2038.12	260.09
Estimated income (£)	Never Takers (Autopay)	0.7393	2574.37	18.55
Unsecured Debt to Income (DTI) Ratio	All	1	3.3030	0.0262
Unsecured Debt to Income (DTI) Ratio	Always Takers (No Autopay)	0.2189	3.0764	0.0721
Unsecured Debt to Income (DTI) Ratio	Compliers (Autopay to No Autopay)	0.0418	2.7169	0.6232
Unsecured Debt to Income (DTI) Ratio	Never Takers (Autopay)	0.7393	3.4032	0.0452
Age (years)	All	1	36.53	0.06
Age (years)	Always Takers (No Autopay)	0.2189	33.38	0.18
Age (years)	Compliers (Autopay to No Autopay)	0.0418	31.53	1.55
Age (years)	Never Takers (Autopay)	0.7393	37.75	0.10
Female (% cards)	All	1	0.4609	0.0026
Female (% cards)	Always Takers (No Autopay)	0.2189	0.4683	0.0074
Female (% cards)	Compliers (Autopay to No Autopay)	0.0418	0.5005	0.0606
Female (% cards)	Never Takers (Autopay)	0.7393	0.4564	0.0042
Credit limit (£)	All	1	4347.77	16.67
Credit limit (£)	Always Takers (No Autopay)	0.2189	3260.20	44.10
Credit limit (£)	Compliers (Autopay to No Autopay)	0.0418	2572.29	434.34
Credit limit (£)	Never Takers (Autopay)	0.7393	4770.16	29.14
Purchases rate (%)	All	1	22.83	0.03
Purchases rate (%)	Always Takers (No Autopay)	0.2189	24.82	0.10
Purchases rate (%)	Compliers (Autopay to No Autopay)	0.0418	24.41	0.73
Purchases rate (%)	Never Takers (Autopay)	0.7393	22.15	0.04
Number of credit cards	All	1	2.18	0.01
Number of credit cards	Always Takers (No Autopay)	0.2189	1.71	0.02
Number of credit cards	Compliers (Autopay to No Autopay)	0.0418	1.62	0.23
Number of credit cards	Never Takers (Autopay)	0.7393	2.36	0.02
Number of credit cards with debt	All	1	0.91	0.01
Number of credit cards with debt	Always Takers (No Autopay)	0.2189	0.66	0.01
Number of credit cards with debt	Compliers (Autopay to No Autopay)	0.0418	0.65	0.13
Number of credit cards with debt	Never Takers (Autopay)	0.7393	0.99	0.01
Credit card portfolio balances net of payments (£)	All	1	2036.48	17.70
Credit card portfolio balances net of payments (£)	Always Takers (No Autopay)	0.2189	1290.67	39.18
Credit card portfolio balances net of payments (£)	Compliers (Autopay to No Autopay)	0.0418	826.69	436.51
Credit card portfolio balances net of payments (£)	Never Takers (Autopay)	0.7393	2325.70	30.56
Non-Mortgage Debt Value (£)	All	1	7132.58	51.22
Non-Mortgage Debt Value (£)	Always Takers (No Autopay)	0.2189	5726.35	128.15
Non-Mortgage Debt Value (£)	Compliers (Autopay to No Autopay)	0.0418	6668.40	1198.62
Non-Mortgage Debt Value (£)	Never Takers (Autopay)	0.7393	7575.25	84.05

Notes: Table describes consumers by their observable characteristics at the time of card opening (or before for variables constructed from consumer credit reporting data). We use the approach of Marbach and Hangartner (2020); Hangartner et al. (2021) to estimate the characteristics of three consumer types (as summarized in table below): "Always Takers" who do not receive the treatment and do enroll in any Autopay; "Compliers" who would have enrolled in any Autopay without the treatment but with the treatment do not enroll in any Autopay; and "Never Takers" who receive the treatment and do enroll in any Autopay. These are under the assumption of monotonicity such that the treatment does not make consumers go from no Autopay enrollment to any Autopay enrollment (i.e., No "Defiers"). Autopay enrollment is measured at the seventh statement cycle. N is 40,708 consumers.

	CONTROL (0)	**TREATMENT (1)**
AUTOPAY (0)	Compliers & Never Takers	Never Takers ~~& Defiers~~
NO AUTOPAY (1)	Always Takers ~~& Defiers~~	Compliers & Always Takers

Table A8—Describing compliers (no minimum payment)

Outcome	Group	Share	Mean	S.E.
Credit score (0-100)	All	1	0.6431	0.0005
Credit score (0-100)	Always Takers (No Min Pay)	0.6988	0.6476	0.0009
Credit score (0-100)	Compliers (Min Pay to No Min Pay)	0.0689	0.6412	0.0079
Credit score (0-100)	Never Takers (Min Pay)	0.2323	0.6301	0.0017
Estimated income (£)	All	1	2434.08	10.92
Estimated income (£)	Always Takers (No Min Pay)	0.6988	2386.67	17.44
Estimated income (£)	Compliers (Min Pay to No Min Pay)	0.0689	2619.91	150.66
Estimated income (£)	Never Takers (Min Pay)	0.2323	2521.56	31.71
Unsecured Debt to Income (DTI) Ratio	All	1	3.3030	0.0259
Unsecured Debt to Income (DTI) Ratio	Always Takers (No Min Pay)	0.6988	2.8477	0.0420
Unsecured Debt to Income (DTI) Ratio	Compliers (Min Pay to No Min Pay)	0.0689	3.9706	0.3876
Unsecured Debt to Income (DTI) Ratio	Never Takers (Min Pay)	0.2323	4.4747	0.0930
Age (years)	All	1	36.53	0.06
Age (years)	Always Takers (No Min Pay)	0.6988	36.37	0.11
Age (years)	Compliers (Min Pay to No Min Pay)	0.0689	38.73	0.90
Age (years)	Never Takers (Min Pay)	0.2323	36.37	0.16
Female (% cards)	All	1	0.4609	0.0024
Female (% cards)	Always Takers (No Min Pay)	0.6988	0.4607	0.0042
Female (% cards)	Compliers (Min Pay to No Min Pay)	0.0689	0.4704	0.0359
Female (% cards)	Never Takers (Min Pay)	0.2323	0.4585	0.0074
Credit limit (£)	All	1	4347.77	16.82
Credit limit (£)	Always Takers (No Min Pay)	0.6988	3995.30	26.66
Credit limit (£)	Compliers (Min Pay to No Min Pay)	0.0689	4421.98	237.10
Credit limit (£)	Never Takers (Min Pay)	0.2323	5386.20	54.22
Purchases rate (%)	All	1	22.83	0.03
Purchases rate (%)	Always Takers (No Min Pay)	0.6988	23.16	0.05
Purchases rate (%)	Compliers (Min Pay to No Min Pay)	0.0689	23.22	0.44
Purchases rate (%)	Never Takers (Min Pay)	0.2323	21.73	0.07
Number of credit cards	All	1	2.18	0.01
Number of credit cards	Always Takers (No Min Pay)	0.6988	1.99	0.01
Number of credit cards	Compliers (Min Pay to No Min Pay)	0.0689	2.43	0.13
Number of credit cards	Never Takers (Min Pay)	0.2323	2.69	0.03
Number of credit cards with debt	All	1	0.91	0.01
Number of credit cards with debt	Always Takers (No Min Pay)	0.6988	0.74	0.01
Number of credit cards with debt	Compliers (Min Pay to No Min Pay)	0.0689	1.25	0.08
Number of credit cards with debt	Never Takers (Min Pay)	0.2323	1.30	0.02
Credit card portfolio balances net of payments (£)	All	1	2036.48	17.62
Credit card portfolio balances net of payments (£)	Always Takers (No Min Pay)	0.6988	1494.74	23.53
Credit card portfolio balances net of payments (£)	Compliers (Min Pay to No Min Pay)	0.0689	2875.48	251.62
Credit card portfolio balances net of payments (£)	Never Takers (Min Pay)	0.2323	3417.46	65.75
Non-Mortgage Debt Value (£)	All	1	7132.58	49.33
Non-Mortgage Debt Value (£)	Always Takers (No Min Pay)	0.6988	5972.58	74.66
Non-Mortgage Debt Value (£)	Compliers (Min Pay to No Min Pay)	0.0689	9101.07	674.35
Non-Mortgage Debt Value (£)	Never Takers (Min Pay)	0.2323	10038.62	170.11

Notes: Table describes consumers by their observable characteristics at the time of card opening (or before for variables constructed from consumer credit reporting data). We use the approach of Marbach and Hangartner (2020); Hangartner et al. (2021) to estimate the characteristics of three consumer types: "Always Takers" who do not receive the treatment and only pay exactly the minimum payment; "Compliers" who would have only paid exactly the minimum payment without the treatment but with the treatment do not pay exactly the minimum payment (i.e., they may pay more or less); and "Never Takers" who receive the treatment and only pay exactly the minimum payment. These are under the assumption of monotonicity such that the treatment does not make consumers go from not paying exactly the minimum to paying exactly the minimum payment (i.e., No "Defiers"). Minimum payment is measured at the seventh statement cycle. N is 40,708 consumers.

	CONTROL (0)	**TREATMENT (1)**
MINIMUM PAYMENT (0)	Compliers & Never Takers	Never Takers ~~& Defiers~~
NO MINIMUM PAYMENT (1)	Always Takers ~~& Defiers~~	Compliers & Always Takers

Table A9—Lee bounds for average treatment effects for outcomes after seven statement cycles

Outcome	Lower Bound	Upper Bound
Any minimum payment	-0.1057	-0.0532
Any full payment	-0.0028	0.0360
Any missed payment	-0.0009	0.0036
Statement balance net of payments (% statement balance)	-0.0338	0.0059
Costs (% statement balance)	-0.0012	0.0041
Spending (% statement balance)	-0.0020	0.0414
Share of credit card portfolio only paying minimum	-0.0448	0.0060
Share of credit card portfolio making full payment	-0.0188	0.0239
Share of credit card portfolio missing payment	-0.0013	0.0054
Credit card portfolio balances net of payments (% statement balances)	-0.0309	0.0021
Statement balance (£)	-73.19	254.99
Statement balance net of payments (£)	-51.60	262.37
Costs (£)	-0.30	2.99
Cumulative costs (£)	-1.32	13.49
Spending (£)	-15.71	85.84
Cumulative spending (£)	-97.60	310.84
Arrears 1+ payments behind	-0.0002	0.0090
Arrears 2+ payments behind	0.0004	0.0009
Arrears 3+ payments behind	0.0003	0.0005
Any Autopay Payment	0.0080	0.0585
Any Manual Payment	-0.0323	0.0207
Total payments (£)	-19.01	84.66
Automatic payments (£)	-2.0348	42.0977
Manual payments (£)	-16.02	67.07
Total payments (% statement balance)	-0.0008	0.0435
Automatic payments (% statement balance)	0.0046	0.0571
Manual payments (% statement balance)	-0.0091	0.0488
Cumulative total payments (£)	-49.33	304.33
Cumulative automatic payments (£)	21.21	249.63
Cumulative manual payments (£)	-89.30	200.32

Notes: Table shows Lee Bounds (Lee, 2009) for the treatment effects on primary outcomes after seven statement cycles (δ_7). To calculate Lee bounds, we adapted public code from Levy (2021) trimming the excess observations and then run regressions. The term δ_7 is one of the coefficients (δ_τ) on interaction terms between treatment indicator and statement cycle indicators in the OLS regression specified in Equation 1. Regressions also include statement cycle fixed effects, year-month fixed effects, and the following controls: Gender, Age, Age squared, Log Estimated Income, Credit Score, Unsecured Debt-to-Income (DTI) Ratio, Any Mortgage Debt, Log Credit Card Credit Limit, Credit Card Purchases Rate, Subprime Credit Card, Any Credit Card Promotional Rate, Any Credit Card Balance Transfer, Credit Card Open Date, Credit Card Statement Day, Any Credit Card Secondary Cardholder. These are all from the time of card origination except for the variables constructed from consumer credit reporting data (Credit Score, DTI Ratio and Any Mortgage Debt), which are from the month preceding card origination. There are 40,708 consumers with 368,162 observations.

TABLE A10—HETEROGENEOUS TREATMENT EFFECTS ON I. ANY AUTOPAY MIN ENROLLMENT AND II. ANY MINIMUM PAYMENT, BY PRE-TRIAL VARIABLES, POOLED ACROSS ALL STATEMENT CYCLES

I: Any Autopay Min Enrollment

Variable	Group	Estimate	S.E.	95% C.I.	P Value	N
Credit Score	Low	-0.26	(0.01)	[-0.27, -0.25]	0.0000	183,504
Credit Score	High	-0.22	(0.01)	[-0.23, -0.21]	0.0000	184,658
Income	Low	-0.23	(0.01)	[-0.24, -0.22]	0.0000	183,841
Income	High	-0.24	(0.01)	[-0.25, -0.23]	0.0000	184,321
Unsecured Debt-to-Income (DTI) Ratio	Low	-0.20	(0.00)	[-0.21, -0.19]	0.0000	183,994
Unsecured Debt-to-Income (DTI) Ratio	High	-0.28	(0.01)	[-0.29, -0.27]	0.0000	184,168
Age	Low	-0.22	(0.01)	[-0.23, -0.21]	0.0000	191,854
Age	High	-0.26	(0.01)	[-0.27, -0.25]	0.0000	176,308
Gender	Male	-0.24	(0.01)	[-0.25, -0.23]	0.0000	198,216
Gender	Female	-0.23	(0.01)	[-0.24, -0.22]	0.0000	169,946
Credit Limit	Low	-0.24	(0.01)	[-0.25, -0.23]	0.0000	184,928
Credit Limit	High	-0.24	(0.01)	[-0.25, -0.22]	0.0000	183,234
Number of Credit Cards in Portfolio	Low	-0.22	(0.00)	[-0.23, -0.21]	0.0000	240,492
Number of Credit Cards in Portfolio	High	-0.27	(0.01)	[-0.28, -0.26]	0.0000	127,670
Number of Credit Cards in Portfolio With Debt	Low	-0.21	(0.00)	[-0.22, -0.21]	0.0000	285,382
Number of Credit Cards in Portfolio With Debt	High	-0.31	(0.01)	[-0.33, -0.29]	0.0000	82,780
Credit Card Portfolio Balances Net of Payments	Low	-0.19	(0.00)	[-0.20, -0.18]	0.0000	183,423
Credit Card Portfolio Balances Net of Payments	High	-0.28	(0.01)	[-0.29, -0.27]	0.0000	184,739

II: Any Minimum Payment

Variable	Group	Estimate	S.E.	95% C.I.	P Value	N
Credit Score	Low	-0.09	(0.00)	[-0.10, -0.08]	0.0000	183,504
Credit Score	High	-0.07	(0.00)	[-0.08, -0.06]	0.0000	184,658
Income	Low	-0.08	(0.00)	[-0.09, -0.07]	0.0000	183,841
Income	High	-0.08	(0.00)	[-0.09, -0.07]	0.0000	184,321
Unsecured Debt-to-Income (DTI) Ratio	Low	-0.06	(0.00)	[-0.07, -0.06]	0.0000	183,994
Unsecured Debt-to-Income (DTI) Ratio	High	-0.10	(0.01)	[-0.11, -0.09]	0.0000	184,168
Age	Low	-0.07	(0.00)	[-0.08, -0.06]	0.0000	191,854
Age	High	-0.09	(0.00)	[-0.10, -0.09]	0.0000	176,308
Gender	Male	-0.08	(0.00)	[-0.09, -0.07]	0.0000	198,216
Gender	Female	-0.08	(0.00)	[-0.09, -0.07]	0.0000	169,946
Credit Limit	Low	-0.09	(0.00)	[-0.09, -0.08]	0.0000	184,928
Credit Limit	High	-0.08	(0.01)	[-0.09, -0.07]	0.0000	183,234
Number of Credit Cards in Portfolio	Low	-0.08	(0.00)	[-0.08, -0.07]	0.0000	240,492
Number of Credit Cards in Portfolio	High	-0.09	(0.01)	[-0.10, -0.08]	0.0000	127,670
Number of Credit Cards in Portfolio With Debt	Low	-0.07	(0.00)	[-0.08, -0.06]	0.0000	285,382
Number of Credit Cards in Portfolio With Debt	High	-0.11	(0.01)	[-0.13, -0.10]	0.0000	82,780
Credit Card Portfolio Balances Net of Payments	Low	-0.06	(0.00)	[-0.07, -0.05]	0.0000	183,423
Credit Card Portfolio Balances Net of Payments	High	-0.10	(0.01)	[-0.11, -0.09]	0.0000	184,739

Notes: Table shows heterogeneous treatment effects pooled across statement cycles. Estimated treatment effects from the coefficient (δ) on the treatment indicator in the OLS regression specified in Equation 2. Regressions also include statement cycle fixed effects, year-month fixed effects, and the following controls: Gender, Age, Age squared, Log Estimated Income, Credit Score, Unsecured Debt-to-Income (DTI) Ratio, Any Mortgage Debt, Log Credit Card Credit Limit, Credit Card Purchases Rate, Subprime Credit Card, Any Credit Card Promotional Rate, Any Credit Card Balance Transfer, Credit Card Open Date, Credit Card Statement Day, Any Credit Card Secondary Cardholder. These are all from the time of card origination except for the variables constructed from consumer credit reporting data (Credit Score, DTI Ratio and Any Mortgage Debt), which are from the month preceding card origination. Error bars are 95% confidence intervals. Standard errors are clustered at consumer-level. Each estimate is from a separate regression for subsamples by quartiles of each heterogeneous variable. Heterogeneous variables are calculated from consumer credit reporting data in month preceding credit card opening. N = 40,708 consumers in total across heterogeneous groups.

Table A11—Heterogeneous treatment effects on credit card debt, by pre-trial variables, pooled across all statement cycles

I: Credit card debt measured by statement balance net of payments (% statement balance)

Variable	Quartile	Estimate	S.E.	95% C.I.	P Value	N
Credit Score	Low	-0.0076	(0.0038)	[-0.0150, -0.0002]	0.0433	183,504
Credit Score	High	-0.0036	(0.0039)	[-0.0111, 0.0040]	0.3560	184,658
Income	Low	-0.0040	(0.0040)	[-0.0118, 0.0037]	0.3075	183,841
Income	High	-0.0063	(0.0037)	[-0.0135, 0.0010]	0.0895	184,321
Unsecured Debt-to-Income (DTI) Ratio	Low	-0.0143	(0.0043)	[-0.0228, -0.0059]	0.0009	183,994
Unsecured Debt-to-Income (DTI) Ratio	High	0.0025	(0.0032)	[-0.0038, 0.0088]	0.4372	184,168
Age	Low	-0.0093	(0.0039)	[-0.0169, -0.0017]	0.0161	191,854
Age	High	-0.0013	(0.0037)	[-0.0087, 0.0060]	0.7259	176,308
Gender	Male	-0.0080	(0.0038)	[-0.0156, -0.0005]	0.0363	198,216
Gender	Female	-0.0022	(0.0038)	[-0.0097, 0.0052]	0.5560	169,946
Credit Limit	Low	-0.0112	(0.0043)	[-0.0195, -0.0028]	0.0089	184,928
Credit Limit	High	0.0014	(0.0034)	[-0.0052, 0.0079]	0.6834	183,234
Number of Credit Cards in Portfolio	Low	-0.0095	(0.0036)	[-0.0165, -0.0025]	0.0076	240,492
Number of Credit Cards in Portfolio	High	0.0014	(0.0040)	[-0.0064, 0.0091]	0.7301	127,670
Number of Credit Cards in Portfolio With Debt	Low	-0.0083	(0.0033)	[-0.0147, -0.0019]	0.0109	285,382
Number of Credit Cards in Portfolio With Debt	High	0.0014	(0.0040)	[-0.0065, 0.0094]	0.7221	82,780
Credit Card Portfolio Balances Net of Payments	Low	-0.0126	(0.0045)	[-0.0215, -0.0037]	0.0057	183,423
Credit Card Portfolio Balances Net of Payments	High	0.0008	(0.0028)	[-0.0046, 0.0062]	0.7629	184,739

II: Credit card debt measured by statement balance net of payments (£)

Variable	Group	Estimate	S.E.	95% C.I.	P Value	N
Credit Score	Low	-1.83	(17.52)	[-36.17, 32.51]	0.9168	183,504
Credit Score	High	-1.46	(23.90)	[-48.31, 45.39]	0.9514	184,658
Income	Low	23.07	(16.55)	[-9.38, 55.51]	0.1635	183,841
Income	High	-23.12	(23.95)	[-70.06, 23.82]	0.3344	184,321
Unsecured Debt-to-Income (DTI) Ratio	Low	2.74	(16.81)	[-30.21, 35.69]	0.8705	183,994
Unsecured Debt-to-Income (DTI) Ratio	High	-12.79	(22.91)	[-57.69, 32.12]	0.5767	184,168
Age	Low	-32.19	(17.21)	[-65.93, 1.55]	0.0615	191,854
Age	High	42.05	(24.44)	[-5.85, 89.95]	0.0854	176,308
Gender	Male	0.17	(21.22)	[-41.42, 41.76]	0.9936	198,216
Gender	Female	9.66	(20.66)	[-30.83, 50.15]	0.6401	169,946
Credit Limit	Low	-13.88	(9.63)	[-32.75, 4.99]	0.1493	184,928
Credit Limit	High	25.98	(30.79)	[-34.36, 86.32]	0.3987	183,234
Number of Credit Cards in Portfolio	Low	2.83	(15.55)	[-27.66, 33.31]	0.8558	240,492
Number of Credit Cards in Portfolio	High	5.29	(29.59)	[-52.71, 63.29]	0.8581	127,670
Number of Credit Cards in Portfolio With Debt	Low	3.53	(14.93)	[-25.74, 32.79]	0.8133	285,382
Number of Credit Cards in Portfolio With Debt	High	-5.32	(36.87)	[-77.59, 66.94]	0.8852	82,780
Credit Card Portfolio Balances Net of Payments	Low	-10.37	(14.77)	[-39.31, 18.58]	0.4827	183,423
Credit Card Portfolio Balances Net of Payments	High	5.25	(23.11)	[-40.05, 50.55]	0.8203	184,739

Notes: Table shows heterogeneous treatment effects pooled across statement cycles. Outcome in Panel I is statement balance net of payments, as a percent of statement balance. Outcome in Panel II is statement balance net of payments, measured in £. Estimated treatment effects from the coefficient (δ) on the treatment indicator in the OLS regression specified in Equation 2. Regressions also include statement cycle fixed effects, year-month fixed effects, and the following controls: Gender, Age, Age squared, Log Estimated Income, Credit Score, Unsecured Debt-to-Income (DTI) Ratio, Any Mortgage Debt, Log Credit Card Credit Limit, Credit Card Purchases Rate, Subprime Credit Card, Any Credit Card Promotional Rate, Any Credit Card Balance Transfer, Credit Card Open Date, Credit Card Statement Day, Any Credit Card Secondary Cardholder. These are all from the time of card origination except for the variables constructed from consumer credit reporting data (Credit Score, DTI Ratio and Any Mortgage Debt), which are from the month preceding card origination. Error bars are 95% confidence intervals. Standard errors are clustered at consumer-level. Each estimate is from a separate regression for subsamples by quartiles of each heterogeneous variable. Heterogeneous variables are calculated from consumer credit reporting data in month preceding credit card opening. N = 40,708 consumers in total across heterogeneous groups.

B. Results for Second Lender

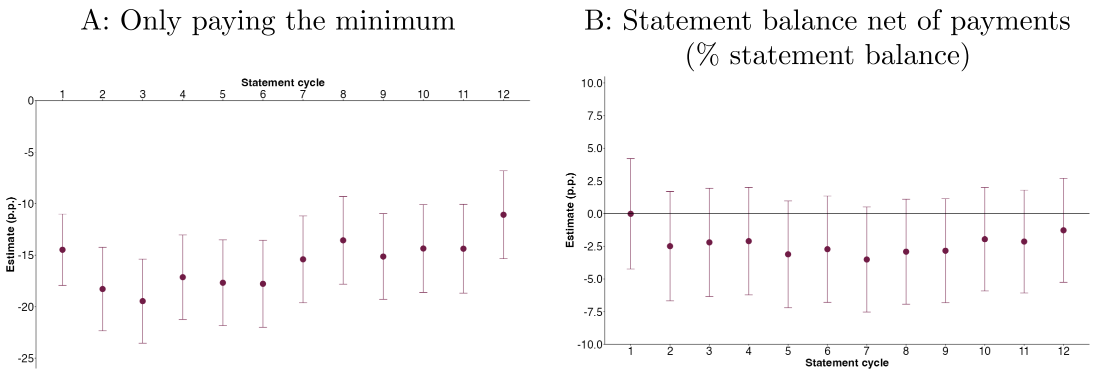


Figure B1. Second Lender - Average treatment effects on making only a minimum payment (panel A) and credit card debt (panel B), across 1-12 statement cycles

Notes: Outcome in Panel A is primary outcome measure for an indicator of making exactly only the minimum payment, and in Panel B is credit card debt is measured by primary outcome measure: statement balance net of payments (% statement balance). Treatment effects from the coefficients (δ_τ) on interaction terms between treatment indicator and statement cycle indicators in the OLS regression specified in Equation 1. Regressions also include statement cycle fixed effects, year-month fixed effects, and the following controls: Gender, Age, Age squared, Log Estimated Income, Credit Score, Unsecured Debt-to-Income (DTI) Ratio, Any Mortgage Debt, Log Credit Card Credit Limit, Credit Card Purchases Rate, Subprime Credit Card, Any Credit Card Promotional Rate, Any Credit Card Balance Transfer, Credit Card Open Date, Credit Card Statement Day, Any Credit Card Secondary Cardholder. These are all from the time of card origination except for the variables constructed from consumer credit reporting data (Credit Score, DTI Ratio and Any Mortgage Debt), which are from the month preceding card origination. Error bars are 95% confidence intervals. Standard errors are clustered at consumer-level. There are 1,531 credit cards with 19,578 observations.

Table B1—Second Lender: Balance comparison

Outcome	Control	Treatment	Difference (p.p.)	95% C.I.
Age (years)	37.05	36.48	-0.57	[-1.78, 0.63]
Female (% cards)	0.4774	0.5264	0.0490	[-0.0016, 0.0995]
Any estimated income	0.9248	0.9395	0.0148	[-0.0107, 0.0402]
Estimated income (£)	2073.02	1890.86	-182.16	[-349.54, -14.78]
Credit limit (£)	608.96	587.39	-21.57	[-82.07, 38.93]
Any credit score	0.9863	0.9897	0.0034	[-0.0076, 0.0144]
Credit score (0-100)	0.5369	0.5406	0.0036	[-0.0057, 0.0129]
Purchases rate (%)	22.97	23.46	0.49	[-0.69, 1.67]
Any balance transfer offered	0.1724	0.1699	-0.0025	[-0.0406, 0.0356]
Number of credit cards	2.04	2.00	-0.04	[-0.18, 0.11]
Number of credit cards with debt	0.64	0.63	-0.01	[-0.10, 0.09]
Credit card portfolio statement balances (£)	934.21	872.64	-61.56	[-269.93, 146.80]
Credit card portfolio balances net of payments (£)	855.74	803.06	-52.68	[-249.61, 144.25]

Notes: N (control) = 740 and N (treatment) = 791 cards.

Table B2—Second Lender: Average treatment effects after seven statement cycles

Outcome	Estimate, p.p. (s.e.)	95% C.I.	P value	Control mean
Any minimum payment	-0.1541	[-0.1962,	0.0000	0.3160
	(0.0215)	-0.1119]		
Any full payment	0.0223	[-0.0207,	0.3092	0.2503
	(0.0219)	0.0653]		
Any missed payment	0.0089	[-0.0244,	0.6011	0.1176
	(0.0170)	0.0421]		
Statement balance net of payments	-0.0351	[-0.0753,	0.0874	0.6753
(% statement balance)	(0.0205)	0.0051]		
Costs	-0.0089	[-0.0168,	0.0276	0.0391
(% statement balance)	(0.0040)	-0.0010]		
Spending	0.0122	[-0.0241,	0.5113	0.2245
(% statement balance)	(0.0185)	0.0485]		
Share of credit card portfolio	-0.0814	[-0.1080,	0.0000	0.2016
only paying minimum	(0.0136)	-0.0549]		
Share of credit card portfolio	0.0089	[-0.0278,	0.6342	0.3455
making full payment	(0.0187)	0.0456]		
Share of credit card portfolio	0.0120	[-0.0123,	0.3315	0.0904
missing payment	(0.0124)	0.0363]		
Credit card portfolio balances	-0.0274	[-0.0627,	0.1276	0.7281
net of payments (% statement balances)	(0.0180)	0.0078]		
Any autopay	-0.0512	[-0.0932,	0.0169	0.7606
	(0.0214)	-0.0092]		
Autopay full	0.0308	[-0.0012,	0.0592	0.1081
	(0.0163)	0.0628]		
Autopay fix	0.3036	[0.2588,	0.0000	0.1860
	(0.0229)	0.3484]		
Autopay min	-0.3856	[-0.4266,	0.0000	0.4665
	(0.0209)	-0.3447]		

Notes: Table shows the treatment effects on primary outcomes after seven statement cycles (δ_7). This treatment effect is one of the coefficients (δ_τ) on interaction terms between treatment indicator and statement cycle indicators in the OLS regression specified in Equation 1. Regressions also include statement cycle fixed effects, year-month fixed effects, and the following controls: Gender, Age, Age squared, Log Estimated Income, Credit Score, Unsecured Debt-to-Income (DTI) Ratio, Any Mortgage Debt, Log Credit Card Credit Limit, Credit Card Purchases Rate, Subprime Credit Card, Any Credit Card Promotional Rate, Any Credit Card Balance Transfer, Credit Card Open Date, Credit Card Statement Day, Any Credit Card Secondary Cardholder. These are all from the time of card origination except for the variables constructed from consumer credit reporting data (Credit Score, DTI Ratio and Any Mortgage Debt), which are from the month preceding card origination. Error bars are 95% confidence intervals. Standard errors are clustered at consumer-level. There are 1,531 credit cards with 19,578 observations.

C. Tertiary Analysis of Liquid Cash Balances

Bank Account Data Sample Restrictions

We keep bank account data on cardholders who appear to be actively using this bank as their primary bank account for a sustained period of time meeting the following criteria: where we observe a solely-held checking account for six months to June 2017, first observed the account at least 180 days before card opening, and where the 3 month moving average of account credits average at least £250 and account debits at least £100 per month during this time (our approach is similar to other research using similar datasets e.g., Ganong and Noel, 2019). For these cardholders we include their liquid cash savings from any other checking accounts held as well as non-checking cash savings accounts with instant access. The choice of threshold used produces similar sample sizes: requiring average account credits and debits are both £500 results in 3,552 cardholders compared to a threshold of £100 that results in 3,831 cardholders. These cardholders are more likely to be younger, with higher incomes and credit scores, fewer credit cards and lower credit card debts as shown in an earlier version of this paper (Guttman-Kenney, 2024).

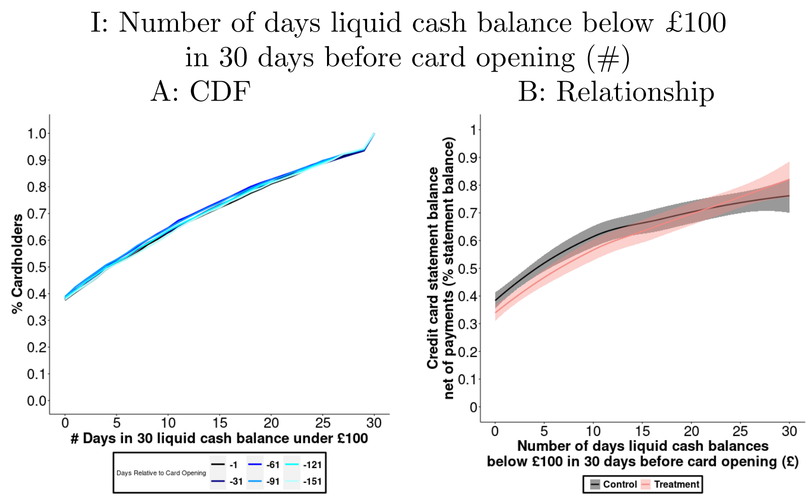


Figure C1. CDF of low liquid cash balances measured before card opening (Panel A) and its non-parametric relationship with credit card debt (statement balance net of payments as a % of statement balance) at statement cycle seven, by treatment group (Panel B)

Notes: N = 3,753 consumers. Panels A is CDF. Panel B is loess. Low Liquid Cash Balance Days shows the number of days when a consumer's liquid cash balances is under £100 in the 30 days before card opening. This is also a dynamic measure where £100 is an arbitrary choice to reflect that not all transactions can be paid with credit cards and therefore consumers may need a positive amount of cash. Different colors in Figure V Panel A show the overall distribution of this variable is stable if calculated at different points-in-time 30 to 150 days before card opening, however, as with our first measure, it may vary for individual consumers over time.

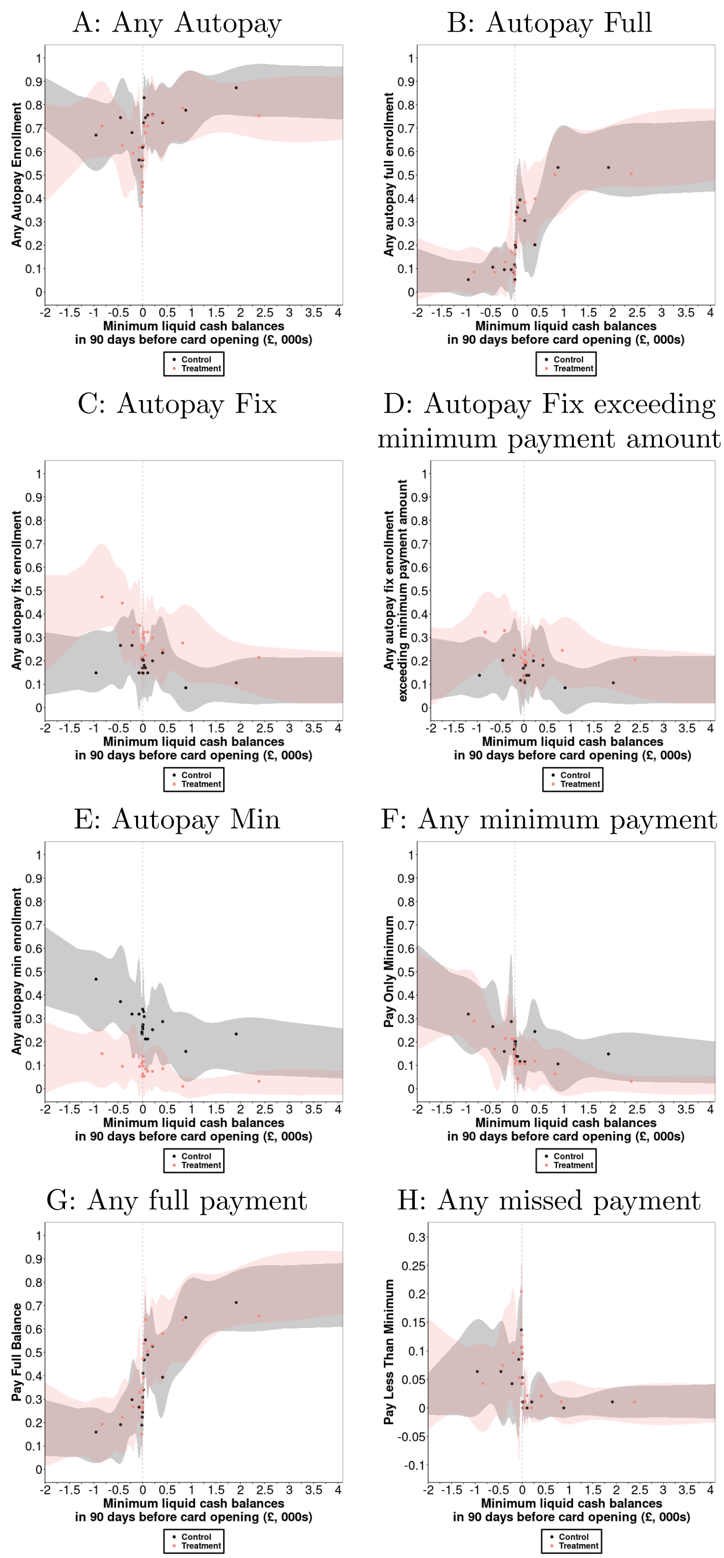


Figure C2. Binned scatterplots of relationship between minimum liquid cash balance during 90 days before card opening with credit card outcomes at statement cycle 7, by treatment group

Notes: N = 3,753 consumers. Liquid cash balances are measured before credit card opening. Panels are binned scatterplots by quantiles of the distribution where error bands are 95% confidence intervals (Cattaneo et al., 2024). X-axes are censored to ease presentation given a fat tail to the distribution of these variables.

Table C1—Summary statistics on I. liquid cash balances by date preceding credit card opening, and II. minimum liquid cash balances over windows preceding credit card opening

I: Liquid cash balances by date preceding credit card opening

Date	Mean	S.D.	P10	P25	P50	P75	P90
-1	2109.85	12324.35	-84.58	48.07	368.65	1,310.91	4,054.58
-31	2142.00	14616.85	-95.17	56.37	364.06	1,297.43	3,757.13
-61	2048.65	9222.26	-61.84	66.93	432.80	1,394.05	4,094.95
-91	2342.60	22005.76	-38.10	66.26	433.57	1,397.41	3,986.56
-121	2164.82	14861.37	-59.16	55.72	396.25	1,401.18	3,949.21
-151	1800.46	7761.59	-75.71	57.62	386.68	1,342.17	3,508.93

II: Minimum liquid cash balances over windows preceding credit card opening

Window	Mean	S.D.	P10	P25	P50	P75	P90
-1 to -31	962.86	5771.79	-487.79	-6.41	24.67	336.62	1,960.99
-1 to -61	780.91	5421.16	-552.73	-14.93	9.50	207.14	1,537.36
-1 to -91	671.38	5107.10	-597.80	-23.85	4.76	142.39	1,296.70
-1 to -121	583.06	4906.39	-629.34	-39.28	2.39	107.63	1,080.03
-1 to -151	485.62	4414.11	-687.15	-51.36	1.08	81.96	909.11

Notes: N = 3,753 consumers. Liquid cash balance is sum of end of day current/checking account and cash saving account balances. Minimum liquid cash balance is minimum value of liquid cash (sum of end of day current/checking account and cash saving account balances) reached by a consumer over 30 to 150 day windows.

Table C2—Correlations with liquid cash balances

Outcome	Liquid Cash Balance	Minimum Liquid Cash Balance	Low Liquid Cash Balance Days
Liquid Cash Balance (£)	0.4720	1	-0.1538
Minimum Liquid Cash Balance (£)	1	0.4720	-0.2083
Low Liquid Cash Balance Days (#)	-0.2083	-0.1538	1
Any minimum payment	-0.0808	-0.0520	0.1545
Any full payment	0.1488	0.1181	-0.3222
Any missed payment	-0.0267	-0.0306	0.1900
Statement balance net of payments (% statement balance)	-0.1554	-0.1213	0.3411
Costs (% statement balance)	-0.0197	-0.0179	0.0622
Spending (% statement balance)	0.0532	0.0274	-0.2091
Share of credit card portfolio only paying minimum	-0.0818	-0.0560	0.1778
Share of credit card portfolio making full payment	0.1406	0.1174	-0.3201
Share of credit card portfolio missing payment	-0.0278	-0.0291	0.1686
Credit card portfolio balances net of payments (% statement balances)	-0.1649	-0.1282	0.3409
Statement balance (£)	-0.1004	-0.0601	0.1633
Statement balance net of payments (£)	-0.1043	-0.0633	0.1764
Cumulative total payments (£)	0.0415	0.0413	-0.0841
Cumulative spending (£)	-0.0427	-0.0144	0.0541
Credit card portfolio statement balances (£)	-0.0770	-0.0378	0.1513
Credit card portfolio balances net of payments (£)	-0.0985	-0.0514	0.1695
Credit score (0-100)	0.0797	0.0803	-0.2347
Estimated income (£)	0.0720	0.1008	-0.0904
Unsecured Debt to Income (DTI) Ratio	-0.0394	-0.0148	0.0603
Age (years)	0.1076	0.1121	-0.0963
Purchases rate (%)	-0.0636	-0.0810	0.1764
Credit limit (£)	0.0576	0.0751	-0.1302

Notes: Table shows correlations between measures of liquid cash balances, outcomes observed after seven completed cycles, and heterogeneous variables observed at card-opening. Liquid cash balances are calculated from bank account data preceding credit card opening. The variable "Minimum Liquid Cash Balance (£)" denotes a heterogeneous cut by the minimum value of liquid cash (sum of end of day current/checking account and cash saving account balances) reached by a consumer in 90 days before card opening. The variable "Minimum Liquid Cash Balance (£)" denotes a heterogeneous cut by the minimum value of liquid cash (sum of end of day current/checking account and cash saving account balances) reached by a consumer in 90 days before card opening. The variable "Liquid Cash Balance

(£)" denotes a heterogeneous cut by the value of liquid cash (sum of end of day current/checking account and cash saving account balances) the day before card opening. The variable "Low Liquid Cash Balance (£)" denotes a heterogeneous cut by the number of days a consumer has under £100 in liquid cash (sum of end of day current/checking account and cash saving account balances) in the 30 days before card opening. N = 3,753 consumers.

Table C3—Heterogeneous treatment effects on I. any Autopay Min enrollment and II. any minimum payment, by pre-trial liquid cash balances, pooled across all statement cycles

I: Any Autopay Min enrollment

Variable	Group	Estimate	S.E.	95% C.I.	P Value	N
Liquid Cash Balance (£)	<£1	-0.3027	(0.0370)	[-0.3752, -0.2302]	0.0000	4,669
Liquid Cash Balance (£)	£1+	-0.1876	(0.0115)	[-0.2102, -0.1650]	0.0000	31,254
Liquid Cash Balance (£)	<£501	-0.2236	(0.0158)	[-0.2545, -0.1927]	0.0000	20,060
Liquid Cash Balance (£)	£501+	-0.1899	(0.0153)	[-0.2199, -0.1600]	0.0000	15,863
Liquid Cash Balance (£)	<£1,001	-0.2166	(0.0140)	[-0.2440, -0.1892]	0.0000	24,970
Liquid Cash Balance (£)	£1,001+	-0.1826	(0.0172)	[-0.2163, -0.1488]	0.0000	10,953
Minimum Liquid Cash Balance (£)	<£1	-0.2574	(0.0193)	[-0.2953, -0.2195]	0.0000	13,434
Minimum Liquid Cash Balance (£)	£1+	-0.1709	(0.0133)	[-0.1969, -0.1448]	0.0000	22,489
Minimum Liquid Cash Balance (£)	<£501	-0.2186	(0.0125)	[-0.2430, -0.1941]	0.0000	30,186
Minimum Liquid Cash Balance (£)	£501+	-0.1159	(0.0209)	[-0.1569, -0.0749]	0.0000	5,737
Minimum Liquid Cash Balance (£)	<£1,001	-0.2133	(0.0121)	[-0.2370, -0.1897]	0.0000	31,841
Minimum Liquid Cash Balance (£)	£1,001+	-0.1236	(0.0211)	[-0.1649, -0.0822]	0.0000	4,082
Low Liquid Cash Balance Days (#)	0 days	-0.1635	(0.0156)	[-0.1942, -0.1329]	0.0000	13,549
Low Liquid Cash Balance Days (#)	1+ days	-0.2264	(0.0148)	[-0.2555, -0.1973]	0.0000	22,374
Low Liquid Cash Balance Days (#)	<16 days	-0.1822	(0.0125)	[-0.2066, -0.1578]	0.0000	25,977
Low Liquid Cash Balance Days (#)	16+ days	-0.2591	(0.0235)	[-0.3053, -0.2130]	0.0000	9,946

II: Any Minimum Payment

Variable	Group	Estimate	S.E.	95% C.I.	P Value	N
Liquid Cash Balance (£)	<£1	-0.0840	(0.0308)	[-0.1443, -0.0236]	0.0066	4,669
Liquid Cash Balance (£)	£1+	-0.0591	(0.0088)	[-0.0764, -0.0419]	0.0000	31,254
Liquid Cash Balance (£)	<£501	-0.0615	(0.0124)	[-0.0858, -0.0371]	0.0000	20,060
Liquid Cash Balance (£)	£501+	-0.0688	(0.0114)	[-0.0912, -0.0464]	0.0000	15,863
Liquid Cash Balance (£)	<£1,001	-0.0549	(0.0109)	[-0.0763, -0.0335]	0.0000	24,970
Liquid Cash Balance (£)	£1,001+	-0.0811	(0.0128)	[-0.1062, -0.0560]	0.0000	10,953
Minimum Liquid Cash Balance (£)	<£1	-0.0794	(0.0160)	[-0.1107, -0.0482]	0.0000	13,434
Minimum Liquid Cash Balance (£)	£1+	-0.0511	(0.0097)	[-0.0702, -0.0320]	0.0000	22,489
Minimum Liquid Cash Balance (£)	<£501	-0.0632	(0.0098)	[-0.0824, -0.0441]	0.0000	30,186
Minimum Liquid Cash Balance (£)	£501+	-0.0522	(0.0162)	[-0.0840, -0.0204]	0.0014	5,737
Minimum Liquid Cash Balance (£)	<£1,001	-0.0638	(0.0094)	[-0.0823, -0.0453]	0.0000	31,841
Minimum Liquid Cash Balance (£)	£1,001+	-0.0493	(0.0173)	[-0.0832, -0.0155]	0.0045	4,082
Low Liquid Cash Balance Days (#)	0 days	-0.0609	(0.0125)	[-0.0854, -0.0364]	0.0000	13,549
Low Liquid Cash Balance Days (#)	1+ days	-0.0620	(0.0115)	[-0.0844, -0.0395]	0.0000	22,374
Low Liquid Cash Balance Days (#)	<16 days	-0.0555	(0.0095)	[-0.0741, -0.0369]	0.0000	25,977
Low Liquid Cash Balance Days (#)	16+ days	-0.0759	(0.0187)	[-0.1126, -0.0392]	0.0001	9,946

Notes: Table shows heterogeneous treatment effects pooled across statement cycles. Outcome in Panel I is any Autopay Min enrollment, and outcome in Panel II is only paying the minimum. Estimated treatment effects from the coefficient (δ) on the treatment indicator in the OLS regression specified in Equation 2. Regressions also include statement cycle fixed effects, year-month fixed effects, and the following controls: Gender, Age, Age squared, Log Estimated Income, Credit Score, Unsecured Debt-to-Income (DTI) Ratio, Any Mortgage Debt, Log Credit Card Credit Limit, Credit Card Purchases Rate, Subprime Credit Card, Any Credit Card Promotional Rate, Any Credit Card Balance Transfer, Credit Card Open Date, Credit Card Statement Day, Any Credit Card Secondary Cardholder. These are all from the time of card origination except for the variables constructed from consumer credit reporting data (Credit Score, DTI Ratio and Any Mortgage Debt), which are from the month preceding card origination. Error bars are 95% confidence intervals. Standard errors are clustered at consumer-level. Each estimate is from a separate regression for subsamples by each heterogeneous variable. Heterogeneous variables are calculated from bank account data preceding credit card opening. The variable "Minimum Liquid Cash Balance (£)" denotes a heterogeneous cut by the minimum value of liquid cash (sum of end of day current/checking account and cash saving account balances) reached by a consumer in 90 days before card opening. The variable "Minimum Liquid Cash Balance (£)" denotes a heterogeneous cut by the minimum value of liquid cash (sum of end of day current/checking account and cash saving account *balances) reached by a consumer in 90 days before card opening. The variable "Liquid Cash Balance (£)" denotes a heterogeneous cut by the value of liquid cash (sum of end of day current/checking account and cash saving account balances) the day before card opening. The variable "Low Liquid Cash Balance (£)" denotes a heterogeneous cut by the number of days a consumer has under £100 in liquid cash (sum of end of day current/checking account and cash saving account balances) in the 30 days before card opening. The column 'Group' denotes the levels of these heterogeneous variables. N = 3,753 consumers in total across heterogeneous groups.*

TABLE C4—HETEROGENEOUS TREATMENT EFFECTS ON CREDIT CARD DEBT, BY PRE-TRIAL LIQUID CASH BALANCES, POOLED ACROSS ALL STATEMENT CYCLES

I: Credit card debt measured by statement balance net of payments (% statement balance)

Variable	Group	Estimate	S.E.	95% C.I.	P Value	N
Liquid Cash Balance (£)	<£1	-0.0276	(0.0232)	[-0.0730, 0.0178]	0.2337	4,669
Liquid Cash Balance (£)	£1+	-0.0178	(0.0113)	[-0.0399, 0.0043]	0.1152	31,254
Liquid Cash Balance (£)	<£501	-0.0130	(0.0137)	[-0.0398, 0.0138]	0.3412	20,060
Liquid Cash Balance (£)	£501+	-0.0342	(0.0149)	[-0.0635, -0.0049]	0.0221	15,863
Liquid Cash Balance (£)	<£1,001	-0.0115	(0.0124)	[-0.0357, 0.0128]	0.3532	24,970
Liquid Cash Balance (£)	£1,001+	-0.0448	(0.0177)	[-0.0795, -0.0100]	0.0117	10,953
Minimum Liquid Cash Balance (£)	<£1	-0.0181	(0.0158)	[-0.0490, 0.0128]	0.2518	13,434
Minimum Liquid Cash Balance (£)	£1+	-0.0163	(0.0131)	[-0.0421, 0.0094]	0.2142	22,489
Minimum Liquid Cash Balance (£)	<£501	-0.0185	(0.0114)	[-0.0407, 0.0038]	0.1043	30,186
Minimum Liquid Cash Balance (£)	£501+	-0.0302	(0.0221)	[-0.0735, 0.0131]	0.1719	5,737
Minimum Liquid Cash Balance (£)	<£1,001	-0.0210	(0.0111)	[-0.0427, 0.0006]	0.0571	31,841
Minimum Liquid Cash Balance (£)	£1,001+	-0.0163	(0.0252)	[-0.0657, 0.0331]	0.5189	4,082
Low Liquid Cash Balance Days (#)	0 days	-0.0237	(0.0163)	[-0.0556, 0.0082]	0.1457	13,549
Low Liquid Cash Balance Days (#)	1+ days	-0.0132	(0.0128)	[-0.0382, 0.0118]	0.3000	22,374
Low Liquid Cash Balance Days (#)	<16 days	-0.0201	(0.0122)	[-0.0440, 0.0039]	0.1010	25,977
Low Liquid Cash Balance Days (#)	16+ days	-0.0036	(0.0175)	[-0.0379, 0.0307]	0.8368	9,946

II: Credit card debt measured by statement balance net of payments (£)

Variable	Group	Estimate	S.E.	95% C.I.	P Value	N
Liquid Cash Balance (£)	<£1	15.14	(108.17)	[-196.88, 227.16]	0.8888	4,669
Liquid Cash Balance (£)	£1+	30.53	(39.52)	[-46.92, 107.99]	0.4398	31,254
Liquid Cash Balance (£)	<£501	-24.32	(48.70)	[-119.77, 71.13]	0.6176	20,060
Liquid Cash Balance (£)	£501+	54.33	(56.34)	[-56.10, 164.76]	0.3350	15,863
Liquid Cash Balance (£)	<£1,001	24.72	(44.49)	[-62.49, 111.92]	0.5786	24,970
Liquid Cash Balance (£)	£1,001+	-13.32	(66.21)	[-143.09, 116.44]	0.8406	10,953
Minimum Liquid Cash Balance (£)	<£1	-12.45	(70.97)	[-151.54, 126.65]	0.8608	13,434
Minimum Liquid Cash Balance (£)	£1+	44.47	(42.27)	[-38.39, 127.32]	0.2930	22,489
Minimum Liquid Cash Balance (£)	<£501	26.97	(42.28)	[-55.89, 109.83]	0.5236	30,186
Minimum Liquid Cash Balance (£)	£501+	-39.34	(70.57)	[-177.66, 98.98]	0.5774	5,737
Minimum Liquid Cash Balance (£)	<£1,001	21.65	(40.79)	[-58.29, 101.59]	0.5955	31,841
Minimum Liquid Cash Balance (£)	£1,001+	24.16	(81.26)	[-135.11, 183.42]	0.7664	4,082
Low Liquid Cash Balance Days (#)	0 days	43.97	(55.99)	[-65.77, 153.70]	0.4324	13,549
Low Liquid Cash Balance Days (#)	1+ days	0.17	(49.76)	[-97.36, 97.69]	0.9973	22,374
Low Liquid Cash Balance Days (#)	<16 days	37.04	(42.54)	[-46.34, 120.41]	0.3840	25,977
Low Liquid Cash Balance Days (#)	16+ days	-7.10	(73.42)	[-151.00, 136.80]	0.9230	9,946

Notes: Table shows heterogeneous treatment effects pooled across statement cycles. Outcome in Panel I is statement balance net of payments, as a percent of statement balance. Outcome in Panel II is statement balance net of payments, measured in £. Estimated treatment effects from the coefficient (δ) on the treatment indicator in the OLS regression specified in Equation 2. Regressions also include statement cycle fixed effects, year-month fixed effects, and the following controls: Gender, Age, Age squared, Log Estimated Income, Credit Score, Unsecured Debt-to-Income (DTI) Ratio, Any Mortgage Debt, Log Credit Card Credit Limit, Credit Card Purchases Rate, Subprime Credit Card, Any Credit Card Promotional Rate, Any Credit Card Balance Transfer, Credit Card Open Date, Credit Card Statement Day, Any Credit Card Secondary Cardholder. These are all from the time of card origination except for the variables constructed from consumer credit reporting data (Credit Score, DTI Ratio and Any Mortgage Debt), which are from the month preceding card origination. Error bars are 95% confidence intervals. Standard errors are clustered at consumer-level. Each estimate is from a separate regression for subsamples by each heterogeneous variable. Heterogeneous variables are calculated from bank account data preceding credit card opening. The variable "Minimum Liquid Cash Balance (£)" denotes a heterogeneous cut by the minimum value of liquid cash (sum of end of day current/checking account and cash saving account balances) reached by a consumer in 90 days before card opening. The variable "Minimum Liquid Cash Balance (£)" denotes a heterogeneous cut by the minimum value of liquid cash *(sum of end of day current/checking account and cash saving account balances) reached by a consumer in 90 days before card opening. The variable "Liquid Cash Balance (£)" denotes a heterogeneous cut by the value of liquid cash (sum of end of day current/checking account and cash saving account balances) the day before card opening. The variable "Low Liquid Cash Balance (£)" denotes a heterogeneous cut by the number of days a consumer has under £100 in liquid cash (sum of end of day current/checking account and cash saving account balances) in the 30 days before card opening. The column 'Group' denotes the levels of these heterogeneous variables. N = 3,753 consumers in total across heterogeneous groups.*

Table C5—T-tests for difference in treatment effects on credit card debt, high compared to low pre-trial liquid cash, pooled across all statement cycles

I: Credit card debt measured by statement balance net of payments (% statement balance)

Variable	Group	High Liquid Cash (%)	High - Low	95% C.I.	P Value
Liquid Cash Balance (£)	£1+	86.97	0.0098	[0.0085, 0.0111]	0.0000
Liquid Cash Balance (£)	£501+	44.10	-0.0212	[-0.0221, -0.0203]	0.0000
Liquid Cash Balance (£)	£1,001+	30.48	-0.0333	[-0.0343, -0.0323]	0.0000
Minimum Liquid Cash Balance (£)	£1+	62.48	0.0018	[0.0009, 0.0027]	0.0002
Minimum Liquid Cash Balance (£)	£501+	15.93	-0.0117	[-0.0129, -0.0105]	0.0000
Minimum Liquid Cash Balance (£)	£1,001+	11.35	0.0047	[0.0033, 0.0061]	0.0000
Low Liquid Cash Balance Days (#)	0 days	37.60	-0.0105	[-0.0114, -0.0096]	0.0000
Low Liquid Cash Balance Days (#)	<16 days	72.18	-0.0165	[-0.0175, -0.0155]	0.0000

II: Credit card debt measured by statement balance net of payments (£)

Variable	Group	High Liquid Cash (%)	High - Low	95% C.I.	P Value
Liquid Cash Balance (£)	£1+	86.97	15.39	[10.30, 20.49]	0.0000
Liquid Cash Balance (£)	£501+	44.10	78.65	[75.29, 82.01]	0.0000
Liquid Cash Balance (£)	£1,001+	30.48	-38.04	[-41.66, -34.42]	0.0000
Minimum Liquid Cash Balance (£)	£1+	62.48	56.91	[53.29, 60.53]	0.0000
Minimum Liquid Cash Balance (£)	£501+	15.93	-66.31	[-70.50, -62.12]	0.0000
Minimum Liquid Cash Balance (£)	£1,001+	11.35	2.50	[-2.25, 7.26]	0.3022
Low Liquid Cash Balance Days (#)	0 days	37.60	43.80	[40.35, 47.25]	0.0000
Low Liquid Cash Balance Days (#)	<16 days	72.18	44.14	[40.35, 47.92]	0.0000

Notes: Table shows t-tests comparing differences in heterogeneous treatment effects by high liquid cash subsample compared to low liquid cash subsample. Outcome in Panel I is statement balance net of payments, as a percent of statement balance. Outcome in Panel II is statement balance net of payments, measured in £. Data are pooled across statement cycles. Estimated treatment effects from the coefficient (δ) on the treatment indicator in the OLS regression specified in Equation 2. Regressions also include statement cycle fixed effects, year-month fixed effects, and the following controls: Gender, Age, Age squared, Log Estimated Income, Credit Score, Unsecured Debt-to-Income (DTI) Ratio, Any Mortgage Debt, Log Credit Card Credit Limit, Credit Card Purchases Rate, Subprime Credit Card, Any Credit Card Promotional Rate, Any Credit Card Balance Transfer, Credit Card Open Date, Credit Card Statement Day, Any Credit Card Secondary Cardholder. These are all from the time of card origination except for the variables constructed from consumer credit reporting data (Credit Score, DTI Ratio and Any Mortgage Debt), which are from the month preceding card origination. Error bars are 95% confidence intervals. Standard errors are clustered at consumer-level. Each estimate is from a separate regression for subsamples by each heterogeneous variable. Heterogeneous variables are calculated from bank account data preceding credit card opening. The variable "Minimum Liquid Cash Balance (£)" denotes a heterogeneous cut by the minimum value of liquid cash (sum of end of day current/checking account and cash saving account balances) reached by a consumer in 90 days before card opening. The variable "Minimum Liquid Cash Balance (£)" denotes a heterogeneous cut by the minimum value of liquid cash (sum of end of day current/checking account and cash saving account balances) reached by a consumer in 90 days before card opening. The variable "Liquid Cash Balance (£)" denotes a heterogeneous cut by the value of liquid cash (sum of end of day current/checking account and cash saving account balances) the day before card opening. The variable "Low Liquid Cash Balance (£)" denotes a heterogeneous cut by the number of days a consumer has under £100 in liquid cash (sum of end of day current/checking account and cash saving account balances) in the 30 days before card opening. The column 'Group' denotes the high liquid cash level of these heterogeneous variables. The column 'High Liquid Cash (%)' denotes the percentage of consumers in the high liquid cash group. The column 'High - Low' denotes the difference in treatment effects for the high liquid cash group less the low liquid cash group, with column '95% C.I.' and 'P Value' from the t-test of this difference. N = 3,753 consumers in total across heterogeneous groups.