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

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Abstract

We study how consumer responses to a nudge counteract its intended effect to reduce credit card debt. The nudge shrouds the option to automatically pay only the contractual minimum and increases the salience of a payment option to automatically amortize debt faster. Despite the intervention causing a 21 percentage point increase in enrollment to this salient payment option, debt is not reduced. Such results are explained by three offsetting consumer responses: (i) Automatic payment amounts selected often bind at the contractual minimum; (ii) Automatic payment enrollment decreases – increasing missed payments; and (iii) Manual payments decrease.

Keywords: Household finance, consumer finance, nudges, credit cards

JEL Codes: D04, D12, D14, D15, D18, D90, D91, G20, G28, G50, G51

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1 Introduction

A decade on from the financial crisis, household debt remains a topic of fervent debate with doubts whether borrowers can feasibly pay back such debt.[1] Of household debt, credit card debt attracts particular public attention given its widespread use, high interest rates and large quantities outstanding – over one trillion dollars across the UK and US by the end of 2017.[2] Whether people are able to pay back their credit card debt matters for a country's macroeconomic performance through impacting consumption choices and bank lending decisions. It also matters for microeconomic consumer welfare, considering whether the financial and non-financial costs of borrowing outweigh consumption benefits.

We study how consumer responses to a 'nudge' intervention – changing the way payment options are presented – counteract its intended effect to reduce credit card debt. The intervention tested followed the increasingly widespread adoption of 'nudges' (Sunstein and Thaler, 2008) by governments and regulators with the OECD recording 202 'nudge' units set up across the world.[3] 'Nudges' are often considered a popular policy tool to increase consumer welfare at relatively low cost and legal risk since they do not restrict consumer choice.

This experiment was designed as an ex-ante test to inform a potential regulation the UK financial regulator – the Financial Conduct Authority (FCA) – was considering given its concern over consumers persistently holding credit card debt.[4] Similar to the US, the UK had experienced a rapid rise in credit card debt having doubled 1999 to 2005.[5] However, while the US experienced a significant deleveraging during and after the financial crisis, the UK did not with debt plateauing. From 2014 debts steadily rose again in both countries

[1] https://www.parliament.uk/business/committees/committees-a-z/commons-select/treasury-committee/news-parliament-2017/household-finances-launch-17-19/

[2] https://www.newyorkfed.org/newsevents/news/research/2018/rp180213
https://www.bankofengland.co.uk/-/media/boe/files/statistics/money-and-credit/2018/february-2018.pdf

[3] 202 as at April 2020 oe.cd/nudge

[4] FCA investigation announced in 2014: https://www.fca.org.uk/publication/market-studies/ms14-6-1.pdf, Final report 2016: https://www.fca.org.uk/publication/market-studies/ms14-6-3-credit-card-market-study-final-findings-report.pdf

[5] Sources: Bank of England, Federal Reserve

further prompting increased regulatory scrutiny.

The credit card options we vary are ‘automatic payment’ – also known as autopay or ‘Direct Debit’ – choices which typically allow consumers to enroll into automatically paying the full amount owed, a fixed amount of their choice or only the contractual minimum each month. We conduct a RCT field experiment on 40,708 newly issued UK credit cards where we remove the appearance of an explicit automatic minimum payment option (but such an option is shrouded as remains implicitly available). By removing the explicit appearance of an automatic payment option to pay only the minimum we increase the salience of the automatic fixed payment option which would automatically amortize debt faster - assuming no other changes in behavior.

Automatic payments are used by 42% UK cards (FCA, 2016) and 16-38% US cards (CFPB, 2019) with growing use in both countries. The automatic minimum payment option may only be used by 13-16% of UK credit cards (FCA, 2016; Sakaguchi et al., 2020), however, cardholders with automatic minimum payments often repeatedly pay only the contractual minimum, so barely pay down their credit card debt and incur high interest costs (Sakaguchi et al., 2020). By one regulatory definition of credit card holders in persistent debt – making 9+ minimum payments in a year on interest-bearing cards – 75% had automatic minimum payments (FCA, 2016). As part of a general trend of increasing use of automatic payments over time, automatic minimum payments is also a channel increasingly used by new card openings - for the lender in our trial it accounted for over 20% of new card openings.[6]

We find that this intervention caused a ‘large’ initial effect on automatic payment choices: increasing initial automatic fixed payment enrollment by 21 percentage points. This translates into causing the likelihood of only paying the contractual minimum to fall by seven percentage points. These effects are persistent over time. However, it does not cause an average treatment effect on outcomes of broader economic importance. We observe null effects, on average, on spending, total payments, debt and borrowing costs.

[6] https://www.ukfinance.org.uk/system/files/Summary-UK-Payment-Markets-2018.pdf

Such a large, initial effect which would appear a success, not translating into real economic outcomes is puzzling. Our results are explained by three offsetting consumer responses.

The first offsetting response is automatic fixed payment amounts selected by consumers are often 'too low' – binding at the contractual minimum. By the seventh completed statement cycle the effect of the treatment on enrolling in an automatic fixed payment for an amount *exceeding* the contractual minimum payment is 8.7 percentage points which is less than half the initial 21 percentage point increase in automatic fixed payment enrollment.

The second offsetting effect is that the treatment causes enrollment in *any* type of automatic payment to decrease. Un-enrolled consumers are more likely to miss payments and fall into arrears. The increasing rate of arrears caused by the intervention is temporary. Consumers recover from a missed payment as opposed to entering more severe arrears. This pattern is consistent with un-enrolled consumers forgetting to make a manual payment as shown in Sakaguchi et al. (2020). Yet such temporary arrears are not costless, as consumers often incur late payment fees as a result of missing a payment and, by missing a payment, do not pay down their debt.

The third and final offsetting effect is that although the intervention increased automatic payments (the intended mechanism) this is crowded out by decreased manual payments (e.g. online) among those enrolled in automatic payments. These manual payments are often large, round numbers paid on an infrequent and ad hoc basis. Among consumers with automatic payments set up, manual payments account for over 40% of the total value of payments made. This is despite fewer than one in ten cardholders making a manual payment in a particular month. The average value of a manual payment when made is large - over £400 - compared to automatic payments which average nearer £50. Comparing the effects on automatic compared to manual payments shows the effects almost perfectly offset one another. The intervention is changing the mechanism of payments (automatic vs. manual) not the payment amount.

Our results demonstrate how important it is to consider offsetting consumer responses to nudge interventions. This fits into a broader discussion on the effects of nudges with a growing literature that these may be a less effective policy tool than they initially appeared – though still a valuable addition to a policymaker's armory given their near-zero costs of implementing (Egan, 2013; Allcott and Kessler, 2019; Beshears et al., 2017; Loewenstein and Chater, 2017; Benkert and Netzer, 2018; Jachimowicz et al., 2019; DellaVigna and Linos, 2020).

One remarkable aspect of our findings are the persistence of the effects. We are causing a persistent change in the *type* of payment methods across the statements observed but not the *amounts* of payments. When considering these findings in the theoretical literature two potential explanations come to mind. An adjustment cost model (Bertola and Caballero, 1990) could explain payment behavior but needs a behavioral element to explain the differences in initial automatic payment choices (e.g. automatic minimum payment option operates as a focal point). Alternatively, a rational inattention model (Caplin and Dean, 2015) could explain behavior: consumers regard their initial automatic payment choice as unimportant because they intend to make manual payments (for debt reduction) later on but still typically want an automatic payment set-up as insurance against forgetting to make a payment. If so, consumers are indifferent between automatic minimum payments and automatic fixed payments for amounts above the minimum. For some consumers it may be the mental cost of selecting an automatic fixed amount is too great and opt out of making a decision at all.

An implication of this research is that credit card borrowers are not as inert as they appeared (by rarely altering automatic payment choices, rarely making manual payments and repeatedly making only payments at the contractual minimum). What is ultimately constraining credit card payments? One possibility is borrowers want to reduce their debt but are bounded by economic constraints such as limited liquidity (Carroll, 2001; Gross and Souleles, 2002). Another explanation is psychological barriers such as mental accounting (Thaler, 1985; Prelec and Loewenstein, 1998) prevent them from paying more to reduce their debt.

2 Credit Card Payments

Credit cards have an important role in the economy helping consumers to manage temporary liquidity constraints that may occur, for example, within a monthly pay cycle (e.g. paychecks arriving after a rent payment is due). They enable consumers to borrow when liquidity constrained and smooth consumption over their life-cycle which can increase lifetime consumption (Bertola et al., 2006). Yet such benefits may not be realized if consumers are unable to pay off their debts causing lenders to incur costs of writing off debts and restricting credit access (Zinman, 2015; Agarwal et al., 2017).

If consumers are barely paying down their credit card debt (e.g. servicing the interest payments without paying down capital) borrowing costs accumulate (Ausubel, 1991). Credit card interest rates in 2018 were typically close to 20% (when central bank base rates are under 1%) and for higher credit risk borrowers can be 30% or higher. This can mean that the interest costs cumulate to sizable amounts without a salient event prompting consumers to consider the relative costs of borrowing. This contrasts with the salience of late fees from missed payments (Gathergood et al., 2018). Persistently holding credit card debt can also adversely impact credit scores limiting current and future access to credit. Given these borrowers are often liquidity constrained, interest savings from paying down credit card debt would be expected to pass through to increase consumption (Carroll, 2001; Gross and Souleles, 2002; Fulford and Schuh, 2015; Agarwal et al., 2015, 2017). Persistent indebtedness could also be harming borrowers' psychological well-being – though causal evidence is limited (Gathergood, 2012) in this regard there is evidence suggestive of this (Richardson et al., 2013; Gathergood and Guttman-Kenney, 2016).

It therefore appears that if some consumers held less credit card debt this would be welfare improving. Reducing debt appears to be a 'hard' financial decision for credit card borrowers who are often present biased (Laibson, 1997; Meier and Sprenger, 2010; Kuchler and Pagel, 2019), with self-control problems (Heidhues and Kőszegi, 2010) or lack financial sophistication (Agarwal et al., 2009; Stango and Zinman, 2009, 2011). Consumers have a large discretion in how much to pay on their credit card each month – in contrast to fixed term loans (i.e. mortgages, auto loans) – and paying down debt requires a repayment strategy (not a simple calculation) and restraint to keep to such a repayment plan and not spend more. Considering these factors it is arguably an area where there is a role for policy intervention – though a difficult one given a wide heterogeneity in how credit cards are used (Campbell, 2016).

The minimum amount required to pay on a credit card – its 'contractual minimum payment' due – varies monthly depending on how much the credit card is used. Contractual minimum payments in the UK are typically calculated by a formula such as Equation 1 that is similar to that used in the US - as shown in Agarwal et al. (2015) and Keys and Wang (2019).[7] Such an equation means that for consumers with a balance of £500, their minimum payment may be £13 (£5 as 1% of outstanding balance + £7 interest). If the balance drops a little under £200 then the minimum payment remains at £5, as 1% of outstanding balance + interest would be less than £5.[8] For cards with balances £5 or less the minimum payment is the statement balance – if the balance is zero (or less) no payment is due.

This minimum payment formula ensures that, if contractual payments are met, borrowing costs do not compound. Yet debt reduction only happens if pay down of debt principal exceeds new spending. And even then repayment schedules can be decades long.

Equation 1

$$contractual\ minimum\ payment\ =$$
$$max\ \{£5,\ total\ interest\ +\ total\ fees\ +\ 1\%\ outstanding\ balance\}$$

When faced with their credit card payment decision, approximately one in four credit

[7]Some UK credit cards, typically issued to higher risk credit applicants with high APRs and low credit limits, have higher percentages of outstanding balances in their minimum payment rules. Some UK credit card brands have a minimum of £25 rather than £5. Some credit cards issued before 2011 have minimum payment rules which may not pay off debt.

[8]This is a simplified example assuming zero fees.It is not a global solution as the precise threshold this kink occurs varies with the interest rate.

card accounts in the UK pay at or near the contractual minimum (FCA, 2016) similar to three in ten US cards (Keys and Wang, 2019). The strongly bi-modal distribution of payments is similar across countries with most cards either paying off debt in full or making payments at or very close to the contractual minimum. Such a distribution of payments is largely attributed to the 'anchoring effect' (Stewart, 2009; Navarro-Martinez et al., 2011; Keys and Wang, 2019; Guttman-Kenney et al., 2018) or 'targeting effect' (Bartels and Sussman, 2016) whereby the mere appearance of the contractual minimum payment results in more people paying exactly the minimum and the broader distribution of payments being anchored down towards the minimum. Those with multiple cards in the US and UK are both found to commonly reduce the complexity of the choice by applying a simple balance-matching heuristic: selecting an amount to pay and allocating it across cards in proportion to debt balances (Gathergood et al., 2019b,a).

Given the complexity of deciding how much to pay each month and it being easy to forget to make a payment it is common for consumers to enroll in 'automatic payments' (also known as 'Direct Debits' or 'autopay').[9] These automatically attempt to make a payment directly from a consumer's bank accounts and thus avoid incurring the mental cost of remembering to make a payment every month. Forgetting to make a payment can result in a (£12) late fee and future access to credit being adversely affected (Agarwal et al., 2008; Medina, 2017; Gathergood et al., 2018). All automated payments are subject to the cardholder having sufficient funds in their checking account for the payment request to be fulfilled. Automatic payments are a commonly-used and growing method of paying UK household bills – 90% of UK consumers use these to pay at least some of their bills – often being set-up when opening a new account.[10]

[9] In more cumbersome jargon it is also described as an Automated Clearing House (ACH) transfer initiated by the biller.

[10] Compared to the US, UK payment infrastructure is more advanced. This means that 'automatic payments' are commonly used as a means of payments for credit cards, other financial products and household bills payments. Bank transactions are cleared quickly in the UK (typically within two hours) and checks are mainly used by an older demographic (who less commonly have credit cards), are declining in use and are much more rarely used than in the US. https://www.ukfinance.org.uk/system/files/Summary-UK-Payment-Markets-2018.pdf

There is no requirement to have an automatic payment set-up. Consumers have to opt-in if they would like to pay by this method (i.e. there is no automatic enrollment into having any type of automatic payments). Often consumers are offered the opportunity to enroll when opening a new credit card. Those enrolled can make manual payments instead of or as well as automatic payments and can change their enrollment at any point.

Automatic payments for credit cards come in three forms: set to only pay the contractual minimum ('automatic minimum payment'), the full statement balance ('automatic full payment') or a fixed amount of their choice ('automatic fixed payment'). The automatic fixed payment option covers the contractual minimum payment in circumstances when this exceeds the fixed amount of their choice (as shown in Equation 2).[11] For example, if a consumer had an automatic fixed payment set up for £25 and their minimum payment was £25 (or less) then £25 would automatically be attempted to be taken from their account that month. If, instead, their minimum payment was higher, say £50, which is greater than their automatic fixed payment of £25 then £50 would automatically be attempted to be taken from their account.

Equation 2

$$Automatic\ minimum\ payment\ =\ max\ \{fixed\ \pounds\ amount,\ contractual\ minimum\ payment\}$$

As Sakaguchi et al. (2020) describe, selecting an automatic minimum payment option initially appears a somewhat sophisticated strategy as it insures people against forgetting to pay their bill while leaving discretion to make additional manual payments (e.g. if not liquidity constrained a particular month). However, such an automatic minimum payment strategy means the borrower never needs to consciously make a payment decision again. Instead it is easy to slip into the inert behavior of repeatedly only paying the minimum with interest costs building up each month in a way that is far less salient than a one-off missed

[11] There are processing time lags in UK automated payments which means that if a manual payment is made shortly before an automated payment is already due to go through it would not replace it.

fee charge.

In the UK the credit people who repeatedly pay only the contractual minimum, and so incur especially high borrowing costs from barely paying off their debt, are commonly enrolled in automatic minimum payments (FCA, 2016). Consumers rarely revise their initial automatic minimum payment choice even if prompted to do so by targeted, personalized disclosures (Adams et al., 2018). Can the inertia of initial automatic payment choices be harnessed 'for good' to enable people to carry less credit card debt?

3 Experimental Design

Experimental Setup

We conducted a randomized controlled trial (RCT) in the field on 40,708 credit cards newly issued by a large UK lender between February and May 2017.[12] This sample size was selected to provide sufficient statistical power to differentiate economically meaningful effects from null results.

We also ran this experiment with a second lender. This second lender stopped the experiment after one week of fieldwork due to concern over the large size of the initial effects on automatic payment choices. The experiment was not restarted and the pre-agreed target sample size was not reached. The achieved sample size of 1,531 cards is therefore a result of p-hacking and is also insufficiently powered to distinguish between null results and real effects. For completeness results from the second lender are in the supplementary annex.[13] The rest of this paper is based on the experiment conducted with the first lender.

Before putting the RCT into the field, we carried out qualitative consumer testing to ensure people would understand how to navigate the intervention, conducted an ethical review to consider the potential for unintended consumer harm and sought feedback from all UK credit card providers and consumer organizations. Following best practice in conducting

[12] We targeted at least 20,000 cards in each of control and treatment group. The final figure was slightly higher as we left the trial running until the end of May.

[13] Online Appendix, Tables A11-13 and Figures A13-14

field experiments (Harrison and List, 2004; Duflo and Banerjee, 2017) we pre-registered our empirical methodology before analyzing data.[14] This pre-registration outlined the structure of analysis including the regression specifications and statistical significance tests we planned to run. In line with (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.[15] This approach applies a tougher threshold than the typical 0.05 significance level historically used and thus limits false positives (similar to applying Bonferroni or familywise error corrections on 5% significance levels).

We structured our overall analysis in three parts – primary, secondary and tertiary. This structure limits the potential issues for data mining or p-hacking (Simmons et al., 2011). The primary analysis focuses on ten outcomes measuring the effects on: any minimum payment, any full payment, any missed payment and outstanding debt as a percent of statement balance (to normalize in order to deal with fat tailed credit card balances). We apply this for both the card in the trial and peoples' portfolio of credit cards – the final two primary outcomes were the cost of borrowing as a percent of statement balance and total of purchases as a percent of statement balance.[16] Pre-registered secondary analysis considers a broader set of outcomes and empirical approaches to check the robustness of the primary results and understand the mechanisms driving the results in greater detail. Conducting secondary analysis depended on the results from the primary outcomes. Finally, we designed and implemented the tertiary analysis after examining the data.

The trial varies the 'choice architecture' (Johnson et al., 2012) of how automatic payment options are presented to people at card opening. When a consumer takes out a new credit card online they typically have the option to opt-in to enroll in automatic payments. If they decide to do so they are normally presented with three automatic payment options: full,

[14] As this experiment was informing potential Financial Conduct Authority rule-making, legal constraints meant we were unable to externally publish the pre-registration ahead of the working paper's publication.

[15] Significance at 0.5% aligns with Bayes factors of 14+ which is often considered as substantial evidence for a hypothesis.

[16] Variables as a percent of statement balance are bounded between zero and one.

fixed or minimum. Or at this stage they can still decide against setting up an automatic payment by not completing the setup process. This was not a one-time shot so they could return and complete the process later on.

The treatment (Figure 1, Panel B) webpage shrouds automatic minimum payments. This is done by removing the explicit appearance of the automatic minimum payment option shown to the control group (Panel A). This increases the salience of the automatic fixed payment option.

While there is no longer an explicit automatic minimum payment option, people can choose an option which is mathematically identical to it if they set an automatic fixed payment of £5. These two are equivalent because – given Equation 1 – the contractual minimum payment 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 automatic payment attempted to be taken will adjust accordingly, regardless of whether a consumer has an automatic fixed payment of £5 or an automatic minimum payment (two worked examples of this are in the footnote).[17] This equivalence is not highlighted to consumers and we do not expect them to be aware of this or work this out, nor is there a strong reason why they should. We explain this here to show that the intervention does not restrict consumer choice of an automatic minimum payment option – and so the intervention is a nudge rather than a restriction – instead such an option is just no longer prominently labelled on the website. If a consumer in the treatment group phoned the lender's call center they could still set-up an explicit automatic minimum payment if they asked to do so but consumers were not directed to this option as part of the trial.

Without an explicit automatic minimum payment option consumers are forced to make

[17]Example 1: If a consumer had a £5 minimum payment due then £5 would be attempted to be taken if the consumer had an automatic minimum payment set up. If a consumer had an automatic fixed payment of £5 then £5 would be attempted.
Example 2: If a consumer had a £10 minimum payment due then £10 would be attempted to be taken if the consumer had an automatic minimum payment set up. If a consumer had an automatic fixed payment of £5 then £10 would be attempted (as the minimum was higher than the fixed amount).

a more active choice – considering how much they can afford to regularly pay each month.[18] Given heterogeneity of credit card borrowers' circumstances we designed our intervention to avoid anchoring people to follow a particular payment schedule.

The rationale of this intervention is that if people have an automatic fixed payment instead of an automatic minimum payment it will significantly shorten the hypothetical repayment schedule if there are no other changes in behavior (e.g. changes in spending). This is because while the contractual minimum payment (and therefore automatic minimum payment) typically declines with balances, a fixed payment sticks to the higher amount in a ratchet-like way smoothing payments over time. For example, a typical credit card balance of £1,000 would take 18 years and 6 months to pay off if only the minimum was paid each month (which would start around £25 and reduces to £5). However, by fixing to paying £25 each month it could be dramatically reduced to 5 years and 1 month, saving over £750 in interest costs.

Further, over and above having a fixed payment which does not reduce with the balance, choosing a slightly higher payment also greatly reduces amortization times and borrowing costs. For example, a balance of £1,000 is paid off in 5 years and 1 month with an interest cost of £509 with a monthly fixed payment of £25, but with a monthly payment of £50 the balance is paid off in 2 years costing £191 in interest (assume 18.9% APR and no further card spending). When choosing a payment manually, if cardholders do not choose the minimum they have a tendency to choose round-numbered payments above the minimum (Sakaguchi et al., 2020). £50 is among the most prominent of these round numbers. So, holding all else constant, we would expect higher automatic payments to yield lower debt and borrowing costs. This would also possibly result in second order effects of increased consumer spending from increased credit limit availability, given the findings of consumer responses to credit limit increases (Gross and Souleles, 2002; Agarwal et al., 2017).

The treatment therefore aims to work by first increasing automatic fixed payment en-

[18] Keller et al. (2011) reviews active choice literature. Carroll et al. (2009) study active choice in pension saving and Haggag and Paci (2014) in taxi tips.

rollment which would be expected to increase automatic payments which, in turn, increases payments above the contractual minimum and, assuming spending is unchanged, reduces debt and interest costs. This intervention was designed to be a preventative measure against consumers persistently carrying high credit card debt balances. In a separate set of trials we also examined the role for disclosures to change behavior of existing cardholders with automatic minimum payments and found these to have limited impact (Adams et al., 2018).

We apply this intervention to new credit cards with the randomization process carried out 'live' after the consumer's card application has been accepted. When a consumer is applying for a credit card online and has been provisionally accepted they have the option to set-up automatic payments on this new card. If a consumer selected the option confirming that they wanted to enroll for automatic payments they were included in the experiment. This inclusion in the experiment is irrespective of whether this enrollment process is completed after reaching this screen. At this point they were navigated to treatment or control group screens.[19] Once allocated to control or treatment they would view these choice architectures if they returned to the pages to enroll in or change their automatic payment choices within 30 days of applying for the card.

Data

Our data was gathered by the UK financial regulator — the Financial Conduct Authority (FCA). These contain detailed microdata on every credit card in the experiment. We observe data recorded at card origination (e.g. opening date, interest rates, initial credit limit) and across statements (e.g. statement balances, transactions, borrowing costs). For effectively all cards (99.9%) we see seven completed statements and up to eleven for the cards opened earliest in the trial. Each payment made against these statements is observed including the date, amount and channel (e.g. automatic or manual).

Credit files were gathered for all the individuals in the trial enabling us to observe effects across the portfolio of credit cards held by a consumer. These provide monthly, product-level

[19] This was carried out through a random number generator JAVA script created by the lender.

data on up to six years of credit use showing credit limits, balances, payments and arrears. For credit cards we also observe additional data on statement balances and binary indicators for whether a card only made a minimum payment. We also observe statement balances and payments made against credit cards. For two points-in-time we observe credit risk scores and income estimates where available - the month before the card was opened and nine months afterwards.

Experimental Methodology

We construct an unbalanced panel with one observation for each credit card's (i) statement cycle (t) observed. This panel is unbalanced as some cards are opened earlier than others. We estimate an OLS regression with standard errors clustered at the card-level. Equation 3 shows the regression specification used to derive average treatment effects. Average treatment effects are the variable of interest (as opposed to treatment on the treated) as the intervention was a potential regulatory policy which was being considered to be applied across the UK market.

Equation 3

$$y_{i,t} = \alpha + \sum_{k=1}^{K} \beta_k CONTROLS_{k,i} + \sum_{v=2}^{V} \theta_v \; MONTH_v \; + \delta_1 \; TREATMENT_i + \sum_{t=2}^{11} \Big(\gamma_t \; CYCLE_t + \delta_t \; TREATMENT_i * CYCLE_t \Big) + \varepsilon_{i,t}$$

This regression includes a constant (α), a series of K time-invariant control variables ($CONTROLS_{k,i}$) constructed using information on the target credit card and cardholder from before the start of the trial, dummies for the month-year ($MONTH_v$) and statement cycle ($CYCLE_t$) the outcome is observed (see footnote for all controls).[20] In this specification

[20]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 were all from the time of card origination (or month preceding card origination where consumer rather

$\delta_1 + \delta_t$ shows the average treatment effect t cycles since the start of the trial. We hypothesized that treatment effects will vary over time but we did not impose a functional form because it was unclear what the appropriate functional form would be. For our primary analysis we focus on the outcomes from the last cycle where the panel is balanced.

Summary Statistics and Balance Checks

Table 1 displays summary statistics on the characteristics of consumers taking out cards in this trial. As these are new cards we cannot show pre-treatment behavior on the card itself. Instead, we show summary statistics from the control group during their first seven cycles of using their card. This shows that in the control group, 19% of cards have made payments only equal to the contractual minimum payment for at least six of their first seven statements.

Consumers with automatic payments generally make one payment (mean 1.1, median 1) in total (automatic or manual) per credit card statement cycle. Consumers with automatic minimum payments rarely make additional payments – fewer than one in ten in the control group do so for a given statement.

Allocation of consumers to the treatment group is balanced, on average, and across the distributions. However, we do see some small differences. The likelihood of being in the treatment group slightly varies with credit limit.[21] Investigation of why this is reveals that the 'live' randomization code used by the lender was not completely random – 526 more consumers (0.65%) were allocated to control than treatment. As people applying for credit cards were unaware (and unable to manipulate) their likelihood of being allocated treatment we can recover balance between treatment and control without a selection bias through conditioning on covariates. Conditioning on observables does not change our overall results and their implications when compared against results from unconditional means.[22].

than Credit Card specific variables). For outcomes constructed from credit reference agency (CRA) data up to eleven dummies for lags of outcomes were included for months preceding the start of the trial.
CYCLE and MONTH are both included because statement cycles do not perfectly align with calendar months and trials went into the field at different points-in-time.

[21]Online Appendix, Table A1

[22]Online Appendix, Table A2, A3 displays tests for primary and selected secondary outcomes

4 Experimental Results

The first effect we examine is the mechanism the treatment is designed to work through: changing automatic payment choices by the time of their first full credit card statement.[23] Figure 2A shows the intervention caused significant initial effects in such choices. The intervention raises the fraction of cardholders enrolling in automatic fixed payments by 21 percentage points: a 72% increase on the control group mean. The automatic fixed payment amounts people initially choose are frequently round numbers that are rarely revised. 62% of automatic fixed payments are for the following round numbers (in descending order of frequency): £100, £50, £200, £150, £30, £20 or £25. For comparison, Figure 2B displays these proximate effects are even larger for the second lender who stopped the trial early: a 40 percentage point (216%) increase in automatic fixed payments (subsequent results are all based on the main lender).

Almost all of this mass is redistributed from the fraction of cardholders enrolling in automatic minimum payments in the control group. Automatic minimum payments are not entirely eliminated as it was possible for individuals in the treatment group to sign-up for these through other ways (e.g. telephoning the call center). 0.78% of the treatment group set an automatic fixed payment of £5 (which is identical to an automatic minimum payment). We consider this an economically trivial level though we note it is a statistically significant increase relative to 0.06% in the control group.[24]

The intervention also causes a very small increase in the proportion of people selecting automatic full payment though this is significant at the 5% but not the 0.5% level.

When we examine our primary outcomes of interest in Table 2, seven statement cycles after card-opening ($\delta_1+\delta_7$ in Equation 3), we observe that the intervention causes a significant reduction in the likelihood of only paying exactly the contractual minimum (Figure 3). The

[23] As a new card's first statement often does not last a full month or have a payment due the first full statement consistently across cards is their second statement.

[24] As effectively no one sets an automatic fixed payment of £5 this distinction does not affect the results if we code such automatic fixed payments as automatic minimum payments.

treatment effect falls from 10.9 to 7.1 percentage points from statements two to seven. This effect on making only contractual minimum payments is smaller than the initial effect on automatic minimum payment choices. Why? Because some people with automatic minimum payments make additional manual payments to pay more than the minimum and some people have no minimum payment due (and therefore no payment is taken).

We look at how this effect translates to the fraction of all a cardholder's credit cards where minimum contractual payments are made. This reveals an average treatment effect a third of the size on the card for which the treatment was targeted. This smaller overall effect across the credit card portfolio is due to consumers holding multiple cards – only one of which would be in the trial – so the effects are limited to the card in the trial.

Beyond the effects on contractual minimum payments we find no significant average treatment effects on other primary outcomes for the card in the trial (Table 2). We find no average treatment effects on the likelihood of paying debt in full, debt net of payments, borrowing costs or purchases. We similarly find no significant effects on the likelihood of paying in full, missing payments or outstanding debt when aggregating across the portfolio of credit cards held.

Our intervention does not appear to be reducing credit card debt by the seventh statement cycle (Figure 4, Panel A). As the estimates are persistently, slightly (but statistically insignificantly) below zero, we check the robustness of this result in tertiary analysis by aggregating across all statement cycles to provide more statistical power. By doing so we can say that, if the intervention has any average effect on debt, the average effect of the intervention reducing debt is at most a 1.1 percentage point reduction (given 95% confidence intervals) as shown in Table 3. As a robustness check we look at debt in pounds and find no statistically significant effect (Figure 4, Panel B).

The lack of average treatment effects in spite of a seemingly large, initial change in choices is surprising. It is robust to a variety of secondary outcomes displayed in Table 5.

So we have a conundrum. How can it be that the treatment is not, on average, reducing debt if one in five more people have automatic fixed payments and are spending no more on their card?

We find three offsetting consumer responses to the intervention. The first of these is some automatic fixed payments are set 'too low' binding at the contractual minimum or being above it by a trivial amount. As card balances accumulate over the first few months of card ownership, the minimum required payment amount rises, causing the minimum payment amount to exceed many of the fixed payments. After seven statement cycles, the proportion of people in the treatment group with an automatic fixed payment set at an amount that exceeds the minimum required payment is 73%, slightly down from 78% in the second cycle.[25] While the treatment caused a 16.8 percentage point increase in automatic fixed payment enrollment by statement seven, the treatment effect on an automatic fixed payment enrollment that is greater the contractual minimum is half the size: 8.7 percentage points which is a 34% increase on the control group mean (Table 5).

The second offsetting effect is that the intervention initially causes one in twenty fewer people to be in enrolled in automatic payments (of any kind). This lower enrollment results in a slight increase in arrears as un-enrolled people forget to make payments. While this increase is borderline statistically significant when examining any particular statement cycle, it is clearly significant when conducting a joint significance test across statement cycles (while still clustering at the card-level) as displayed in Table 3.

The intervention itself appears to have an effect on arrears through this change in automatic payment use and not via other potential mechanisms (e.g. automatic fixed payments at unsustainably high amounts which consumers could not maintain). The effect on arrears is solely on missing a single payment: precise zeros are estimated on missing two or three payments (Table A9). Such temporary arrears does not appear in the credit file outcome for missed credit card payments – this is because temporary arrears is not always reported to credit bureaus so would not affect people's credit scores.

[25] Online Appendix, Figure A4

The intervention does not lead to consumers being classified as being in more severe arrears which is often defined as being two, three (or more) payments behind. This indicates that not having an automatic payment 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 consumers to spiral into a terminal state of financial distress that they cannot recover from.

The primary mechanism our treatment was designed to apply was through raising automatic payments. But the third and final offsetting factor we observe is the treatment reduces manual payments. We found this by conducting tertiary analysis by disaggregating payments based on whether they are made automatically or manually. These payments are cumulated across cycles to observe patterns more clearly. We show the result of this in the top panel (A) of Figure 5 (estimates in Table 5). Here we can see that the intervention results in the value of automatic payments increasing, but these are almost totally offset by manual payments decreasing. Thus when aggregating manual and automatic payments (i.e. total payments) we see a precise zero overall effect.

We further examine this by cutting the data on an endogenous variable to examine the subset of consumers with and without automatic payments set-up at statement cycle seven. This approach takes Equation 3 and conditions upon use of automatic payments ($AUTOPAY_{7,i}$) as shown in Equation 4. As before we also disaggregate payments into automatic and manual methods.

Table 4 reports the treatment effects conditional upon automatic payment enrollment. Given an automatic payment has been set up, it is 26.5 percentage points less likely to be for the minimum and 24.7 percentage points more likely to be for a fixed payment.

Equation 4

$$y_{i,t} = \alpha + \sum_{k=1}^{K} \beta_k CONTROLS_{k,i} + \sum_{v=2}^{V} \theta_v\ MONTH_v + \delta_1\ TREATMENT_i +$$
$$\sum_{t=2}^{11} \Big(\gamma_t\ CYCLE_t + \delta_t\ TREATMENT_i * CYCLE_t \Big) + \varepsilon_{i,t}\ if\ AUTOPAY_{7,i} = 0$$
$$y_{i,t} = \alpha + \sum_{k=1}^{K} \beta_k CONTROLS_{k,i} + \sum_{v=2}^{V} \theta_v\ MONTH_v + \delta_1\ TREATMENT_i +$$
$$\sum_{t=2}^{11} \Big(\gamma_t\ CYCLE_t + \delta_t\ TREATMENT_i * CYCLE_t \Big) + \varepsilon_{i,t}\ if\ AUTOPAY_{7,i} = 1$$

Figure 5 plots the cumulative payments across the first seven cycles. The middle panel (B) shows, for cards with automatic payments, the higher automatic payments in the treatment group are crowded out by lower manual payments. The average effect on overall payments (automatic and manual) is zero. We are confident that any increase is no greater than £50 (95% confidence interval) – this can be evaluated relative to average cumulative payments baseline of £1,280.[26] Credit card purchases remain unchanged for this sub-group of consumers.

Not everyone in the experiment enrols into automatic payments after being allocated to control or treatment. The lower panel (C) of Figure 5 shows that, for cardholders who did not set an automatic payment, the treatment has no significant effect on payments.[27]

We find consumers with an automatic payment are slightly, 2.4 percentage points, more likely to make a manual payment as a result of the treatment. This is an average treatment effect of 1.3 percentage points as not all cards in the experiment have automatic payments set up – this increase is in spite of the treatment reducing automatic payment enrollment. Manual payments by consumers with automatic payments are infrequent – just 8.5% of

[26] £1,280 is the average cumulative payments by cycle seven in the control group for consumers with automatic payments at cycle seven.

[27] It is not a precise zero effect on automatic payments because some consumers without automatic payments at cycle seven had automatic payments in earlier cycles and then cancelled them or set them up after their seventh cycle was issued but before payments were made.

those with automatic payments in the control group make a manual payment in the seventh statement cycle.[28] But they account for 40.3% of the total value of payments made across seven cycles by those in the control group enrolled in automatic payments.[29]

When consumers make infrequent manual payments they are substantially larger in value than automatic payments. In months where manual payments are made by those with automatic payments set up, the mean value of the manual payment is £436.40, with a typical median value of £120.00. Automatic payments in those same months average £106.98 with a median of £54.74 and are similar in months where consumers are not making manual payments. Making such large manual payments initially appears to be counter to consumption smoothing, however, if consumers have fluctuating incomes and liquidity constraints and there is an adjustment cost – physical or psychological – to making a payment above the minimum then such observed behavior can be rationalized.

Most manual payments (by those with automatic payments set up) do not clear a consumer's debt – just 18.4% do so in the control group.[30] 23.0% of manual payments are for round numbers (£50, £100, £150, £200, £250 or £500). It does not appear that consumers are adding up the values of their manual and automatic payments to target particular round numbers. The distribution of total payments (automatic plus manual payments) in months where consumers with automatic payments set up are making manual payments is fairly smooth.[31] The round numbers found to prominently appear in manual payments appear with far less frequency in total payments – just 6.6%.[32]

It does not appear that consumers with automatic payments decide to make manual payments in response to crossing particular heuristic thresholds. We find the distributions of credit card statement balances and utilization rates before payments are deducted to be

[28] This equates to 6.7% of all consumers in the control group (i.e. with and without automatic payments set up), 9.2% of consumers on automatic fixed or minimum payments set up and 6.3% of consumers with automatic minimum payments. 12.7% for consumers with automatic fixed payments.

[29] This is 54.0% for those with automatic fixed or minimum payments set up at statement seven.

[30] This is for consumers with any automatic payment also making a manual payment in the seventh statement cycle.

[31] Online Appendix, Figure A6 displays the distributions of these variables

[32] 8.6% of statements where consumers are not paying the minimum or full amount.

smooth and similar in the months with and without manual payments being made. We also do not find evidence that consumers are making manual payments to target keeping their credit card debt or utilization below particular values.[33]

Thus these three offsetting consumer responses – automatic fixed payments frequently binding at the minimum, drop-out in automatic payment use and crowd-out of higher automatic payments with lower manual payments – explain how a large proximate effect of the nudge ultimately results in precise zero effects on debt.

5 Concluding Discussion

We nudged credit cardholders to adopt automatic fixed payments instead of automatic minimum payments. The proximal treatment effect on such automatic payment choices was 'large' – over 21 percentage points. But the more distal treatment effect was a precise null – no changes to average debt. This was due to three offsetting consumer reactions to the intervention: (i) Automatic payment amounts selected often being 'too low' – binding at the contractual minimum; (ii) Automatic payment enrollment decreasing – increasing missed payments; and (iii) Manual payments decreasing – offsetting increased automatic payments. While it may be coincidence that in this particular experiment heterogeneous effects net out at such a precise zero, the disappearance of the large, initial effect is very clearly a real and important effect. As Abadie (2020) highlights, the reporting of such null results are highly informative for furthering empirical economics more generally.

Our paper demonstrates how important it is to consider offsetting consumer responses to nudge interventions. Doing so can help policymakers to better evaluate whether nudges or paternalistic policies are likely to improve welfare, or if doing nothing is best. This fits into a broader discussion on the effects of nudges. Nudges have been increasingly adopted by governments and regulators worldwide since 2008. Yet there is now a growing literature that nudges may be a less effective policy tool than they initially appeared – though they are

[33]Online Appendix, Figure A7 displays the distributions of these variables after payments.

a valuable addition to a policymaker's armory given their near-zero costs of implementing (Egan, 2013; Allcott and Kessler, 2019; Beshears et al., 2017; Loewenstein and Chater, 2017; Benkert and Netzer, 2018; Jachimowicz et al., 2019; DellaVigna and Linos, 2020).

One remarkable aspect of our findings are the persistence of the effects. We are causing a persistent change in the *type* of payment methods (increasing use of automatic fixed payments, reducing use of automatic minimum payments and reducing enrollment to any type of automatic payment) across the statements observed but not the *amounts* of payments. When considering these findings in the theoretical literature two potential explanations come to mind. An adjustment cost model (Bertola and Caballero, 1990) could explain payment behavior but needs a behavioral element to explain the differences in initial automatic payment choices (e.g. automatic minimum payment option operates as a focal point). Alternatively, a rational inattention model (Caplin and Dean, 2015) could explain behavior: consumers regard their initial automatic payment choice as unimportant because they intend to make manual payments (for debt reduction) later on but still typically want an automatic payment set-up as insurance against forgetting to make a payment. If so, consumers are indifferent between automatic minimum payments and automatic fixed payments for amounts above the minimum. For some consumers it may be that the mental cost of selecting an automatic fixed amount is too great and so they opt out of making a decision at all.

We conclude that credit card borrowers are not as inert as they appeared. What is ultimately constraining credit card payments? One possibility is borrowers want to reduce their debt but are bounded by economic constraints such as limited liquidity (Carroll, 2001; Gross and Souleles, 2002). Another explanation is psychological barriers such as mental accounting (Thaler, 1985; Prelec and Loewenstein, 1998) prevent them from paying more to reduce their debt.

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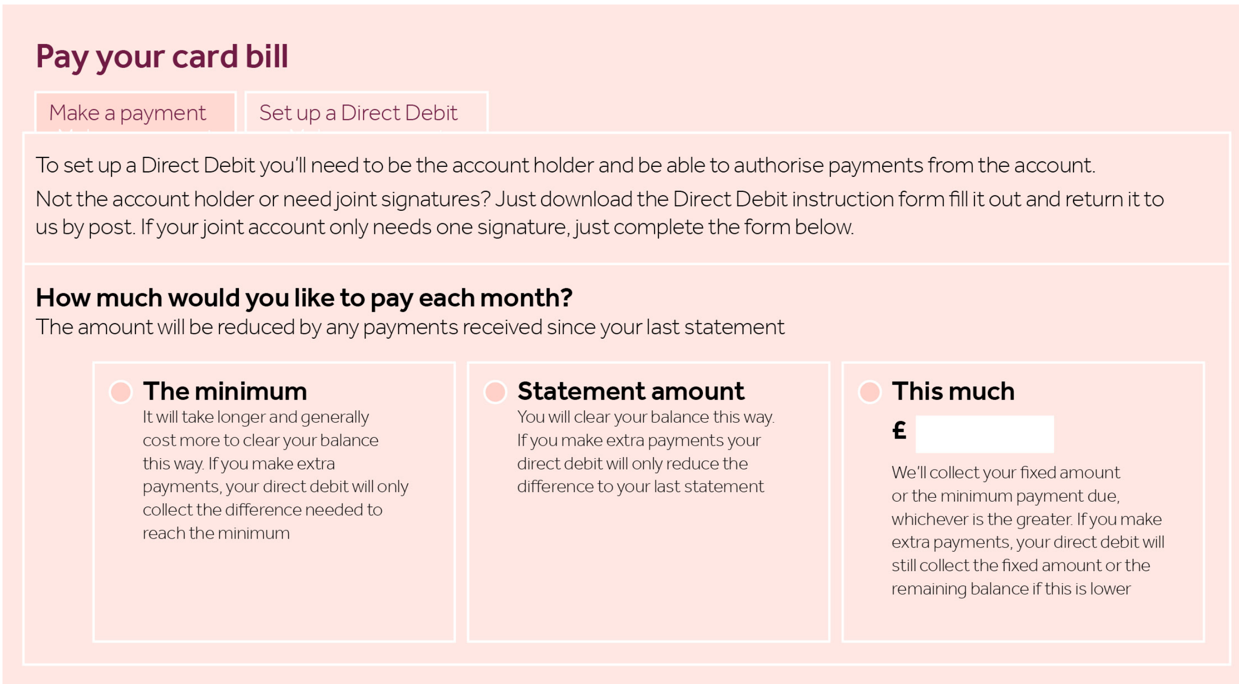
6 Figures & Tables

Figure 1: Automatic payment choice architecture presented to control (panel A) and treatment (panel B) groups

A: Control



B: Treatment

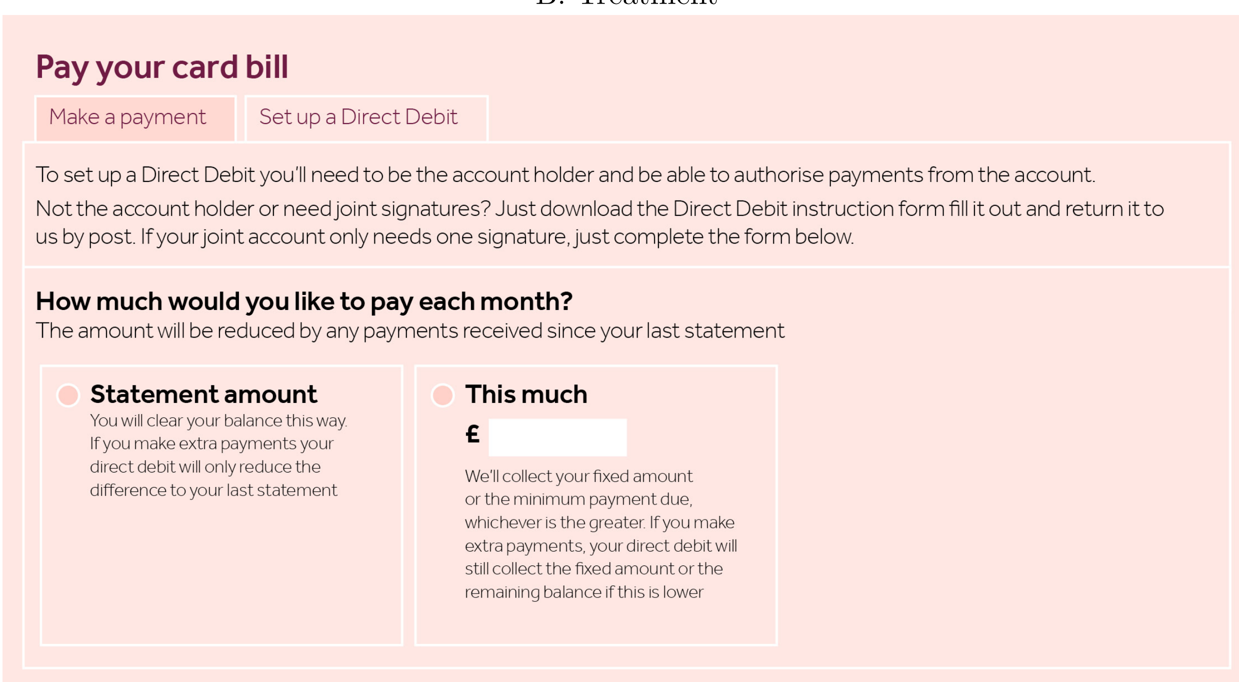
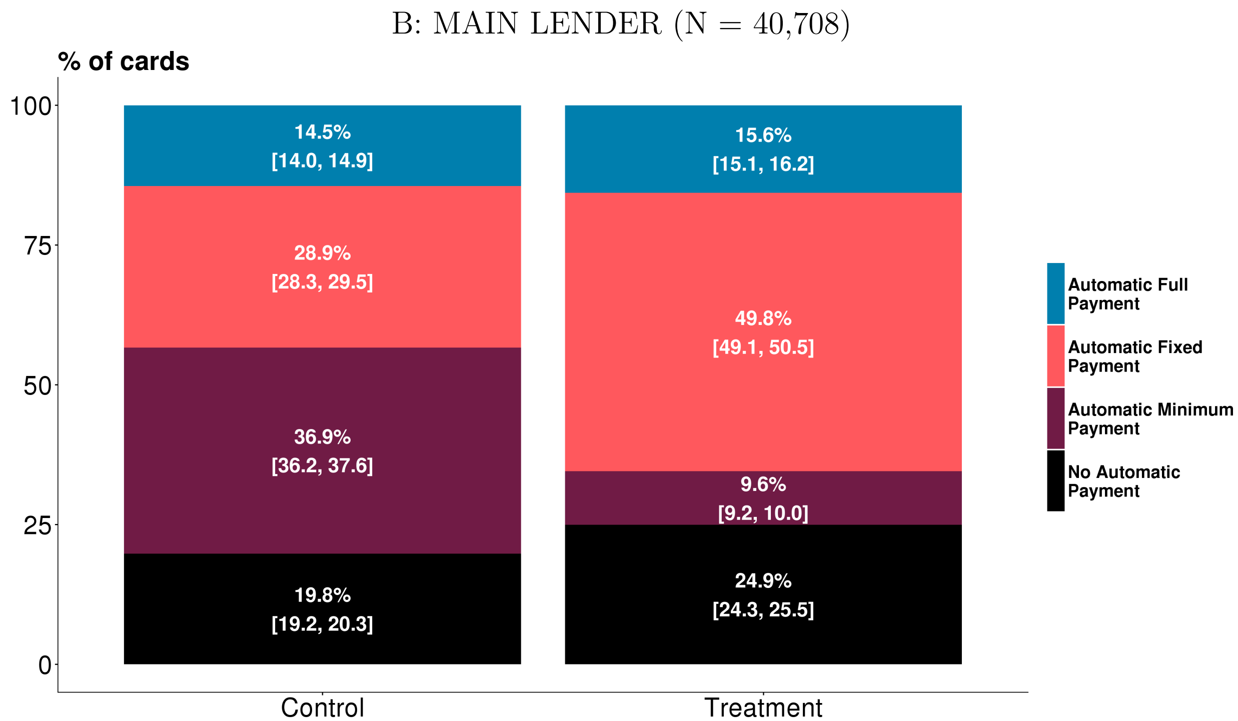
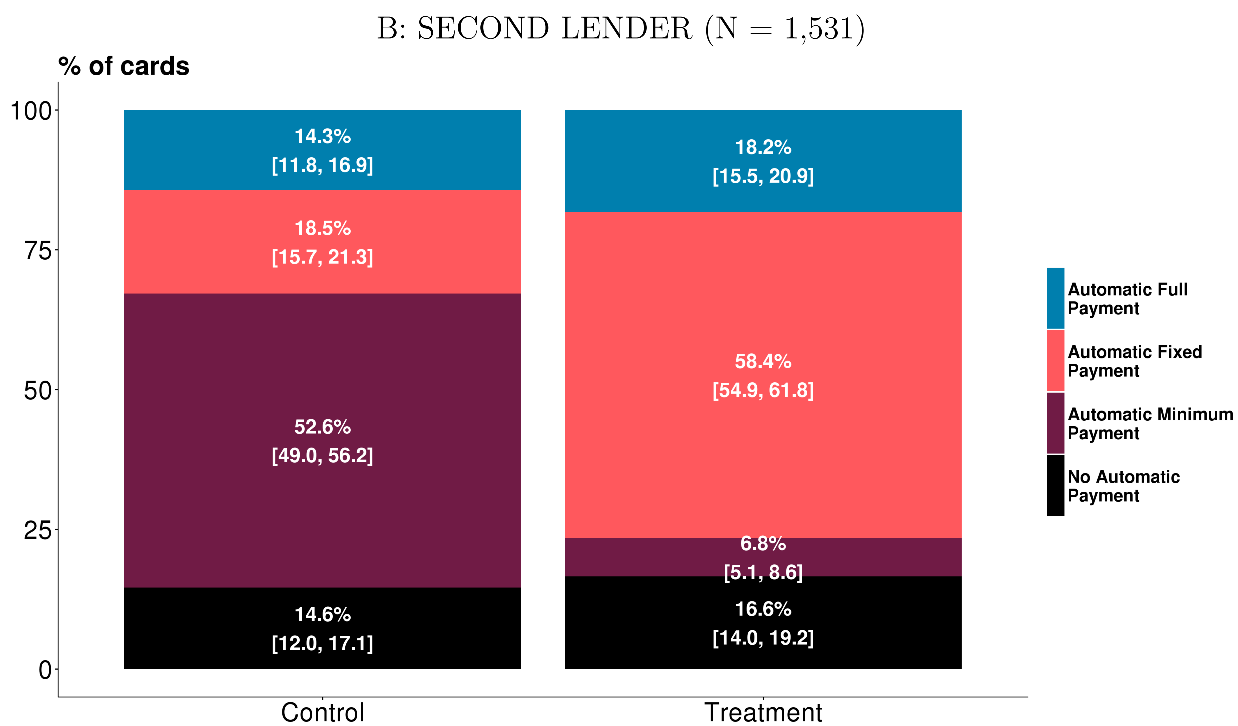


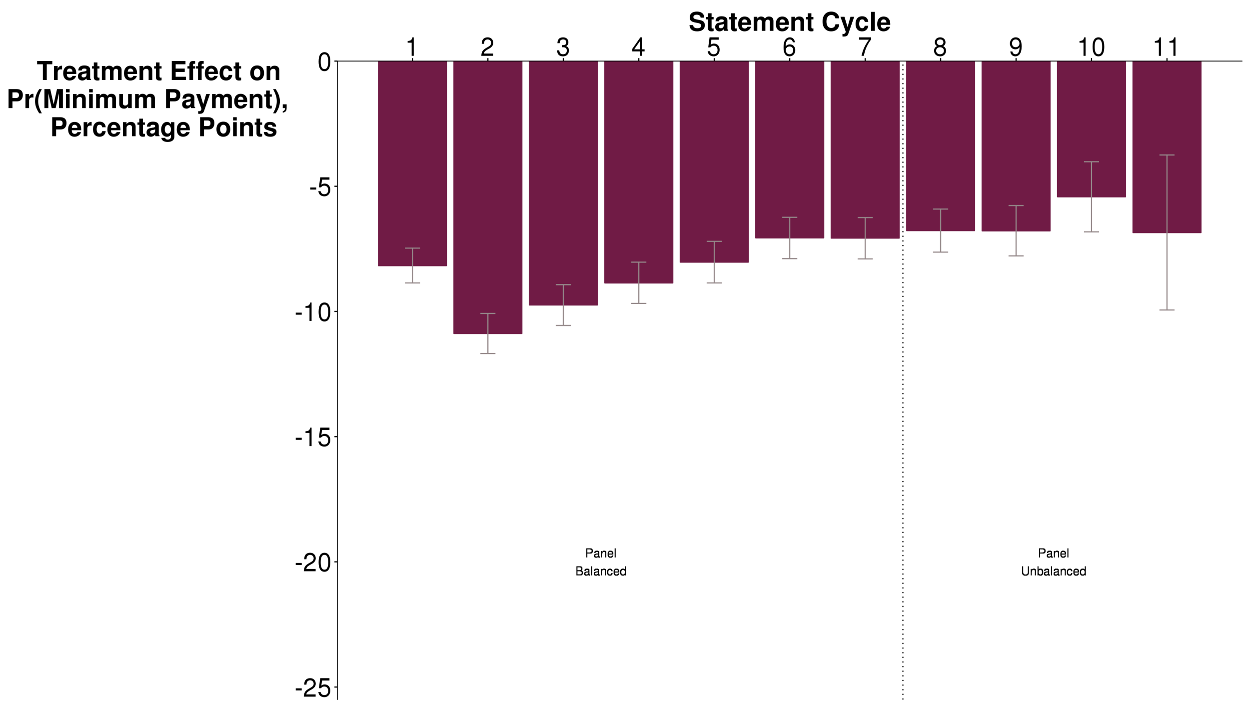
Figure 2: Automatic payment enrollment for control and treatment groups after two statements, split by lender





Numbers display percentage selecting each type of automatic payment. 95% confidence intervals in [ ].

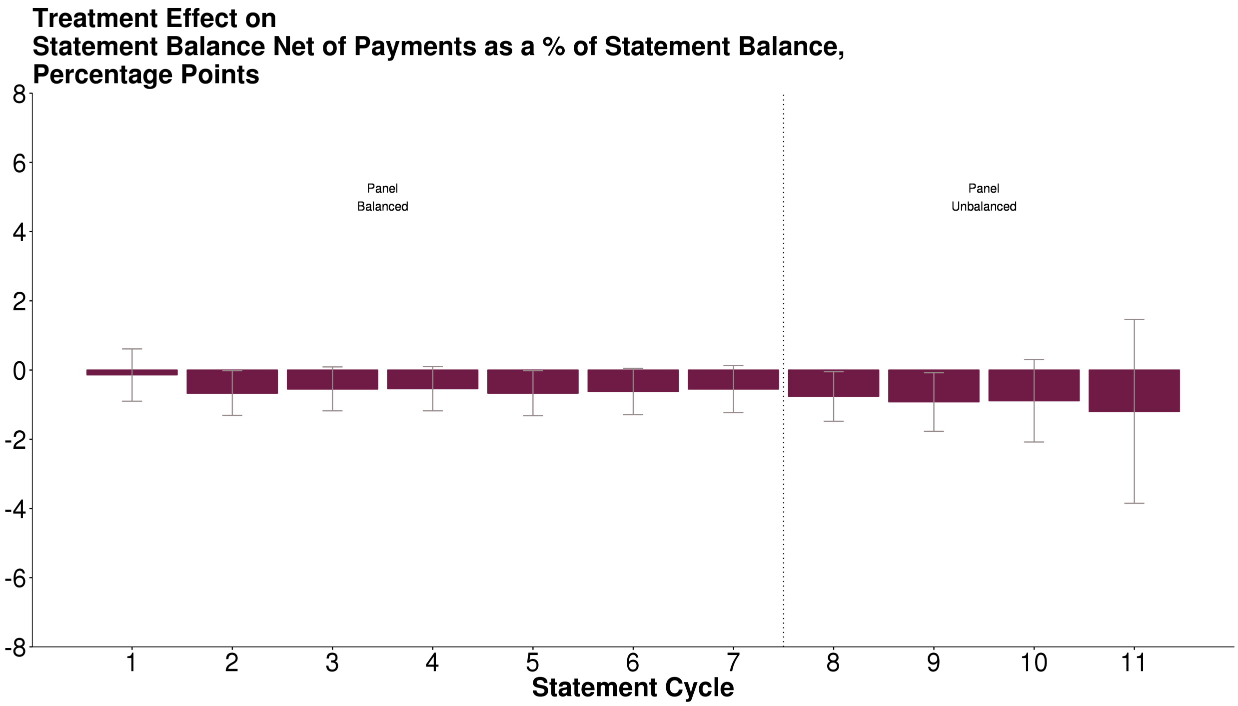
Figure 3: Average treatment effects on making only a minimum payment across 1-11 statement cycles



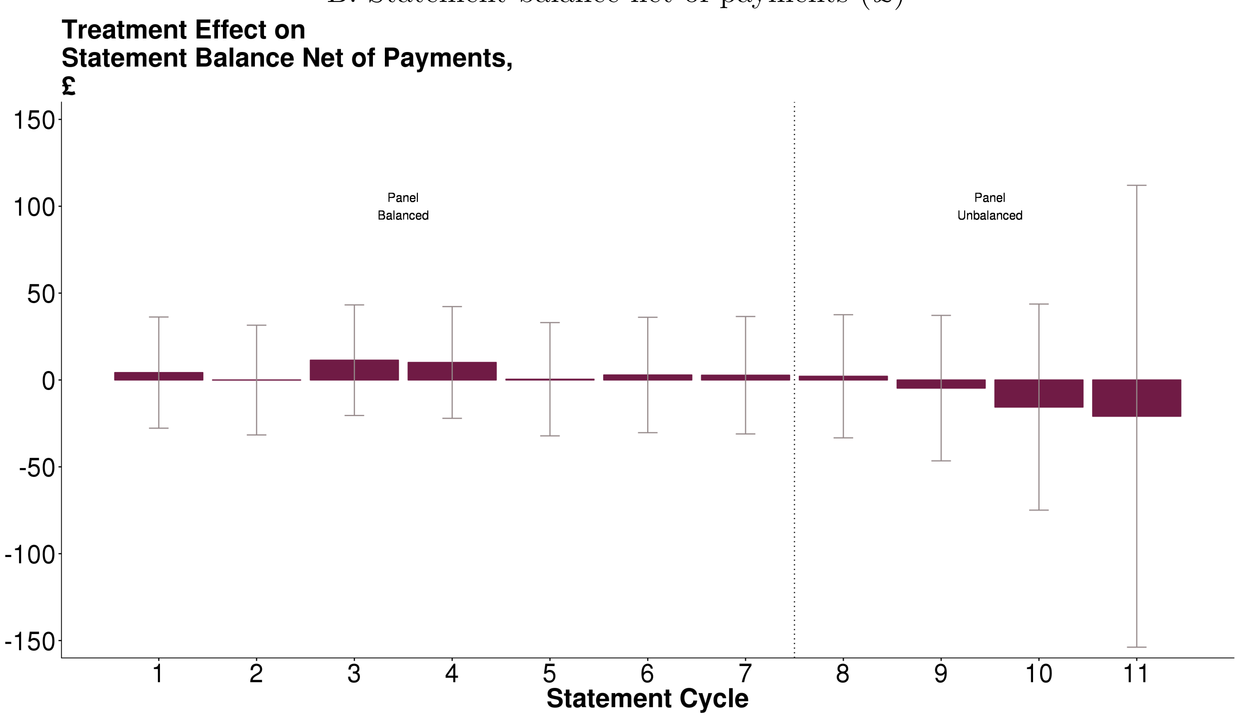
Treatment effects from coefficients $(\delta_1 + \delta_t)$ in OLS regression specified in Equation 3 (standard errors clustered at card-level). Error bars are 95% confidence intervals.

Figure 4: Average treatment effects on credit card debt across 1-11 statement cycles

A: Statement balance net of payments (% statement balance)



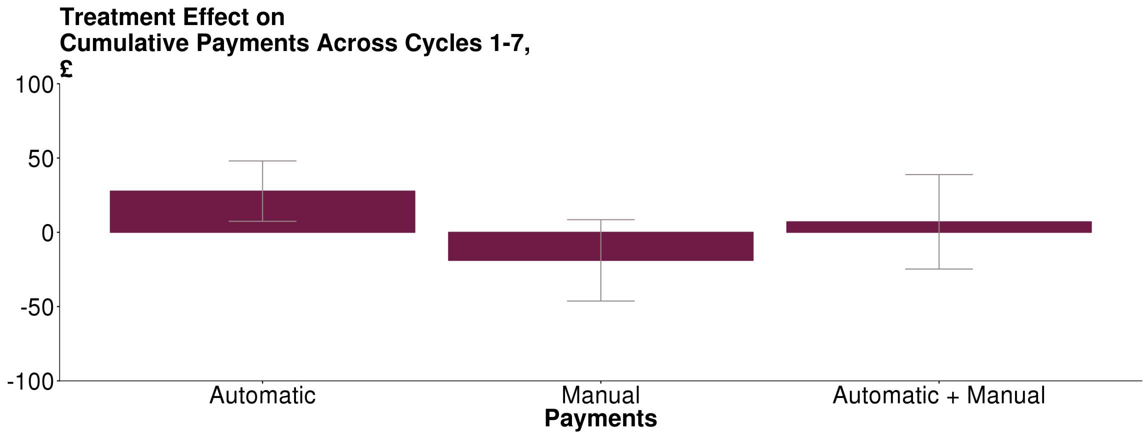
B: Statement balance net of payments (£)



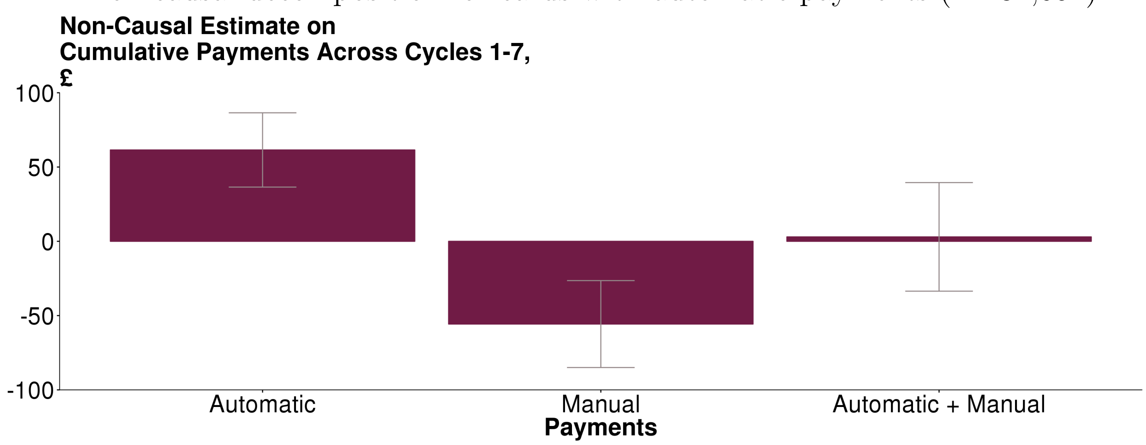
Treatment effects from coefficients $(\delta_1 + \delta_t)$ in OLS regression specified in Equation 3 (standard errors clustered at card-level). Error bars are 95% confidence intervals.

Figure 5: Treatment effects on cumulative payments decomposed by automatic payment enrollment after seven statement cycles

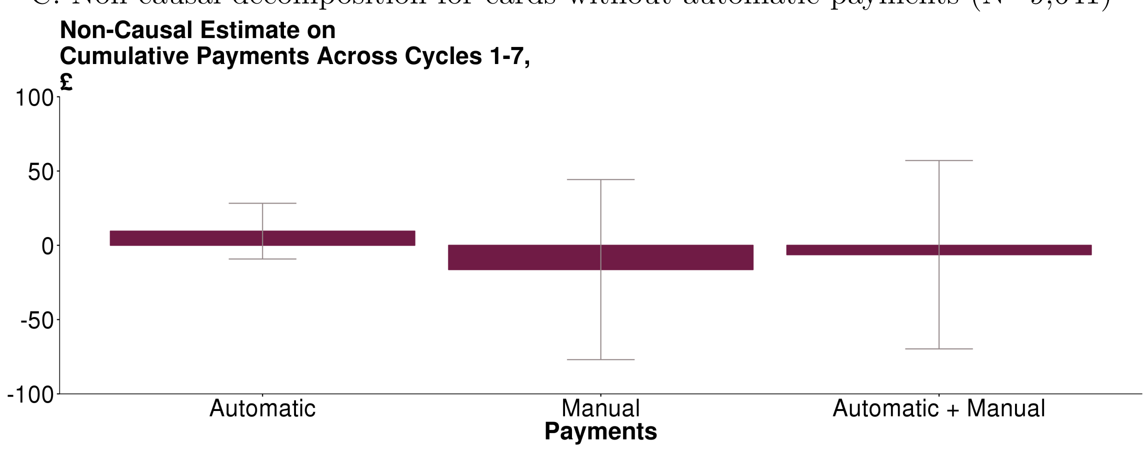
A: Causal estimate for all cards (N=40,693)



B: Non-causal decomposition for cards with automatic payments (N=31,052)



C: Non-causal decomposition for cards without automatic payments (N=9,641)



Treatment effects from coefficients $(\delta_1 + \delta_7)$ in OLS regression specified in Equation 3 for panel A, Equation 4 for panels B and C (standard errors clustered at card-level). Error bars are 95% confidence intervals.

Table 1: Summary statistics

Outcome	Mean	P10	P25	P50	P75	P90
Age (years)	36.46	23	27	34	45	54
Female (% cards)	46.06					
Credit Limit (£)	4312.49	400	1200	3800	6300	9000
Credit Score (0-100)	65.26	55.65	60.62	65.58	70.38	74.49
Purchases Rate (%)	22.85	18.9	18.9	18.9	29.9	34.9
Balance Transfer (% cards)	29.00					
Any Automatic Payment Set-up (% cards)	78.33					
Any Automatic Full Payment Set-up (% cards)	13.09					
Any Automatic Fixed Payment Set-up (% cards)	29.77					
Any Automatic Minimum Payment Set-up (% cards)	35.47					
Credit Card Statement Balance (£)	2164.49	0	372.51	1289.82	3273.7	5436.64
Credit Card Statement Balance Net of Payments (£)	1962.52	0	40.61	1085.54	3069.9	5162.06
Full Payment (% cards)	23.97					
Between Full and Min Payment (% cards)	42.22					
Minimum Payment (% cards)	30.12					
Missed Payment (% cards)	3.69					
Number of Full Payments Across Cycles 1-7	1.90	0	0	1	3	7
Number of Minimum Payments Across Cycles 1-7	2.04	0	0	0	4	7
Full Payments For 6+ Cycles (% cards)	18.05					
Minimum Payments For 6+ Cycles (% cards)	19.18					
Credit Card Statement Balance Net of Payments (% Statement Balance)	69.36	0	17.92	95.04	97.75	97.75
Payments Across Cycles 1-7 (£)	1277.27	154.28	353	703.57	1420.23	2937.46
Purchases Across Cycles 1-7 (£)	350.92	0	0	0	122.54	866.94
Costs Across Cycles 1-7 (£)	76.02	0	5.23	45.32	109.95	191.65
Interest Across Cycles 1-7 (£)	19.77	0	0	0	14.92	63.16
Fees Across Cycles 1-7 (£)	56.26	0	1.81	30	80.1	147.2
Total Credit Card Statement Balances (£)	2364.92	0	0	878	3168	6636.2
Total Credit Card Statement Balances Net of Payments (£)	2001.35	0	0	360	2708	5945.2

Calculated for control group as at the seventh statement cycle. For comparison a representative sample of UK credit cards opened at the same period of time (and also evalauted after seven statements) has the following mean (median) characteristics: borrower age 42 (40), credit limit £3,500 (£2,500), statement balance net of payments £1,216 (262).

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

Outcome	Estimate (S.E.)	95% C.I.	P Value	Adj. R2
Any minimum payment	-0.0707*** (0.0042)	[-0.079, -0.0625]	0	0.0841
Any full payment	0.0044 (0.0037)	[-0.0028, 0.0116]	0.2286	0.2971
Any payment less than minimum payment	0.0038* (0.0019)	[0.0001, 0.0074]	0.0436	0.0333
Statement balance net of payments (% statement balance)	-0.0055 (0.0035)	[-0.0123, 0.0013]	0.1125	0.3292
Costs (% statement balance)	-0.0003 (0.0006)	[-0.0015, 0.001]	0.6852	0.017
Transactions (% statement balance)	0.0027 (0.0031)	[-0.0035, 0.0089]	0.3885	0.2345
CRA share of credit cards only paying minimum	-0.0264*** (0.0027)	[-0.0318, -0.0211]	0	0.1818
CRA share of credit cards making full payment	0.0013 (0.0033)	[-0.0052, 0.0078]	0.6891	0.2967
CRA share of credit cards missing payment	-0.0001 (0.0013)	[-0.0026, 0.0024]	0.9485	0.0609
CRA total credit card statement balances net of payments (% statement balance)	-0.0056 (0.0031)	[-0.0117, 0.0006]	0.0768	0.4115

Statistical significance denoted at *** 0.5%, ** 1.0%, * 5.0%. Table shows average treatment effects after seven statement cycles. OLS regressions as specified by Equation 3 with standard errors clustered at card-level. 40,708 credit cards with 368,043 degrees of freedom and 368,032 for CRA (credit reference agency) outcomes as latter includes controls for lags of outcomes.

Table 3: Average treatment effects for primary outcomes pooled across all statement cycles

Outcome	Estimate (S.E.)	95% C.I.	P Value	Adj. R2
Any minimum payment	-0.0809*** (0.0033)	[-0.0874, -0.0745]	0	0.0824
Any full payment	0.0044 (0.0028)	[-0.0011, 0.01]	0.1135	0.2869
Any payment less than minimum payment	0.004*** (0.0011)	[0.0018, 0.0061]	0.0003	0.0332
Statement balance net of payments (% statement balance)	-0.006* (0.0027)	[-0.0114, -0.0007]	0.0261	0.32
Costs (% statement balance)	-0.0001 (0.0002)	[-0.0006, 0.0003]	0.5435	0.0166
Transactions (% statement balance)	0.0015 (0.002)	[-0.0024, 0.0055]	0.4505	0.2089
CRA share of credit cards only paying minimum	-0.0267*** (0.0017)	[-0.0299, -0.0234]	0	0.1632
CRA share of credit cards making full payment	0.0005 (0.0023)	[-0.004, 0.005]	0.8345	0.2576
CRA share of credit cards missing payment	0.0004 (0.0007)	[-0.0009, 0.0017]	0.5742	0.0589
CRA total credit card statement balances net of payments (% statement balance)	-0.0039 (0.0022)	[-0.0082, 0.0003]	0.0692	0.368

Statistical significance denoted at *** 0.5%, ** 1.0%, * 5.0%. Table shows average treatment effects pooled across all completed statement cycles. OLS regressions from Equation 3 where time-varying treatment-cycle interactions replaced with a single time-invariant treatment coefficient. Standard errors clustered at card-level. 40,708 credit cards with 368,063 degrees of freedom and 368,052 for CRA (credit reference agency) outcomes as latter includes controls for lags of outcomes.

Table 4: Decomposition of average treatment effects for primary outcomes by automatic payment enrolment after seven statement cycles

Outcome	Enrolled	Not Enrolled
Any minimum payment	-0.088***	0.0178**
	(0.005)	(0.0066)
Any full payment	0.0078*	-0.0116
	(0.0039)	(0.0088)
Any payment less than minimum payment	-0.0003	-0.0088
	(0.0007)	(0.007)
Statement balance net of payments	-0.0096**	0.012
(% statement balance)	(0.0037)	(0.0083)
Costs	-0.0007	-0.0004
(% statement balance)	(0.0006)	(0.0018)
Transactions	0.0071*	-0.0049
(% statement balance)	(0.0035)	(0.0067)
CRA share of credit cards only paying minimum	-0.0355***	0.0151***
	(0.0032)	(0.0052)
CRA share of credit cards making full payment	0.0048	-0.004
	(0.0036)	(0.0076)
CRA share of credit cards missing payment	-0.0009	-0.0094*
	(0.0006)	(0.0047)
CRA total credit card statement balances	-0.0092**	0.0046
net of payments (% statement balance)	(0.0034)	(0.0075)

Statistical significance denoted at *** 0.5%, ** 1.0%, * 5.0%. Table shows coefficients (standard errors) from decomposition of average treatment effects by automatic payment choice after seven statement cycles. Decomposition as specified in Equation 4 with OLS regressions and standard errors clustered at card-level. 31,052 credit cards with automatic payments and 9,656 without automatic payments as of the seventh statement cycle.

Table 5: Decomposition of average treatment effects for selected secondary outcomes by automatic payment enrolment after seven statement cycles

Outcome	All	Enrolled	Not Enrolled
Any automatic payment set-up	-0.0427***		
	(0.0041)		
Any automatic minimum payment set-up	-0.2173***	-0.2653***	
	(0.0041)	(0.0049)	
Any automatic fixed payment set-up	0.1678***	0.2473***	
	(0.0045)	(0.0051)	
Any automatic fixed payment set-up	0.0865***	0.1341***	
exceeding contractual minimum payment	(0.0043)	(0.0052)	
Any automatic full payment set-up	0.0069*	0.0176***	
	(0.0028)	(0.0034)	
Cumulative payments across statements	7.0689	2.9775	-6.3296
	(16.219)	(18.646)	(32.3425)
Cumulative automatic payments across statements	27.7215**	61.501***	9.5325
	(10.364)	(12.7604)	(9.5681)
Cumulative manual payments across statements	-18.888	-55.7081***	-16.3532
	(13.9749)	(14.9303)	(30.9214)
Total payments (% statement balance)	0.0064	0.0123***	-0.0064
	(0.0034)	(0.0037)	(0.008)
Automatic payments (% statement balance)	0.0075**	0.0167***	0.0019
	(0.0027)	(0.0032)	(0.0011)
Manual payments (% statement balance)	-0.0005	-0.0032	-0.0081
	(0.003)	(0.0031)	(0.008)
Payments via both automatic AND manual	0.0131***	0.0235***	0.0002
	(0.0026)	(0.0033)	(0.0012)
Automatic payments as a % of total payments	-0.0061	0.0306***	-0.0021
	(0.0051)	(0.0044)	(0.0033)
Statement balance	-1.6073	-9.4396	41.8898
	(17.2714)	(19.7173)	(33.9096)
Statement balance net of payments	2.7377	-3.3432	40.8693
	(17.2434)	(19.7232)	(33.5576)
Statement balance as a % of credit limit	-0.0002	-0.007*	0.0167*
	(0.0032)	(0.0033)	(0.0082)
Cumulative purchases across statements	-19.5082	-26.9291	-4.4421
	(12.7219)	(14.9544)	(24.3599)
CRA total credit card payments	9.0376	6.7686	2.0523
	(9.3864)	(11.0392)	(17.4438)
CRA total credit card statement balance net of payments	9.0636	10.3639	47.1523
	(31.1348)	(36.957)	(55.8298)

Statistical significance denoted at *** 0.5%, ** 1.0%, * 5.0%. Table shows coefficients (standard errors) from decomposition of average treatment effects by automatic payment choice after seven statement cycles. Average treatment effects for all cards as specified in Equation 3. Decomposition as specified in Equation 4 with OLS regressions and standard errors clustered at card-level. 31,052 credit cards with automatic payments and 9,656 without automatic payments as of the seventh statement cycle.

7 Online Appendix

Accompanying “The Semblance of Success in Nudging Consumers to Pay Down Credit Card Debt” by Benedict Guttman-Kenney, Paul D. Adams, Stefan Hunt, David Laibson and Neil Stewart

Table A6: Balance checks between treatment and control

Variable	Control	Treatment	Difference	95% C.I.
Age (years)	36.46	36.61	0.15	[-0.09, 0.39]
Female (% cards)	46.05	46.13	0.08	[-0.89, 1.04]
Credit Limit (£)	4312.64	4384.31	71.66*	[5.3, 138.02]
Credit Score (0-100)	65.26	65.38	0.12	[-0.03, 0.26]
Purchases Rate (%)	22.85	22.82	-0.03	[-0.15, 0.09]
Balance Transfer (% cards)	28.99	29.76	0.77	[-0.11, 1.66]
Total Credit Card Statement Balances (£)	2364.66	2439.02	74.36	[-0.57, 149.29]
Total Credit Card Statement Balances Net of Payments (£)	2000.92	2072.44	71.52*	[2.95, 140.09]

Statistical significance denoted at *** 0.5%, ** 1.0%, * 5.0%. N (control) = 20,617 and N (treatment) = 20,091 cards.

Table A7: Unconditional mean comparison of treatment effects for primary outcomes after seven statement cycles

Outcome	Control	Treatment	Difference	95% C.I.
Any minimum payment	0.3012	0.2323	-0.0689***	[-0.0775, -0.0603]
Any full payment	0.2397	0.2417	0.0019	[-0.0064, 0.0102]
Any payment less than minimum payment	0.0369	0.0403	0.0034	[-0.0003, 0.0071]
Statement balance net of payments (% statement balance)	0.6936	0.691	-0.0026	[-0.0106, 0.0054]
Costs (% statement balance)	0.0111	0.0107	-0.0004	[-0.0016, 0.0009]
Transactions (% statement balance)	0.2007	0.2013	0.0006	[-0.0062, 0.0075]
CRA share of credit cards only paying minimum	0.2012	0.1775	-0.0237***	[-0.0295, -0.0179]
CRA share of credit cards making full payment	0.4414	0.4424	0.0011	[-0.0062, 0.0084]
CRA share of credit cards missing payment	0.0236	0.0231	-0.0004	[-0.003, 0.0021]
CRA total credit card statement balances net of payments (% statement balances)	0.6954	0.6912	-0.0042	[-0.0117, 0.0034]

Statistical significance denoted at *** 0.5%, ** 1.0%, * 5.0%. N (control) = 20,617 and N (treatment) = 20,091 cards.

Table A8: Unconditional mean comparison of treatment effects for secondary outcomes after seven statement cycles

Outcome	Control	Treatment	Difference	95% C.I.
Any automatic payment set-up	0.7833	0.7423	-0.041***	[-0.0492, -0.0327]
Any automatic minimum payment set-up	0.3547	0.138	-0.2167***	[-0.2248, -0.2086]
Automatic fixed payment set to £5	0.0006	0.0073	0.0067***	[0.0055, 0.008]
Any automatic fixed payment set-up	0.2977	0.4679	0.1702***	[0.1609, 0.1795]
Any automatic fixed payment set-up exceeding contractual minimum payment	0.2529	0.3412	0.0883***	[0.0794, 0.0971]
Any automatic full payment set-up	0.1309	0.1364	0.0056	[-0.0011, 0.0122]
Cumulative times repaid less than minimum payment	0.1892	0.2153	0.0261***	[0.011, 0.0412]
Cumulative times repaid only minimum payment	2.0444	1.4594	-0.585***	[-0.6329, -0.5372]
Cumulative times repaid in full	1.902	1.9081	0.0061	[-0.0439, 0.056]
Cumulative payments across statements (£)	1277.2667	1288.3119	11.0453	[-22.899, 44.9895]
Cumulative automatic payments across statements (£)	573.7899	605.2636	31.4737***	[9.6362, 53.3112]
Cumulative manual payments across statements (£)	711.9684	693.1835	-18.785	[-46.7112, 9.1412]
Total payments (% statement balance)	0.2271	0.2305	0.0034	[-0.004, 0.0107]
Automatic payments (% statement balance)	0.1101	0.1164	0.0062*	[0.0007, 0.0118]
Manual payments (% statement balance)	0.1212	0.1189	-0.0023	[-0.0081, 0.0035]
Payments via both automatic AND manual	0.0672	0.0797	0.0125***	[0.0074, 0.0176]
Automatic payments as a % of total payments	0.6643	0.6624	-0.0019	[-0.0115, 0.0077]
Statement balance (£)	2164.4948	2203.7629	39.2681	[-7.975, 86.5112]
Statement balance net of payments (£)	1962.519	2005.4041	42.8851	[-3.4588, 89.229]
Statement balance as a % of credit limit	0.5223	0.5217	-0.0006	[-0.0076, 0.0065]
Cumulative purchases across statements (£)	350.922	330.6475	-20.2745	[-46.4748, 5.9257]
CRA total credit card payments	485.7041	508.1641	22.46*	[0.8591, 44.0608]
CRA total credit card payments (% statement balance)	0.2564	0.2559	-0.0005	[-0.0076, 0.0066]
CRA total credit card statement balance net of payments	3431.6852	3510.78	79.0948	[-15.6258, 173.8153]

Statistical significance denoted at *** 0.5%, ** 1.0%, * 5.0%. N (control) = 20,617 and N (treatment) = 20,091 cards.

Table A9: Average treatment effects for tertiary arrears outcomes pooled across all statement cycles

Outcome	Estimate (S.E.)	95% C.I.	P Value	Adj. R2
Arrears (1+ payments behind)	0.003*** (0.001)	[0.001, 0.005]	0.0029	0.038
Arrears (2+ payments behind)	0.0004 (0.0007)	[-0.001, 0.0018]	0.5681	0.0273
Arrears (3+ payments behind)	0.0001 (0.0005)	[-0.0009, 0.0012]	0.7862	0.0204

Statistical significance denoted at *** 0.5%, ** 1.0%, * 5.0%. Table shows average treatment effects pooled across all completed statement cycles. OLS regressions from Equation 3 where time-varying treatment-cycle interactions replaced with a single time-invariant treatment coefficient. Standard errors clustered at card-level. 40,708 credit cards with 368,063 degrees of freedom .

Table A10: Decomposition of average treatment effects for additional selected secondary outcomes by automatic payment enrolment after seven statement cycles

Outcome	All	Enrolled	Not Enrolled
Automatic fixed payment set to £5	0.0068***		
	(0.0006)		
Cumulative times repaid less than minimum payment	0.0274***	0.0151***	-0.0431
	(0.0075)	(0.0032)	(0.0276)
Cumulative times repaid only minimum payment	-0.5949***	-0.7378***	0.0404
	(0.0232)	(0.0281)	(0.0312)
Cumulative times repaid in full	0.0211	0.0458*	-0.091*
	(0.0201)	(0.0221)	(0.0455)
Log (statement balance)	-0.0111	-0.0137	0.076
	(0.0216)	(0.0224)	(0.0544)
Log (statement balance net of payments)	-0.0227	-0.0463	0.0946
	(0.0264)	(0.0282)	(0.0627)
Positive statement balance	-0.0004	0.0011	0.0072
	(0.0029)	(0.003)	(0.0073)
Any new purchases	0.0016	0.0053	-0.0145
	(0.004)	(0.0044)	(0.0089)
CRA total credit card payments (% statement balance)	0.002	0.0048	-0.0056
	(0.0032)	(0.0035)	(0.0078)

Statistical significance denoted at *** 0.5%, ** 1.0%, * 5.0%. Table shows coefficients (standard errors) from decomposition of average treatment effects by automatic payment choice after seven statement cycles. Average treatment effects for all cards as specified in Equation 3. Decomposition as specified in Equation 4 with OLS regressions and standard errors clustered at card-level. 31,052 credit cards with automatic payments and 9,656 without automatic payments as of the seventh statement cycle.

Table A11: SECOND LENDER - Balance checks between treatment and control

Variable	Control	Treatment	Difference	95% C.I.
Age (years)	37.04	36.41	-0.63	[-1.83, 0.57]
Female (% cards)	47.7	52.21	4.51	[-0.5, 9.52]
Credit Limit (£)	571.49	538.31	-33.18	[-90.28, 23.92]
Credit Score (0-100)	53.75	54.2	0.44	[-0.48, 1.37]
Purchases Rate (%)	22.93	23.46	0.53	[-0.64, 1.7]
Balance Transfer (% cards)	17.43	17.57	0.14	[-3.67, 3.95]
Total Credit Card Statement Balances (£)	956.9	885.6	-71.3	[-279.39, 136.79]
Total Credit Card Statement Balances Net of Payments (£)	871.52	813.65	-57.87	[-253.6, 137.87]

Statistical significance denoted at *** 0.5%, ** 1.0%, * 5.0%. N (control) = 740 and N (treatment) = 791 cards.

Table A12: SECOND LENDER - Average treatment effects for primary outcomes after seven statement cycles

Outcome	Estimate (S.E.)	95% C.I.	P Value	Adj. R2
Any minimum payment	-0.1562***	[-0.1982,	0	0.0926
	(0.0214)	-0.1141]		
Any full payment	0.0242	[-0.0188,	0.2702	0.13
	(0.0219)	0.0671]		
Any payment less than minimum payment	0.0083	[-0.025,	0.6251	0.3044
	(0.017)	0.0415]		
Statement balance net of payments	-0.037	[-0.0771,	0.0708	0.1513
(% statement balance)	(0.0205)	0.0031]		
Costs	-0.0089*	[-0.0168,	0.0267	0.0221
(% statement balance)	(0.004)	-0.001]		
Transactions	0.0121	[-0.0242,	0.5136	0.1877
(% statement balance)	(0.0185)	0.0485]		
CRA share of credit cards only paying minimum	-0.082***	[-0.1085,	0	0.224
	(0.0136)	-0.0554]		
CRA share of credit cards making full payment	0.0094	[-0.0273,	0.6152	0.5422
	(0.0187)	0.0461]		
CRA share of credit cards missing payment	0.012	[-0.0123,	0.3329	0.1143
	(0.0124)	0.0363]		
CRA total credit card statement balances	-0.028	[-0.0633,	0.12	0.5748
net of payments (% statement balance)	(0.018)	0.0073]		

Statistical significance denoted at *** 0.5%, ** 1.0%, * 5.0%. Table shows average treatment effects after seven statement cycles. OLS regressions as specified by Equation 3 with standard errors clustered at card-level. 1,531 credit cards with 19,460 degrees of freedom and 19,449 for CRA (credit reference agency) outcomes as latter includes controls for lags of outcomes.

Table A13: SECOND LENDER - Average treatment effects for automatic payment enrolment outcomes after seven statement cycles

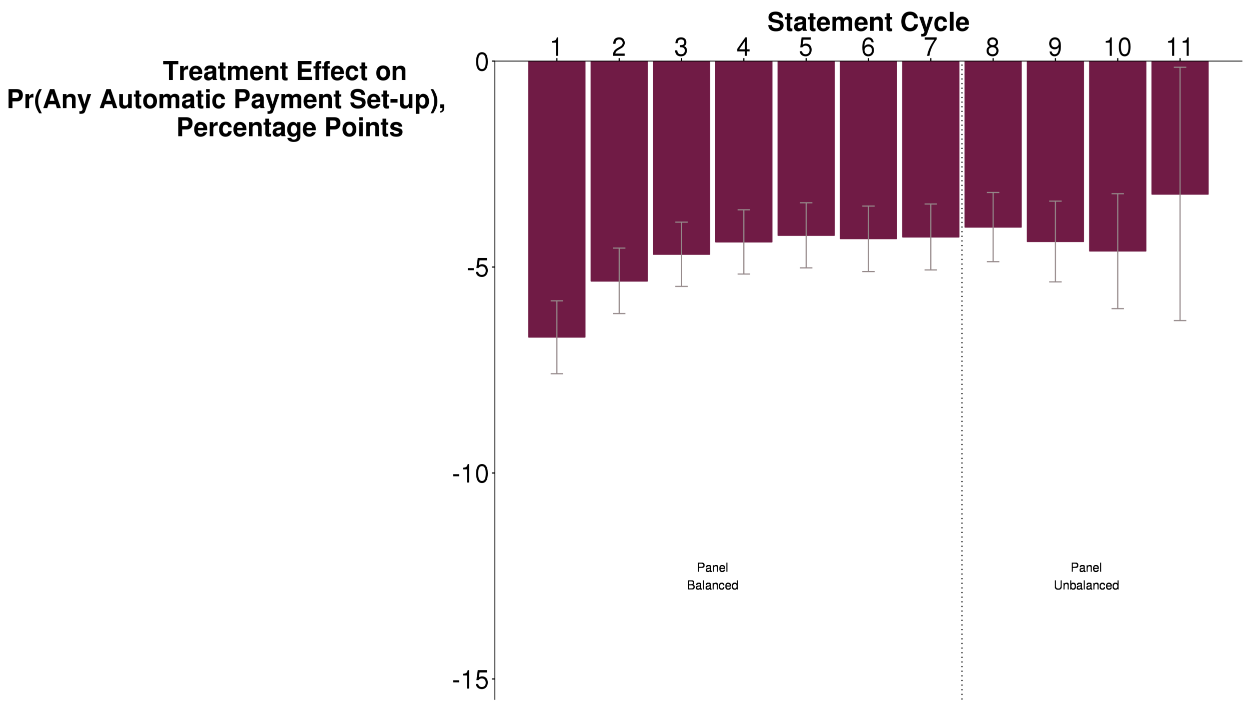
Outcome	Estimate (S.E.)	95% C.I.	P Value	Adj. R2
Any automatic payment set-up	-0.0504* (0.0214)	[-0.0924, -0.0084]	0.0188	0.1756
Any automatic minimum payment set-up	-0.3873*** (0.0209)	[-0.4282, -0.3464]	0	0.234
Any automatic fixed payment set-up	0.3053*** (0.0228)	[0.2606, 0.35]	0	0.204
Any automatic fixed payment set-up exceeding contractual minimum payment	0.205*** (0.022)	[0.1618, 0.2482]	0	0.1469
Any automatic full payment set-up	0.0316 (0.0163)	[-0.0003, 0.0636]	0.0524	0.1182

Statistical significance denoted at *** 0.5%, ** 1.0%, * 5.0%. Table shows average treatment effects after seven statement cycles. OLS regressions as specified by Equation 3 with standard errors clustered at card-level. 1,531 credit cards with 19,460 degrees of freedom and 19,449 for CRA (credit reference agency) outcomes as latter includes controls for lags of outcomes.

Figure A6: Automatic payment enrollment for control and treatment groups split by statement cycles one to seven

Numbers display percentage selecting each type of automatic payment. 95% confidence intervals in [ ].

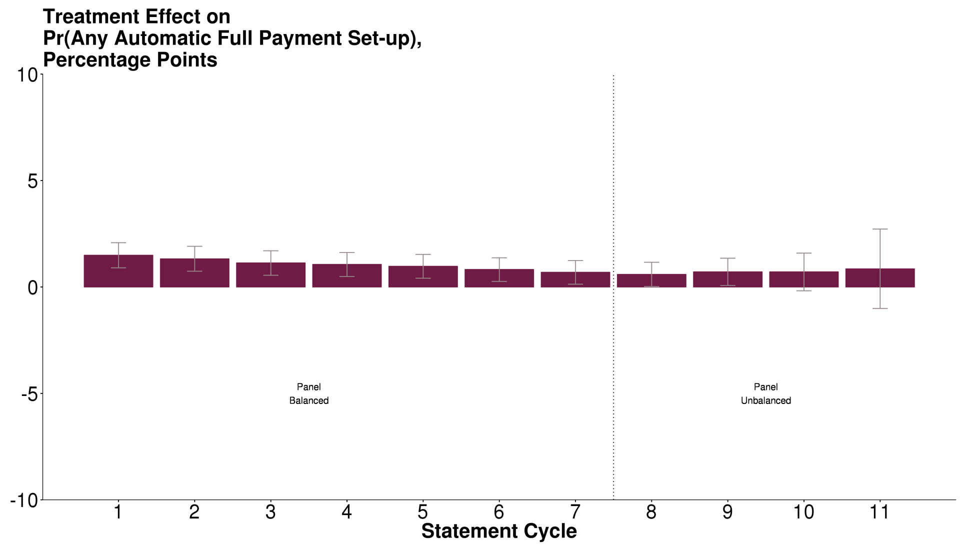
Figure A7: Average treatment effects on automatic payment enrollment across 1-11 statement cycles



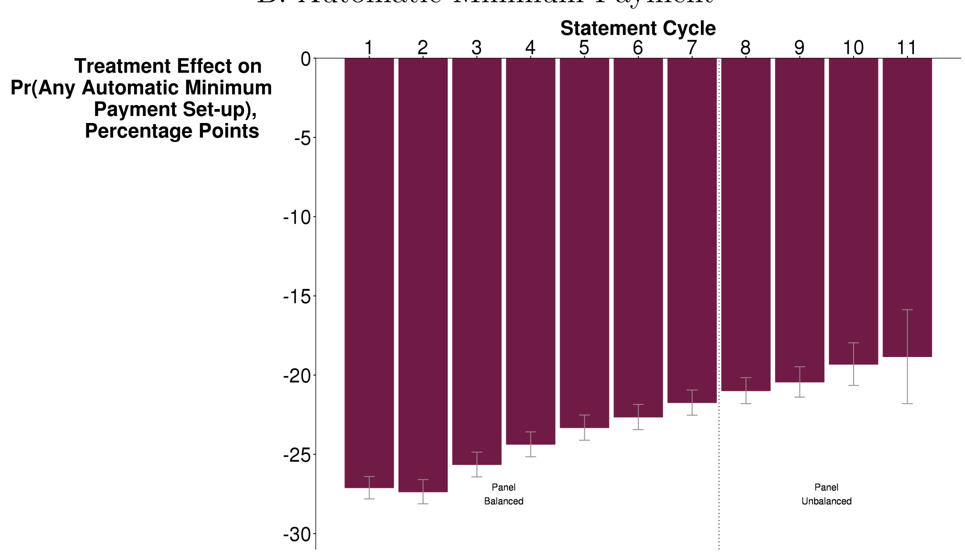
Treatment effects from coefficients ($\delta_1 + \delta_t$) in OLS regression specified in Equation 2 (standard errors clustered at card-level). Error bars are 95% confidence intervals.

Figure A8: Average treatment effects on automatic full (panel A) and minimum (panel B) payment enrollments across 1-11 statement cycles

A: Automatic Full Payment



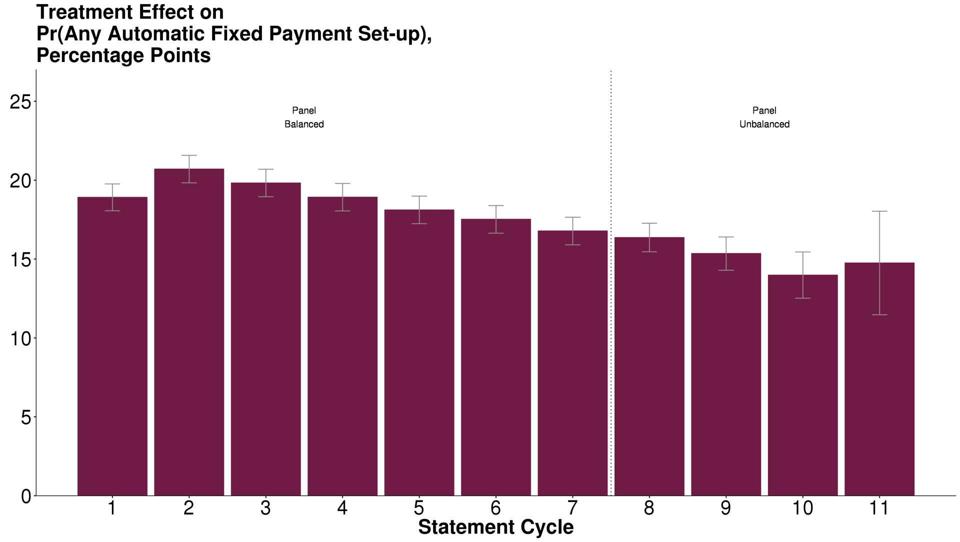
B: Automatic Minimum Payment



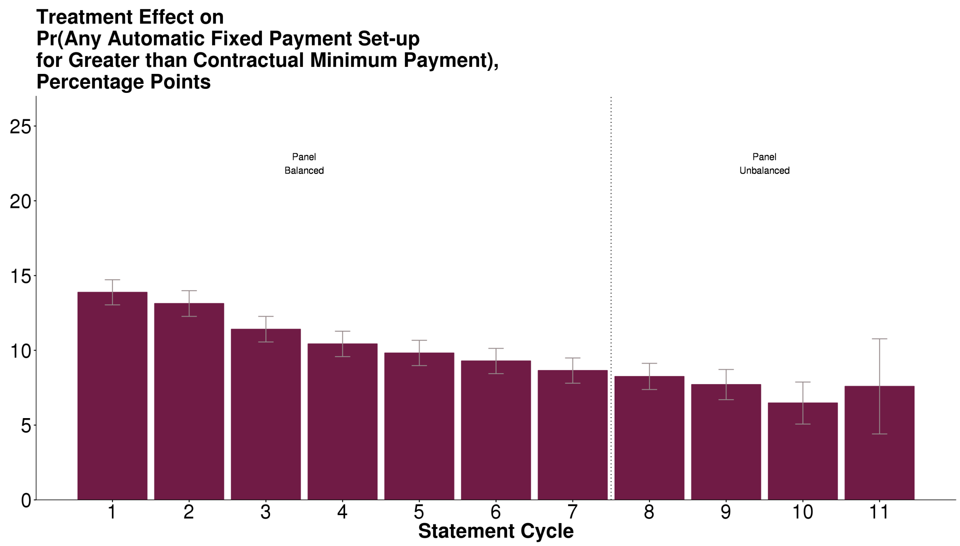
Treatment effects from coefficients ($\delta_1 + \delta_t$) in OLS regression specified in Equation 2 (standard errors clustered at card-level). Error bars are 95% confidence intervals.

Figure A9: Average treatment effects on automatic fixed payment enrollment across 1-11 statement cycles

A: Automatic Fixed Payment



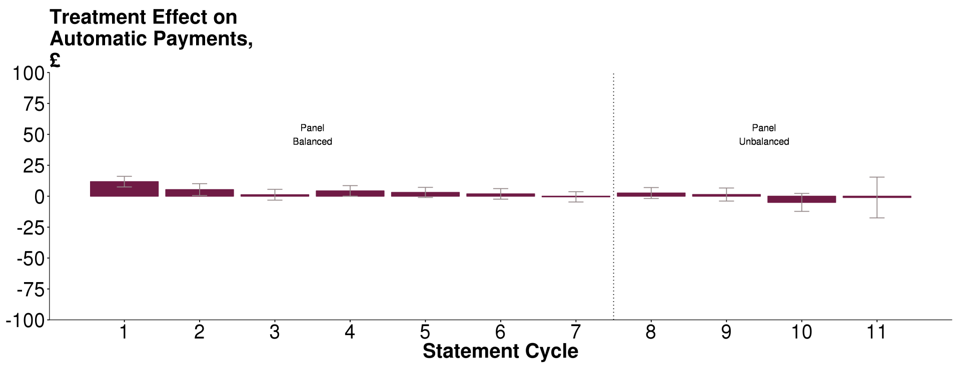
B: Automatic Fixed Payment > Contractual Minimum Payment



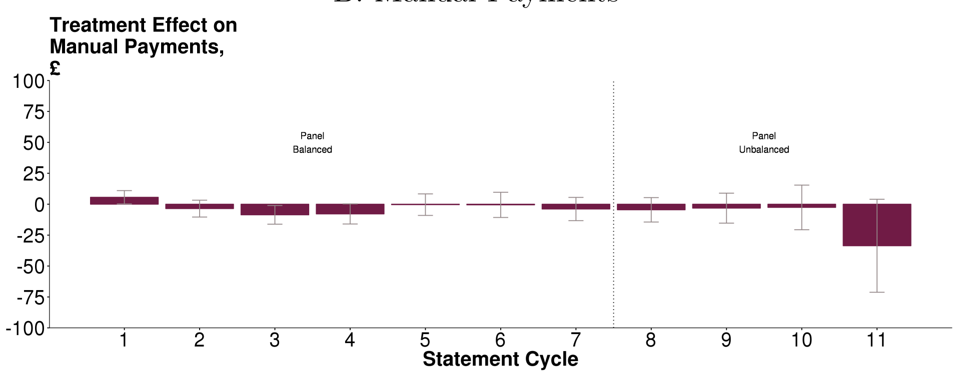
Treatment effects from coefficients ($\delta_1 + \delta_t$) in OLS regression specified in Equation 2 (standard errors clustered at card-level). Error bars are 95% confidence intervals.

Figure A10: Treatment effects on payments across 1-11 statement cycles split by payment mechanism

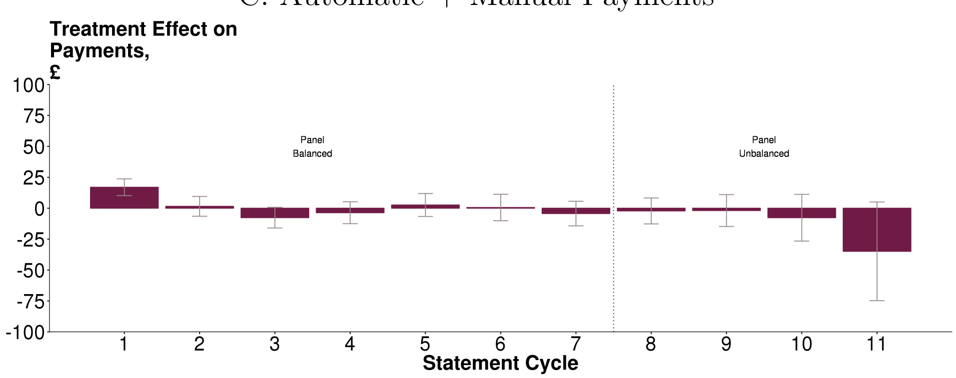
A: Automatic Payments



B: Manual Payments



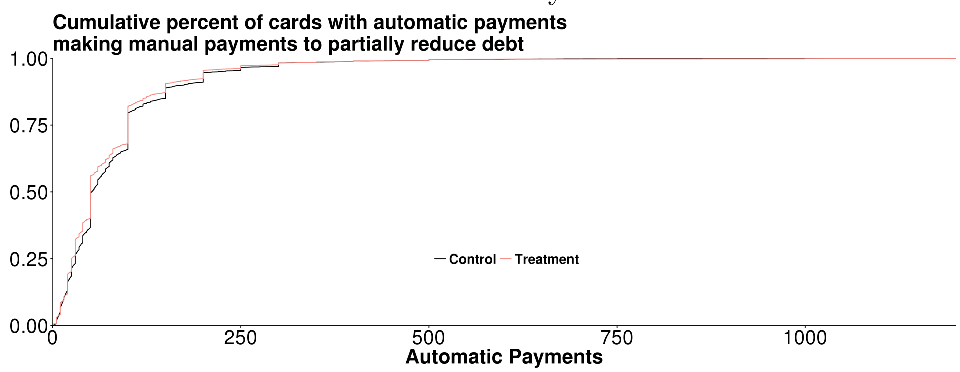
C: Automatic + Manual Payments



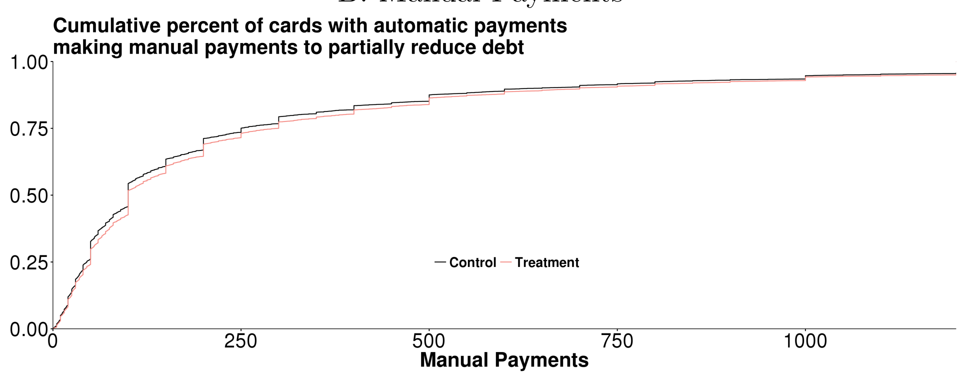
Treatment effects from coefficients ($\delta_1 + \delta_t$) in OLS regression specified in Equation 2 (standard errors clustered at card-level). Error bars are 95% confidence intervals.

Figure A11: Cumulative distributions of payments in cycles where consumers enrolled in automatic payments and make manual payments that partially reduce debt

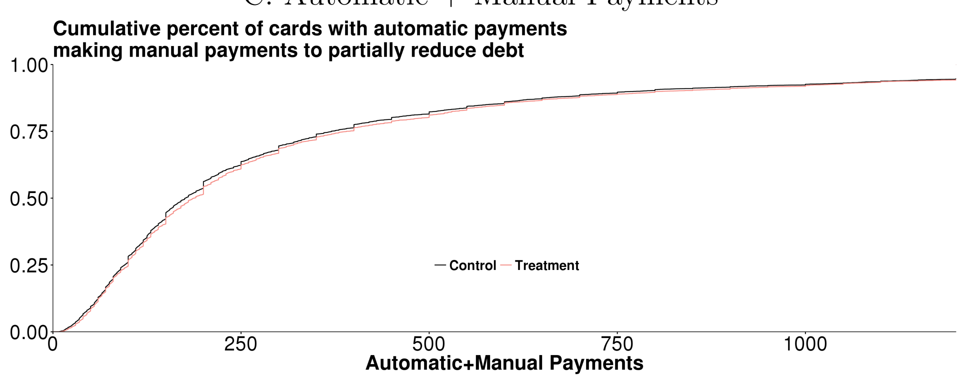
A: Automatic Payments



B: Manual Payments

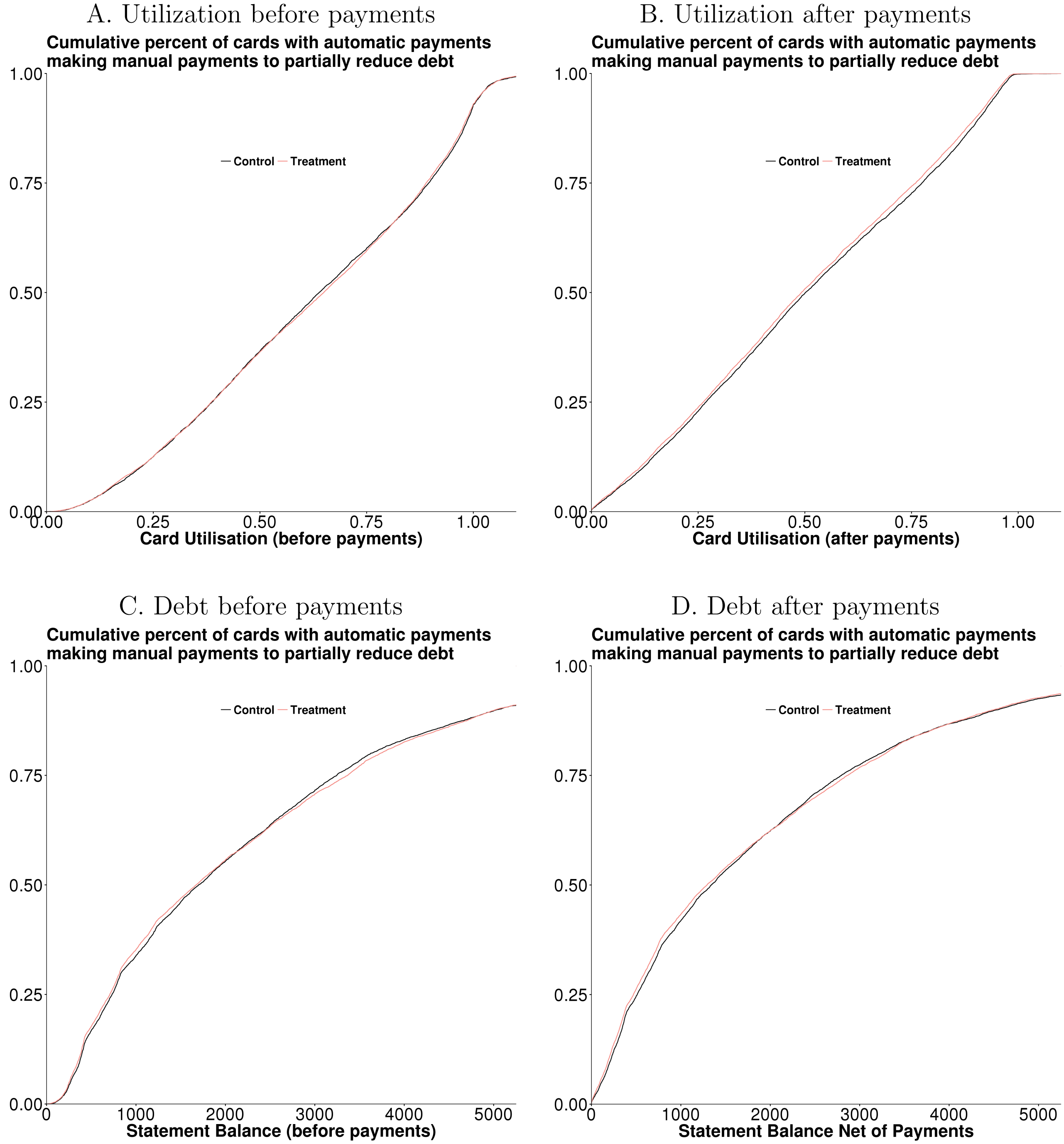


C: Automatic + Manual Payments



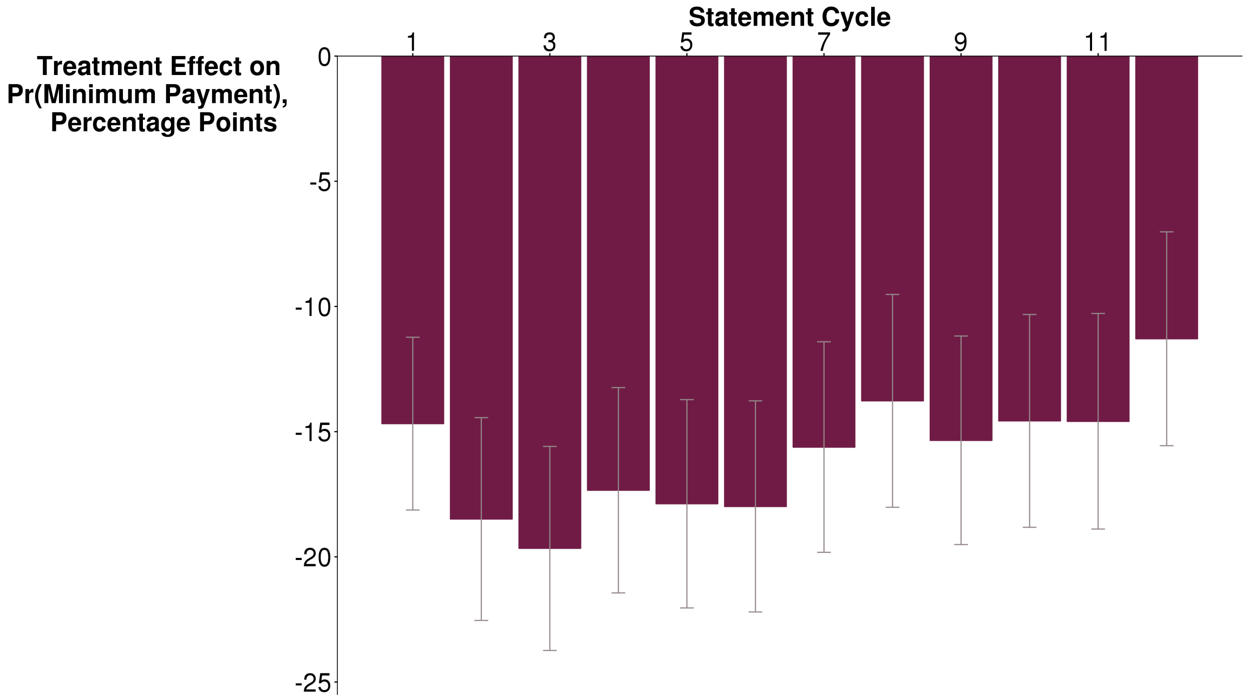
All statements from cycles 1-7 included where cards enrolled in automatic payments and make a manual payment for an amount less than to pay off debt in full. N=18,680 out of 161,618 card statements with automatic payments.

Figure A12: Cumulative distributions of utilisation rates (panels A and B) and debt (panels C and D) in cycles where consumers enrolled in automatic payments and make manual payments that partially reduce debt



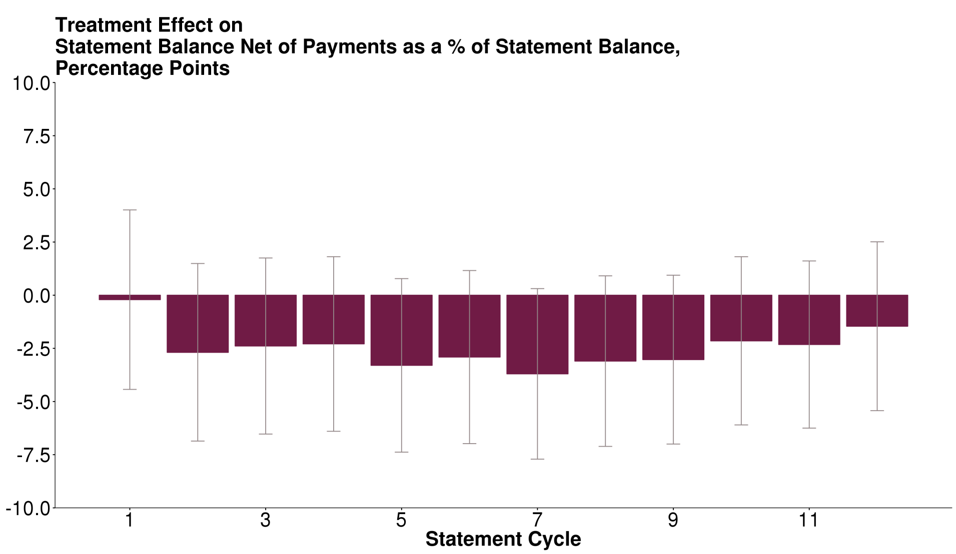
All statements from cycles 1-7 included where cards enrolled in automatic payments and make a manual payment for an amount less than to pay off debt in full. N=18,680 out of 161,618 card statements with automatic payments.

Figure A13: SECOND LENDER - Average treatment effects on making only a minimum payment across 1-12 statement cycles



Treatment effects from coefficients ($\delta_1 + \delta_t$) in OLS regression specified in Equation 2 (standard errors clustered at card-level). Error bars are 95% confidence intervals.

Figure A14: SECOND LENDER - Average treatment effects on credit card debt across 1-12 statement cycles



Treatment effects from coefficients ($\delta_1 + \delta_t$) in OLS regression specified in Equation 2 (standard errors clustered at card-level). Error bars are 95% confidence intervals.