When Setting a Default Payment Harms Credit Card Holders

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Automatic payments are increasingly common. The psychologies of the prominent of number, defaults and inattention combine to create an unexpected side effect of automatic payments. We see that credit card holders set a default automatic payment to match their modal repayment behavior. For those often paying in full, an automatic full repayment almost completely eliminates late fees caused when people forget to pay their bill. For those often paying only the minimum, an automatic minimum repayment locks in their modal minimum payment behavior. But it was their amodal behavior—occasionally making larger repayments at prominent amounts (e.g., £100, £200, £500)—that was reducing their balance. Without the need to address their bill each month, card holders make these additional repayments less often, and as a result incur 2–3 times more in interest charges than the late-payment fees that they avoid by automating their payments. We estimate that the reduction in prominent amount repayments as people switch to automatic minimum repayment is responsible for 12% of all of the interest ever paid on credit cards.

Keywords: default; inattention; prominence; automatic repayment; credit card

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Automatic bill payments are very common, regularly used by people for payments on continuity products including mortgages, cell phone bills and credit cards. One might expect automatic payments to make consumers' payments more reliable by setting a strong default option—and they do. But here we document how three psychological phenomena—defaults, inattention, and the prominence of number—combine to create a large and negative side effect of automatic payments. The ubiquity of automatic payments in the UK and the increase in the US makes automatic payments important, and we are the first to present evidence in the academic literature. This downside we present here is economically very large: The interest caused because of consumer inattention as people self-select into a strong default is about 12% of all of the interest ever paid in the credit card market.

We focus on the case of credit card repayments because people face an explicit choice as to the level of the automatic payment (unlike, for example, a cell phone bill which has to be paid in full every month). Credit card holders can choose to set up automatic payments to cover the full balance on their credit card, they can choose to pay a fixed sum of money each month (with only the balance taken if the balance is lower than the fixed sum), or to pay only the minimum amount due (which avoids late payment fees). In these latter two cases of fixed or minimum repayment, card holders carry their remaining debt over to the next month's bill (termed revolving the debt) and pay interest on the debt they carry over.

Here we use data from a large sample of accounts drawn from five credit card companies to show that, when switching to an automatic payment, card holders overwhelmingly select the automatic payment that most closely matches their pre-switch behavior. For those switching to an automatic full repayment, the upside is that switching eliminates late payment fees, because payment is made automatically and there is no longer any scope for forgetting or otherwise omitting to pay. For those switching to an automatic fixed repayment, we also see that forgetting to repay is nearly completely eliminated, but these cardholders and also less likely to repay their bill in full.

Our primary interest for this paper is in the unintended consequences that card holders experience by switching to an automatic *minimum* repayment. As with the other automatic repayments, automatic minimum repayments almost completely eliminate late payment fees. But the automatic minimum repayment locks in the card holders' modal minimum payment behavior. The less frequent behavior of manually paying larger fixed prominent amounts (like £100, £200, and £500) is now greatly reduced—but these were the only repayments appreciably reducing the balance and hence the interest charged. In fact, we find that automatic minimum payment card holders pay 2–3 times more in extra interest than the late payment fees that they save because they pay down their debt much more rarely.

This is the first field evidence on the effects of using automatic payment, and the effects we find are economically significant—as we describe above the extra interest is 12% of all of the interest ever paid in the credit card market. Our results relate to earlier studies which show that minimum payments can be important determinants of repayment behavior (Navarro-Martinez, 2011; Salisbury, 2014; Stewart; 2009) and more generally to the broader literature on the effects of default options, inattention, and the prominence of number, which we discuss below.

THEORETICAL FRAMEWORK

Automatic Payment as a Default

Setting an automatic payment is, in effect, consumers opting in to a default. Defaults can be powerful. Perhaps the most well-known and well-evidenced behavioral science intervention is the default option ‘nudge’ whereby the status-quo option for a decision is changed by a policymaker (Thaler & Sunstein, 2008). One prominent example is the adoption of an opt-out policy for organ donation instead of an opt-in policy. Opt-out is associated with substantially increased organ donation rates (Johnson & Goldstein, 2003). Setting a default option is a powerful tool which has been used in a variety of important settings including pension saving (Cronqvist & Thaler, 2004), insurance coverage (Johnson, Hershey, Meszaros, & Kunreuther, 1993), web marketing (Johnson, Bellman, & Lohse, 2002), and energy markets (Momsen & Stoerk, 2014).

Defaults change the status-quo choice, but do not limit the options available to the individual, and thus preserve individual freedom (Sunstein, 2014). Psychological theories suggest that a default option has a large probability of being chosen because of people’s cognitive laziness or status quo bias (Johnson & Goldstein, 2003). However, default options can potentially lead to unintended effects. Given the power of default options to influence individual behavior their design, and use, are important issues (Thaler, Sunstein, & Balz, 2014).

Through automatic payments, credit card companies and card holders are creating a default option which changes the status quo repayment. Traditionally, customers had to settle their bills each month by manual payment. However, payments technology now allows credit card companies to offer automatic payments, including the option to automatically pay the minimum amount due. This seems like a great idea—no longer will people forget to pay their bills, and be charged late fees, because the minimum to keep the account good is paid automatically. At the same time, the consumer is free to pay more if he or she wishes. As a default option, the automatic minimum payment default is, theoretically, near perfect because it protects the consumer without limiting their freedom to pay more—this is the libertarian part of libertarian paternalism (Thaler & Sunstein, 2008). The default almost entirely eliminates the late fees, as intended, without, apparently, making it harder to pay down more debt—the mechanisms for making manual repayments remain unchanged. We think it is this near-perfect nudge property that makes automatic payments attractive to card holders. We find that card holders are able to set a default option that closely matches their manual repayment history, and we see that card holders can and do make additional manual repayments.

Automatic Payment and the Top of the Mind

An upside of automatic payment is that, because payments are automatic, late fees are avoided. A downside of automatic payment default is that, after switching to the new default, payments are no longer at the top of consumers' minds (Karlan et al., 2016): When a credit card bill arrives the customer does not have to do anything to address the bill and hence the bill is no longer salient, reducing their attention to repayments. Moreover, if people have present-biased preferences and prefer to postpone unpleasant activities like paying credit card bills, automatic payments might aid procrastination and lead to higher future debts (O'Donoghue & Rabin, 1999). Although we see that card holders with automatic payments set can and do make additional manual repayments, we believe that procrastination and inattention underlies our finding that people do not make manual repayments as often, deferring their manual repayment decision for future months.

Manual Repayments Cluster at Prominent Amounts

We observe that manual repayments cluster at prominent amounts. Not including the minimum repayments and full repayments (which are obvious repayment options but are also almost always non-round amounts) repayments cluster around prominent numbers. Albers (1997) defined prominent numbers as powers of ten, their doubles, and their halves (e.g., 5, 10, 20, 50, 100, 200, 500, 1000, 2000, …). We see this pattern extremely clearly in the manual repayments before people set an automatic minimum repayment (and we have a formal model of the prominence of amounts of money in preparation). We take this to indicate that repayments are chosen to minimize cognitive effort (Albers, 2001; Dennis, 2012). The tendency for people to prefer prominent numbers has been evident in both experimental (Whynes, Philips, & Frew, 2005) and field data (Ball, Torous, & Tschoegl, 1985; Christie & Schultz, 1994; Dennis, 2012; Harris, 1991; Kandel, Sarig, & Wohl, 2001). For example, in field data, Dennis (2012) found that trade sizes in the US stock markets highly cluster at prominent numbers (e.g., 2,000 shares) and at sums of two prominent numbers (e.g., 1,000 + 500 = 1,500 shares).

Before people set an automatic minimum repayment, prominent numbers remain as psychologically attractive possible repayments, and attracting card holders away from paying only the minimum. For example, a credit card bill of £1,234.00 will have a 1% minimum payment of £12.43. Before automatic minimum repayments, people might repay what are evidently very attractive prominent numbers of £50, £100, or £200. But after automatic minimum repayment people will neglect to make an additional manual repayment and thus only repay the minimum of £12.34. Without attending to the bill, the psychological prominence of higher, round repayments no longer has an effect. Because of the non-linear effect of repayment on the total interest charged, even though the prominent repayments are a small fraction of the bill (all less than 20% in this example), paying just a little over the minimum has a large beneficial effect on the total interest charged over the life of the debt, and this benefit is greatly reduced by automatic repayment.

A NATURAL EXPERIMENT

In our analysis we compare repayment behavior of individuals over time before-and-after they switch to an automatic minimum repayment on their credit card account. Therefore, our analysis is not contaminated with unobservable, time-invariant individual characteristics. However, individuals might switch to automatic repayment as a result of a decision to repay less in future. To address this, and as a robustness check, we exploit a natural experiment in the data: we repeat the analysis on individuals who switched after forgetting to repay and then received a refund of the late payment fee. For these individuals, the trigger for setting up an automatic minimum repayment is random forgetting and the intention to avoid further fees rather than their intention to reduce repayments in future.

Our analysis should be interpreted with the caveat that we cannot undertake a pure randomized control trial to evaluate the effects of switching to an automatic minimum repayment. That is, we are able to describe the effects of automatic payments on consumers who choose to switch to automatic payments, but we cannot control for selection into automatic payments. While a field randomized control trial would allow us to estimate the effects of automatic payments as a policy prescription for all consumers, such experiments are prohibited by financial regulations governing consumer rights in repayment decisions. Nevertheless, seeing the same pattern for refund-triggered changes to automatic minimum repayment is strong evidence of a causal linkage between automatic minimum repayment and the increased interest costs being incurred by consumers.

DATA

The data were provided by five UK credit card issuers, who together cover 40% of all UK credit card consumers. (Note, credit cards in the UK function almost exactly as they do in the US.) Cardholders and issuers were not identified. The data were extracted and provided by Argus Information & Advisory Services in collaboration with the UK Cards Association, without constraint on the research agenda. Complete R source code is available for all steps from importing the data export from Argus to the statistics, tables, and figures in this paper. We are retaining the data for 10 years. The data are a 10% random sample of all UK consumers who held a credit card during January 2013 to December 2014 within Argus's database, which covers nearly 100% of UK card holders.

The data include card numbers (anonymized), balances, purchase amounts, purchase types, repayment amounts, and various types of fees and finance charges for 1,790,191 cards during 24 months from January 2013 to December 2014. In the data, repayments appear in the statement for the month after the statement containing the balance. For example, repayments reported in December 2014 statements were made against the bill showing the balance and the required minimum in November 2014. Because no repayment data are available for January 2015, repayments for balances in December 2014 are unknown. Thus, the data provide at maximum 23 balance-repayment observations per card from January 2013 to November 2014.

An advantage of our data is that manual repayments and automatic repayments are reported separately. Automatic repayments are made by a mechanism known as "Direct Debit". Direct Debit is an extremely common method for paying bills in the UK. The analogous mechanism in the US has been introduced more recently and is variously known as "AutoPay" or "automatic payment".

The data also include required minimum amounts. The minimum amount people must pay each month is, in the UK, normally interest and fees accrued within the month plus 1% of the card balance, or a fixed sum such as £5 or £10, whichever is the greater. Making a repayment of at least the monthly accrued interest ensures that the value of the debt does not grow. Additionally, repaying 1% of the balance implies that over time the debt will be repaid, though the pay-down horizon is typically many years.

We extracted only cards which had a full set of 23 balance-repayment observations and excluded cards closed or charged-off during the data period. Cards which never had positive balances and those which had a zero merchant APR for part of the sample period were excluded from the analysis (in the latter case these cards may not require any repayment in some months). In addition, cards with a balance transfer were excluded. (Note that cards were treated as having a balance transfer when an aggregation of the beginning balance and all transaction amounts within a month including purchases, cash advances, fees, finance charges, and repayments differ from the end of the month balance by £10 or more.) All cards which had an unclassified transaction were excluded. After the data restriction described above, 10,122,300 repayment observations of 440,100 cards remain in our sample.

In this sample we identify cards switching from no automatic payment to (some kind of) automatic repayment. Table 1 presents counts for cards where there is a switch. Overall, we identified 11,904 cards switching to automatic repayment for which we observe 237,833 individual repayments. Among these, we observe 25.6% switching to an automatic full repayment, 7.6% switching to an automatic fixed repayment, and 33.6% switching to an automatic minimum repayment.

For other cards we have been unable to identify the policy, as we only have records of the absolute size of the automatic repayment in pounds. For example, for 4.5% of cards the balance is sufficiently small in all months that the minimum repayment required is sufficient to clear the balance—and thus we cannot distinguish between a minimum, fixed, and a full automatic repayment policy. For 28.1% of cards, we can see that people make a second switch in automatic repayment, and we do not consider these cards further.

[INSERT TABLE 1 ABOUT HERE]

Our results could potentially be sensitive to our classification of automatic repayment type. Therefore, as a robustness check, we have repeated the analyses below with an alternative and more broad definition of automatic minimum repayment (Appendix 1). The results are nearly identical to those in the main analysis below.

RESULTS

People Switch to Automatic Payments Which Match Their Modal Payment Behavior

Table 2 reports the before and after account summary statistics for those switching to minimum, fixed, and full automatic repayments. These descriptive statistics are quite similar before and after switching, indicating that switching does not appear on average to be associated with changes in account terms (such as APR).

Figure 1 plots the distribution of all monthly repayments before and after switching for those identified as switching to minimum, fixed, and full automatic repayments. Repayment is shown on the x-axis which ranges from ‘missed’ (a repayment below the minimum due), ‘minimum’ (a repayment at the minimum amount), a value of payments in pounds, up to ‘full’ (a repayment of the entire balance outstanding). Prior to switching repayments are entirely manual, by construction. After switching, repayments are at least in part automatic, and any additional manual repayments are included.

[INSERT TABLE 2 ABOUT HERE]

[INSERT FIGURE 1 ABOUT HERE]

There are several salient features of Figure 1. First, missed repayments are nearly eliminated when people switch to any automatic repayment. Having switched to automatic repayment, people cannot forget to repay their bills (but could fail to repay if their deposit account balance is insufficient to cover the automatic payment). Second, the pre-switch distributions of repayments are very different for those switching to minimum, fixed, and full repayments. The pre-switch modal behavior for card holders switching to an automatic minimum repayment is to make only minimum manual repayments. The pre-switch modal behavior for those switching to an automatic full repayment is to make full manual repayments. The pre-switch modal behavior for those switching to an automatic fixed repayment is to make fixed manual repayments. The third feature—that forms the focus of the rest of our analysis—is that the repayments after switching greatly attenuate the non-modal behavior. For those switching to an automatic minimum repayment, full repayment drops from 19.1% to 11.5%, a drop of an absolute 7.6%. For those switching to an automatic fixed repayment, full repayment dropped from 17.0% to 2.7%, a drop of an absolute 14.3%. For those switching to an automatic minimum repayment, payments at prominent numbers are also almost completely eliminated: Before switching the aggregated proportion of the top four repayments (i.e., £100.00, £50.00, £200.00, and £150.00) is 26.4% but afterwards the proportion covered by these top four payments is almost exactly zero.

Multinomial Logit Model of the Effect of Switching to an Automatic Minimum Repayment

To confirm the change in repayments before and after switching to an automatic minimum repayment seen in the top panels of Figure 1, we fitted a multinomial logit model of repayments to control for card characteristics (Equation 1). The model estimates the probability that repayments fall into each of seven categories: Missed, Minimum, Larger 1, Larger 2, Larger 3, Larger 4, and Full. We use this categorical classification because ‘missed’ ‘minimum’ and ‘full’ are discrete repayment types distinguishable from other monetary amounts. Missed includes repayments less than the required minimums. Minimum includes repayments which are equal to or greater than the required minimum and less than the required minimum plus £10. This £10 allowance is for including repayments slightly larger than the minimum, which were possibly caused by rounding up of the required minimum. Larger 1 includes repayments which are not included in Missed and Minimum that are less than 25% of the balance. Larger 2 includes repayments equal to or more than 25% of the balance and less than 50% of the balance. Larger 3 includes repayments equal to or more than 50% of the balance and less than 75% of the balance. Larger 4 includes repayments equal to or more than 75% of the balance and less than the full balance. Full includes repayments equal to or more than the full balance. If a repayment was equal to the required minimum which was also equal to the full balance, the repayment was included in Full. We included $Balance$, $Credit\ Limit$, $Utilization$ (how much of the credit limit is utilized), and $Charge\text{-}off\ Rate$ (a monotonic transform of credit score). The independent variable of interest is $Before\ Min\text{-}Auto$ which is a dichotomous variable having a value of 1 if a card had not started using an automatic minimum repayment, otherwise having a value of 0.

$$\log\left(\frac{\text{P(Repayment Category(t)=Category k)}}{\text{P(Repayment Category(t)=Missed)}}\right) = \beta_0 + \beta_1\text{Balance} + \beta_2\text{Credit Limit} + \beta_3\text{Utilization} + \beta_4\text{Spending Amount} + \beta_5\text{Merchant APR} + \beta_6\text{Cash APR} + \beta_7\text{Charge-off Rate} + \beta_8\text{Before Min-Auto} \quad (1)$$

Figure 2 shows the results. Table 3 reports the coefficients. Consistent with the finding in the top panels of Figure 1, after setting an automatic minimum repayment the likelihood of paying only the minimum within the month increases sharply from 35.1%, 95% CI [33.4%, 36.9%] to 83.9%, 95% CI [83.0%, 84.9%]. The likelihood of other levels of repayment decreases: the likelihood of missing the minimum payment decreases sharply from 14.4%, 95% CI [13.3%, 15.5%] to 1.0%, 95% CI [0.8%, 1.3%], while the likelihood of repayment in Larger 1 category decreased from 36.8%, 95% CI [35.2%, 38.4%] to 8.8%, 95% CI [8.1%, 9.5%] and the likelihood of paying the full balance halves from 4.8%, 95% CI [4.0%, 5.5%] to 2.4%, 95% CI [2.0%, 2.7%]. Thus the logistic regression results in Figure 2 confirms the pattern in the simple histogram in Figure 1: after switching to an automatic minimum repayment card holders are more likely to repay the minimum and are less likely to miss repayments, but are also less likely to make larger repayments.

[INSERT FIGURE 2 ABOUT HERE]

[INSERT TABLE 3 ABOUT HERE]

Robustness Check: Manual Repayments After Switching to an Automatic Minimum Repayment

In Figure 1, it is obvious that the prominent number repayments are almost completely eliminated for those switching to automatic minimum repayment. But in the rare months when those with automatic minimum repayments do make additional manual repayments, their repayments match or are higher than before the switch. Figure 3 compares the distribution of manual repayment amounts before and after the card holders switched to an automatic minimum repayment. Note that, for card-months before switch (the left panel), a manual repayment means the whole amount which the card holder repaid in the month while, for card-months after switch (the right panel), the manual repayment is an additional repayment over and above the automatic minimum repayment. As seen in Figure 3, even after switch, the tendency of card holders making repayments at prominent numbers is still observed in the months where they make a manual repayment over and above the automatic minimum repayment, indicating that the absence of repayments at prominent numbers is likely to be because card holders simply ignore their card bill after setting up an automatic minimum repayment, rather than because people cannot afford to repay their bill. That is, because of inattention, people do not have to take a manual repayment decision, and thus cannot be attracted by psychologically prominent numbers as repayments. But when they do pay attention (i.e., in the post-switch months where there is a manual repayment) people are just as attracted to prominent number repayments as before the switch.

[INSERT FIGURE 3 ABOUT HERE]

We examine how the probability of card holders repaying in full changes in months with a manual repayment (i.e., months in which card holders paid attention to a repayment) before and after switching to an automatic minimum repayment. We conducted a logistic regression (Equation 2). The dependent variable is a dichotomous indicator variable taking the value of 1 if the card was repaid in full (i.e. fraction equal to or greater than 1) and 0 otherwise. $Balance$, $Credit\ Limit$, $Utilization$, $Spending\ Amount$, $Merchant\ APR$, $Cash\ APR$, and $Charge\text{-}off\ Rate$ were included as continuous control variables. The independent variable of interest is $Before\ Min\text{-}Auto$ which is a dichotomous variable having a value of 1 if a card had not started using an automatic minimum repayment, otherwise having a value of 0. The data were restricted to repayments above the minimum (i.e., card months with manual repayments above the minimum before switching and card months with an additional manual repayment over and above the automatic payment of the minimum after switching).

$$\log\left(\frac{\mathrm{P(Full\ Repayment)}}{1-\mathrm{P(Full\ Repayment)}}\right) = \beta_1\mathrm{Balance} + \beta_2\mathrm{Credit\ Limit} + \beta_3\mathrm{Utilization} + \beta_4\mathrm{Spending\ Amount} + \beta_5\mathrm{Merchant\ APR} + \beta_6\mathrm{Cash\ APR} + \beta_7\mathrm{Charge\text{-}off\ Rate} + \beta_8\mathrm{Before\ Min\text{-}Auto} \quad (2)$$

Figure 4 shows the model prediction for the probability of full repayments, conditional that a manual repayment is made. The results show that, when card holders made a manual repayment over an automatic minimum repayment, they are more likely to repay in full than before they switch, indicating that the absence of prominent number repayments after the switch is unlikely to be due to financial difficulty and is more consistent with the inattention account.

[INSERT FIGURE 4 ABOUT HERE]

[INSERT TABLE 4 ABOUT HERE]

Together these simple histograms and the logistic regression suggest that card holders' ability to repay in full may not be very different before and after the switch to an automatic minimum repayment. Instead it is forgetting or inattention to one's credit card after switching to an automatic minimum repayment that causes the reduction in larger and full repayments.

Robustness Check and Natural Experiment: Switching to an Automatic Minimum Repayment After Forgetting a Repayment

One potential concern with our analysis so far of the negative effect of automatic minimum repayments is that cardholders may endogenously select into automatic minimum repayments because of their intentions to reduce future repayments. In order to address this concern we exploit a natural experiment, where there is a (likely exogenous) inducement to set up an automatic minimum repayment. In the data many consumers receive a late payment fee after forgetting to pay their credit card bill. We see that 6.5% of late fees are refunded in our sample, and this occurs when card holders contact their credit card company to complain about the fee. Of those card holders who receive a refunded late fee, we see that about 10.5% go on to set up an automatic minimum repayment. These consumers are likely to have been prompted by their card provider to set up the automatic repayment to avoid the chance of further late fees rather than because of an ongoing intention to repay only the minimum. This is an arguably exogenous inducement to set up an automatic minimum repayment. So, to exploit this natural experiment, we further restricted the sample to cardholders setting up an automatic minimum repayment within two months of the refund of a late payment fee and compared their repayment behavior before and after switching.

Figure 5 compares the distribution of repayments before and after the refund-triggered card holders switched to an automatic minimum repayment. Before the switch, 23.8% of the cards are repaid in full each month and 20.7% of cards pay only the minimum. After the switch, 16.9 % of cards are repaid in full each month, and 64.2% were the minimum repayments. The distribution looks similar to that seen in the top panels of Figure 1. (Note that, before switch, the proportion of missed repayments is quite high. This is because we restricted the sample to individuals who missed a repayment.) In summary, this analysis suggests that the effect of an automatic minimum repayment is unlikely to be due to cardholders' intentions to make small repayments in future.

[INSERT FIGURE 5 ABOUT HERE]

Note that, because we restricted the sample to cardholders setting up an automatic minimum repayment after a refund of a late payment fee, all cards in the sample missed a minimum repayment at least once. In order to avoid misleading results caused by this sample restriction, we did not conduct a multinomial regression on this sample.

Summary

Thus far, we have demonstrated that: (a) people set up automatic repayments to match their modal manual repayment history, (b) a positive effect of automatic payments in which late fees are eliminated, (c) setting up an automatic minimum repayment greatly reduces the frequency of the months in which people make prominent number repayments, (d) but in the post-switch months with manual repayments, people pay just like in the pre-switch months, (e) a natural experiment (which we present as a robustness check) where people switch to automatic minimum repayment in response to forgetting provides evidence that switching to minimum automatic repayments causes people to greatly reduce their model payments. We close with a series of Monte Carlo simulations to estimate the economic size of this effect.

EXCESS INTEREST COST SIMULATIONS

We have used Monte Carlo simulation to estimate the financial and time costs arising from lower repayments among card holders switching to an automatic minimum repayment. We simulate two types of agents. The first type of agents never switches to automatic repayment (Remaining as Non-Auto Cards) while the second type of agents switches to an automatic minimum repayment (Switching to Min-Auto Cards).

We have conducted two simulations. The first assumes no further purchases and represents people deciding to pay down their debt (Pay-Down-Only Simulation). The second assumes a steady continuation of purchases and repayments (Spending-and-Repayment Simulation). In both simulations, the fraction of the balance repaid each month is drawn from their actual distributions in card-months with similar card profiles. For Remaining as Non-Auto Cards, we use card-months before the card holders set up an automatic minimum repayment. For Switching-to-Auto Cards, we use card-months after they set up an automatic minimum repayment.

In the Pay-Down-Only Simulation, the fraction of the balance repaid each month for an agent is drawn from card-months with a similar card profile and no spending. A card profile consists of balance, utilization, and merchant APR. The credit limit and the merchant APR for initializing the agents were the median values in the month where cardholders in our sample set up Min-Auto (£4,300 and 18.9%, respectively) and were assumed to be constant throughout a simulation. In the Spending-and-Repayment Simulation, the total purchase amount and total cash advance amount for an agent were also drawn. Here the card profile includes total purchase, total cash advance amount, and the cash APR (the cash APR was kept constant at a median value of 24.93%) in addition to balance, utilization, and merchant APR.

The weights used for sampling cards are based on the similarity between the agent card profile and the actual card month profile. Specifically, the similarity is a multivariate normal distribution with the agent card profile in the previous month as the mean and the covariance matrix given by the covariance of the variables in the data.

In both types of simulation, if an agent missed a repayment, a £12 late fee was incurred in the next month (the regulated fee level in the UK). In the Spending-and-Repayment Simulation, if an agent made a cash advance or the utilization rate exceeded 1, a cash advance fee, which is £3 or 3% of the cash advance amount (whichever is greater) and a £12 over-limit fee were also incurred.

Each time step, the balance was updated reflecting a repayment, interest based on the merchant APR, and any late fees in the Pay-Down-Only Simulation. In the Spending-and-Repayment Simulation, new purchases, any new cash advance amount and fee, and any over-limit fee were also added to the balance. A repayment made in a given month was first allocated to the balance for the cash advance, and then any remaining part was used to repay the balance on purchases. Interest on purchase and cash advances were separately calculated in each month with the merchant APR and the cash APR, respectively.

In the Pay-Down-Only Simulation, the simulation terminated when a balance became less than £10 (i.e., the balance was effectively cleared). In the Spending-and-Repayment Simulation, the simulation continued for 20 months. We ran simulations for three initial balances in the months where card holders in our sample switched to Min-Auto: the median balance (£1,412), the mean balance (£2,271), and the 75th percentile balance (£3,056). We assumed that the whole initial balance was on purchases. The simulated results were averaged and the corresponding confidence intervals were calculated with the bootstrap method (1,000 resamples).

Table 5 presents the full results of the Pay-Down-Only Simulation. Switching to Min-Auto Cards nearly doubles the time duration and total costs (interest and fees) until clearing the balance compared with remaining as Non-Auto Cards.

We also conducted a simulation estimating what proportion of total interest and fees incurred by all cards across the entire credit card market is due to automatic minimum repayments (Appendix 2). Cards using automatic minimum repayments at least once in the data period could save about 27% of interest and fees if they did not switch to automatic minimum repayment. This is about 12% (95% CI [8.7%, 15.0%]) of the all interest and fees paid in the credit card market. Even an effect ten times smaller would be very economically significant.

[INSERT TABLE 5 ABOUT HERE]

Figure 6 shows the results of the Spending-and-Repayment Simulation where we see consistently higher balances and higher total costs in the 20-month period. Therefore, even accounting for the higher prevalence of late fees among Remaining as Non-Auto Cards, the simulations show that Switching to Min-Auto Cards creates higher costs of debt for the consumer.

[INSERT FIGURE 6 ABOUT HERE]

DISCUSSION

Automatic minimum payments have an unexpected negative effect. Although setting automatic minimum repayments mostly eliminates the likelihood of missed repayments, it also substantially decreases the likelihood of consumers paying over the required minimum. We had considered the automatic minimum repayment as a near-perfect libertarian default, protecting consumers from late fees without apparently making it any harder to pay down their debt. But consumers choosing automatic minimum repayments are selecting a powerful psychological default, a default which facilitates inattention. Consumers neglect bills and procrastinate in repaying their debt, safe from the fees they once had to engage to avoid; consumers need only passively manage their credit card debt once they set up an automatic minimum payment. This inattention means consumers make manual repayments less often, and without attending to the repayment decision, consumers are not drawn to the larger psychologically prominent fixed and full repayments. This results in repeated minimum repayments, which greatly increases the debt revolved from month to month and thus the interest paid. We estimate that those setting an automatic minimum repayment could save about one third of the cost of their debt by instead remaining as purely manual repayers. This saving equates to 12% of the interest ever paid.

We have focused here upon credit card repayments where consumers face an explicit choice about the size of their automatic payment, and can easily make additional manual repayments. But the power of setting a default repayment is applicable more widely. For example, choosing the term of a mortgage or choosing fixed monthly repayments for a personal loan also set powerful defaults, and these defaults are administratively harder to change, and changes can even incur additional costs. If people are initially conservative in their choice of level, so they can be sure they can meet their monthly repayments, our findings suggest that they are unlikely to get round to making additional repayments over and above the default even if they can afford to make additional repayments to save interest costs.

We suggest that this unintended effect of automatic minimum repayment could be partially addressed through interventions which bring the repayment decision back to the top of the consumer's mind, drawing attention to the repayment decision. More generally, what should policymakers and industry do to avoid introducing nudges with unintended effects? We have two suggestions. The first is to assess the effect of the nudge across as broad a range of outcome behaviors as are available, and to follow up on these assessments. The second is to consider the status quo effects resulting from the nudge itself. The Save More Tomorrow nudge towards retirement saving has both properties (Benartzi & Thaler, 2013). Consumers are automatically enrolled into minimum contributions to a retirement saving scheme to get them started, but contributions automatically escalate, ensuring low saving is not the status quo. Follow-up assessments show the additional pension savings have not come at the cost of savings elsewhere (Benartzi & Thaler, 2013). Smart nudges like this can avoid the pitfalls seen in automatic minimum repayments and ensure choice architecture interventions work in the best interests of consumers.

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Table 1. *Frequencies of Switching from No Automatic Repayment to Different Automatic Repayment Types*

Repayment Type	Full	Fixed	Min	Min=Full	Mixed	Unknown	Total
Num. of Repayments	56,605	19,454	83,105	5,453	71,889	1,327	237,833
(Proportion)	23.8%	8.2%	34.9%	2.3%	30.2%	0.6%	100%
Num. of Cards	3,048	899	4,001	531	3,341	84	11,904
(Proportion)	25.6%	7.6%	33.6%	4.5%	28.1%	0.7%	100%

Note. “Full” column represents automatic full repayment of the balance. “Fixed” column represents automatic fixed repayment covering more than the minimum but less than the full balance. “Min” column represents automatic minimum repayment. “Min=Full” column represents automatic repayments of very small balances where the full balance is also the minimum repayment. “Mixed” column represents automatic repayments which changed between types across months.

Table 2. *Summary Statistics*

Statistics	Switch to Min-Auto		Switch to Fixed-Auto		Switch to Full-Auto	
	Before	After	Before	After	Before	After
Number of observations	35,191	47,914	10,926	8,528	31,540	25,065
Number of accounts	4,001	4,001	899	899	3,048	3,048
Median balance	1,444	1,638	1,242	1,346	355	260
Median credit limit	4,475	4,400	4,000	3,500	5,000	4,900
Median utilization	0.517	0.618	0.495	0.568	0.077	0.060
Median spending amount	55.00	0.00	34.00	0.00	347.00	264.00
Median merchant APR	0.189	0.189	0.189	0.200	0.169	0.169
Median cash APR	0.249	0.260	0.249	0.249	0.249	0.249
Median charged-off rate	0.011	0.016	0.007	0.008	0.002	0.002

Note. "Min-Auto" represents automatic minimum repayment. "Fixed-Auto" represents automatic fixed repayments covering more than the minimum and less than the full balance. "Full-Auto" represents full automatic repayment.

Table 3. *Coefficients for Equation 1*

IV	Estimate	LL	UL	Clustered SE	z value	Pr(>|z|)
Intercept × Minimum	5.618	4.797	6.440	0.419	13.4	0.00000
Intercept × Large1	3.078	2.255	3.901	0.420	7.3	0.00000
Intercept × Large2	3.154	2.209	4.100	0.482	6.5	0.00000
Intercept × Large3	2.705	1.790	3.619	0.467	5.8	0.00000
Intercept × Large4	2.594	1.537	3.650	0.539	4.8	0.00000
Intercept × Full	7.591	6.692	8.489	0.458	16.6	0.00000
Balance × Minimum	0.000	0.000	0.000	0.000	0.7	0.47998
Balance × Large1	0.000	0.000	0.000	0.000	0.0	0.98016
Balance × Large2	0.000	0.000	0.000	0.000	-4.3	0.00002
Balance × Large3	0.000	0.000	0.000	0.000	-3.6	0.00032
Balance × Large4	0.000	0.000	0.000	0.000	-2.4	0.01811
Balance × Full	-0.001	-0.001	-0.001	0.000	-11.4	0.00000
Credit Limit × Minimum	0.000	0.000	0.000	0.000	2.4	0.01655
Credit Limit × Large1	0.000	0.000	0.000	0.000	4.5	0.00001
Credit Limit × Large2	0.000	0.000	0.000	0.000	2.2	0.02899
Credit Limit × Large3	0.000	0.000	0.000	0.000	1.9	0.06085
Credit Limit × Large4	0.000	0.000	0.000	0.000	1.1	0.25780
Credit Limit × Full	0.000	0.000	0.000	0.000	-1.6	0.10781
Utilization × Minimum	0.854	0.568	1.141	0.146	5.8	0.00000
Utilization × Large1	0.808	0.497	1.119	0.159	5.1	0.00000
Utilization × Large2	-0.737	-1.177	-0.297	0.225	-3.3	0.00104
Utilization × Large3	-0.903	-1.448	-0.358	0.278	-3.2	0.00117
Utilization × Large4	-1.172	-1.635	-0.709	0.236	-5.0	0.00000
Utilization × Full	-2.752	-3.184	-2.319	0.221	-12.5	0.00000
Spending Amount × Minimum	-0.001	-0.001	-0.001	0.000	-7.9	0.00000
Spending Amount × Large1	0.000	0.000	0.000	0.000	2.9	0.00397
Spending Amount × Large2	0.001	0.001	0.001	0.000	11.5	0.00000
Spending Amount × Large3	0.001	0.001	0.001	0.000	11.8	0.00000
Spending Amount × Large4	0.001	0.001	0.001	0.000	14.2	0.00000
Spending Amount × Full	0.002	0.002	0.002	0.000	21.1	0.00000
Merchant APR × Minimum	1.195	-0.476	2.867	0.853	1.4	0.16100
Merchant APR × Large1	-3.164	-4.990	-1.337	0.932	-3.4	0.00069
Merchant APR × Large2	-5.393	-7.570	-3.215	1.111	-4.9	0.00000
Merchant APR × Large3	-5.545	-7.868	-3.222	1.185	-4.7	0.00000
Merchant APR × Large4	-4.277	-7.393	-1.161	1.590	-2.7	0.00714
Merchant APR × Full	-8.055	-10.247	-5.863	1.119	-7.2	0.00000
Cash APR × Minimum	-8.144	-11.104	-5.183	1.510	-5.4	0.00000
Cash APR × Large1	-4.049	-7.178	-0.920	1.596	-2.5	0.01120
Cash APR × Large2	-3.578	-7.329	0.174	1.914	-1.9	0.06158
Cash APR × Large3	-3.295	-7.035	0.444	1.908	-1.7	0.08410
Cash APR × Large4	-4.604	-8.458	-0.750	1.966	-2.3	0.01920
Cash APR × Full	-8.987	-12.230	-5.744	1.655	-5.4	0.00000
Charge-off Rate × Minimum	-6.380	-7.402	-5.358	0.522	-12.2	0.00000
Charge-off Rate × Large1	-8.161	-9.565	-6.758	0.716	-11.4	0.00000
Charge-off Rate × Large2	-12.312	-16.159	-8.466	1.962	-6.3	0.00000
Charge-off Rate × Large3	-11.218	-16.846	-5.590	2.871	-3.9	0.00009
Charge-off Rate × Large4	-9.369	-14.580	-4.157	2.659	-3.5	0.00043
Charge-off Rate × Full	-24.578	-32.306	-16.850	3.943	-6.2	0.00000
Before Min-Auto × Minimum	-3.506	-3.808	-3.204	0.154	-22.8	0.00000
Before Min-Auto × Large1	-1.203	-1.497	-0.909	0.150	-8.0	0.00000
Before Min-Auto × Large2	-1.706	-2.019	-1.392	0.160	-10.7	0.00000
Before Min-Auto × Large3	-1.936	-2.260	-1.611	0.165	-11.7	0.00000
Before Min-Auto × Large4	-1.883	-2.209	-1.558	0.166	-11.3	0.00000
Before Min-Auto × Full	-1.930	-2.212	-1.649	0.143	-13.5	0.00000
R2 = .257						
Number of observations = 82,360						

Note. The standard errors were corrected by clustering by card and month.

Table 4. *Coefficients for Equation 2*

IV	Estimate	LL	UL	Clustered SE	z value	Pr(>|z|)
Intercept	3.740	3.075	4.405	0.339	11.0	0.00000
Balance	-0.001	-0.001	0.000	0.000	-9.9	0.00000
Credit Limit	0.000	0.000	0.000	0.000	-5.1	0.00000
Utilization	-3.263	-3.682	-2.843	0.214	-15.2	0.00000
Spending Amount	0.001	0.001	0.001	0.000	19.8	0.00000
Merchant APR	-5.060	-7.193	-2.927	1.088	-4.6	0.00000
Cash APR	-6.402	-8.862	-3.941	1.255	-5.1	0.00000
Charge-off Rate	-4.113	-6.302	-1.925	1.116	-3.7	0.00023
Before Min-Auto	-0.528	-0.640	-0.417	0.057	-9.3	0.00000
R2 = 0.348						
Number of observations = 36,660						

Note. The standard errors were corrected by clustering by card and month.

Table 5. *The Time to Pay-Down the Debt to Less Than £10, and Total Cost of Pay-Down (Total Interest) in the Paydown-Only Simulation*

Initial Balance	Autopay Status	Total Time Until Clearing the Balance (Months)	Total Cost Until Clearing the Balance (£)
Median Balance	Remaining as Non-Auto	13.19	184.98
(£1,412)		[12.6 : 13.79]	[177.19 : 192.51]
	Switching to Min-Auto	25.69	279.97
		[24.48 : 26.97]	[269.92 : 290.87]
Mean Balance	Remaining as Non-Auto	16.17	365.50
(£2,271)		[15.48 : 16.83]	[351.45 : 378.98]
	Switching to Min-Auto	31.03	585.42
		[29.77 : 32.35]	[563.97 : 606.48]
75th Percentile Balance	Remaining as Non-Auto	20.35	619.83
(£3,056)		[19.57 : 21.18]	[599.01 : 644.55]
	Switching to Min-Auto	40.34	1056.65
		[38.79 : 41.9]	[1023.33 : 1090.24]

Note. The numbers in parentheses are 95% confidence intervals.

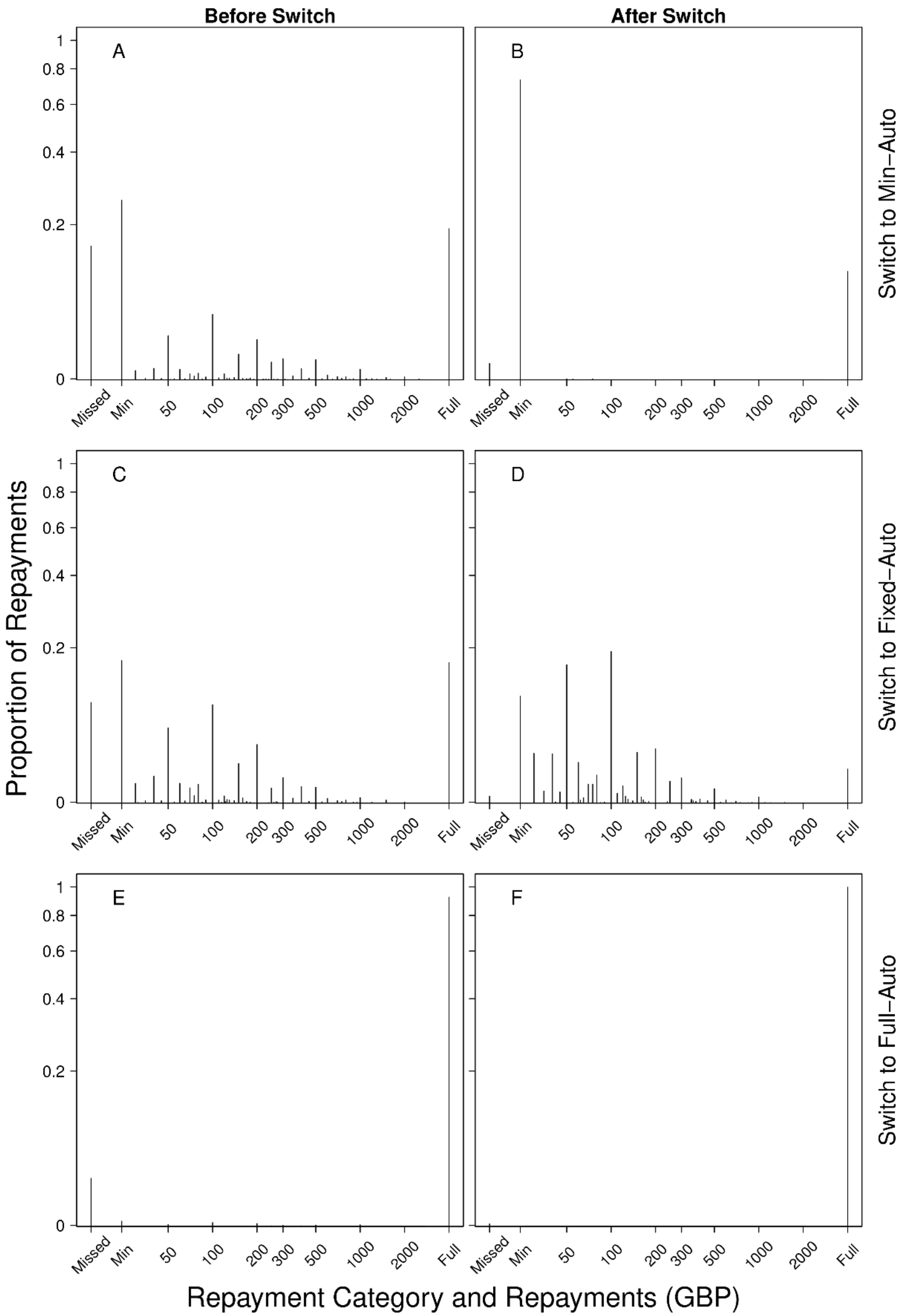

Figure 1. The distribution of the fraction of the balance repaid each month before and after switching to an automatic minimum payment ("min-auto"), automatic fixed repayment ("fixed-auto"), and automatic full repayment ("full-auto"). For the fixed amounts, each bar is a 1-penny-wide bin.

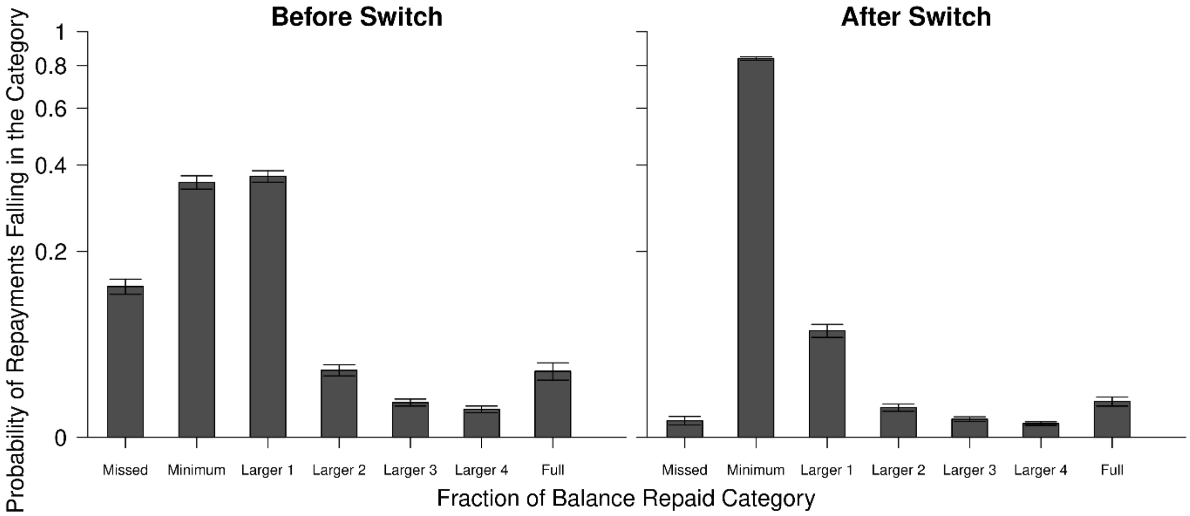

Figure 2. The fraction of balance repaid each month before and after cards switch to an automatic minimum repayment. Repayment category probabilities are from a multinomial logit model. Error bars are 95% confidence intervals. The standard errors were corrected by clustering by cards and months.

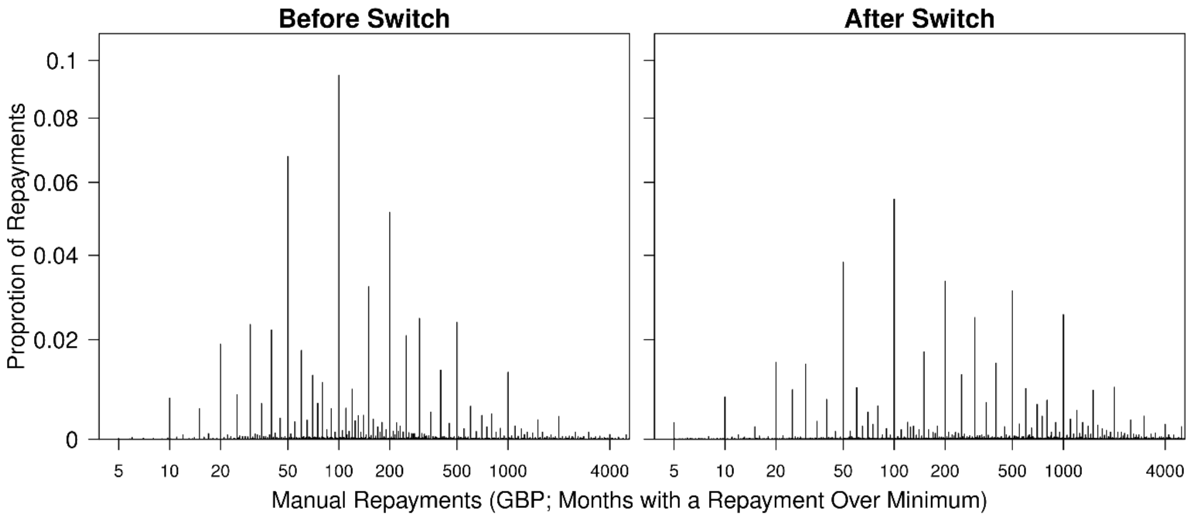

Figure 3. The fraction of the balance repaid for observations in the months where a manual repayment was made.

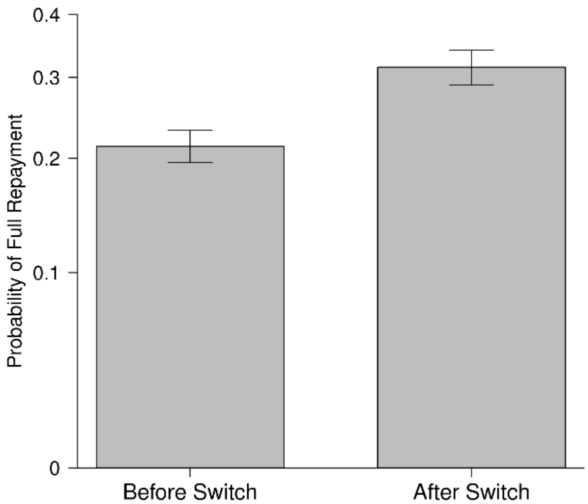

Figure 4. Using only repayments above the minimum, the probability of full repayment before and after cards switch to an automatic minimum repayment. The probabilities are from a logistic model. Error bars are 95% confidence intervals. The standard errors were corrected by clustering by card and month.

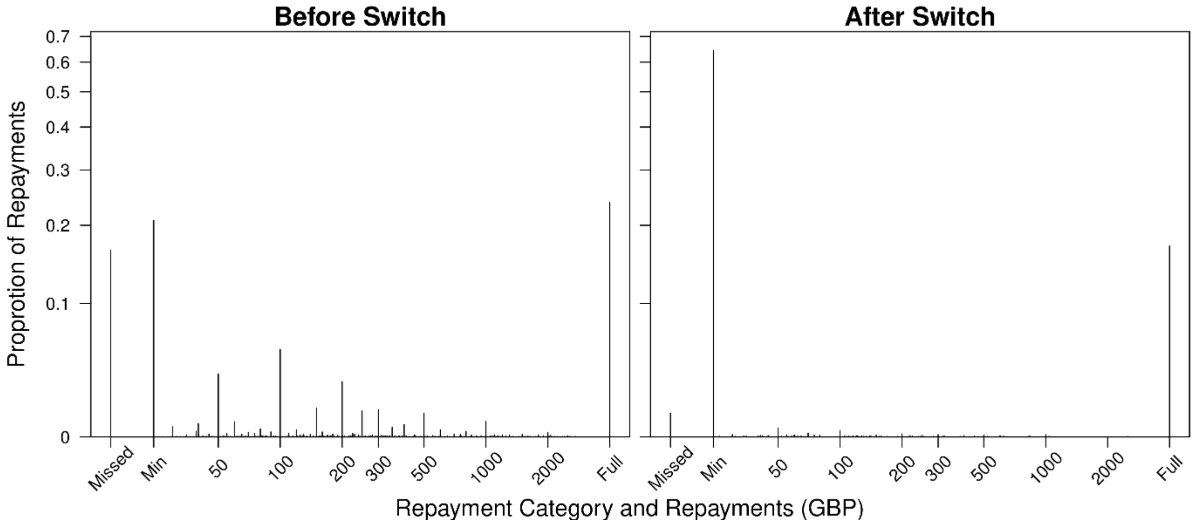

Figure 5. Using only cards switching in response to a late fee, the fraction of balance repaid each month before and after cards switch to an automatic minimum repayment.

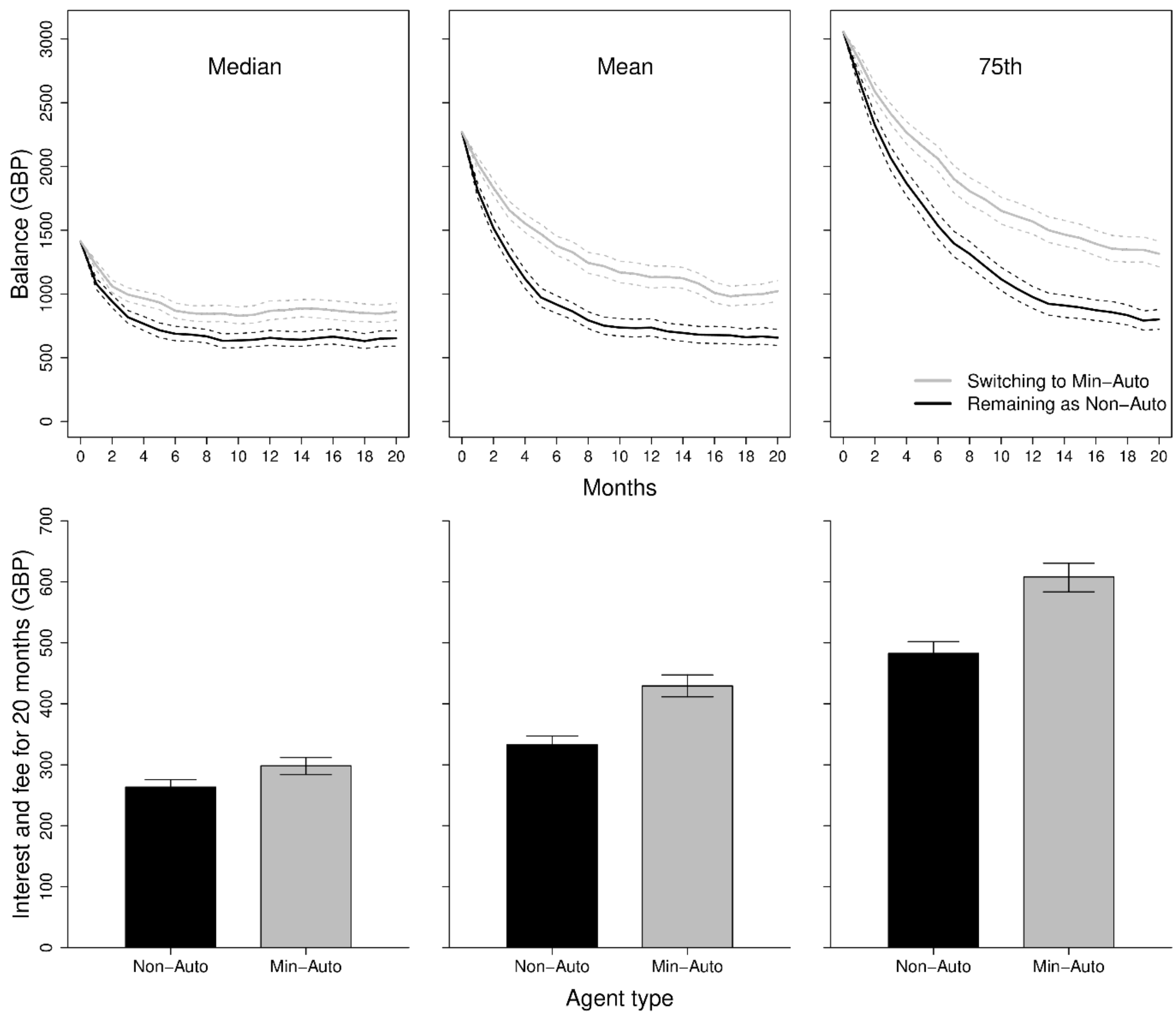

Figure 6. The balance trajectory and corresponding financial cost based on the Spending-and-Repayment Simulation. The top panels show a balance path over 20 months and the bottom panels show a total interest and fee accrued over those 20 months. The initial balance for the left, the middle, and the right panels are the median, the mean, and 75th percentile balances taken from the data.

APPENDIX 1. ROBUSTNESS CHECK WITH AN ALTERNATIVE DEFINITION OF MIN-AUTO CARDS

In our main analyses we used a strict definition to identify cards with an automatic minimum repayment. Cards were required to have an automatic payment exactly at the minimum in every month with a positive balance after the first automatic repayment. Here we relax this definition to include additional cards. In the UK, if a card holder with an automatic repayment manually repays before the due date of the automatic repayment, the amount manually repaid is subtracted from the automatic payment taken in the month. Because we infer the automatic repayment status from repayment records in the data, we cannot know whether the card holder has maintained their automatic minimum repayment setting or has canceled their automatic repayment. Our first relaxation is to consider as minimum automatic repayment accounts in which the minimum was repaid as little as only once through the automatic repayment with manual repayments in other months. Our second relaxation was to include cards where the automatic minimum repayment was equal to the full balance (i.e., very small balances). These cards might instead have a full automatic repayment set, but are included as minimum automatic repayment cards for this robustness check (and note that balance in included in Equation 1).

Figure A1 shows the results repeated with the alternative definition of automatic minimum repayment cards. As seen in the top panels, after the switch to minimum automatic repayment, the share of minimum payments sharply increased from 18.3% to 51.7%. The bottom panels of Figure A1 show the results of a multinomial regression with Equation 1. Table A1 reports the coefficients. Consistent with the finding in the top panels of Figure A1, after setting up Min-Auto the likelihood of paying only the minimum within the month increases sharply from 19.3%, 95% CI [17.8%, 20.9%] to 57.2%, 95% CI [55.8%, 58.6%], the likelihood of paying the full balance decreases from 27.1%, 95% CI [25.5%, 28.7%] to 20.3%, 95% CI [18.9%, 21.7%], and the likelihood of missing the minimum payment decreases from 11.6%, 95% CI [10.9%, 12.3%] to 2.0%, 95% CI [1.7%, 2.2%]. In summary, our findings do not change with the alternative definition of Min-Auto cards.

[INSERT FIGURE A1 ABOUT HERE]

[INSERT TABLE A1 ABOUT HERE]

APPENDIX 2. DETAILS OF SIMULATIONS FOR TOTAL COST ESTIMATE

We also conducted a final simulation estimating what proportion of total interest and fees incurred by all cards is due to automatic minimum repayment. We randomly sampled 10,000 cards from the whole data (excluding cards with a balance transfer but including cards with a zero merchant APR) and extracted 1,625 cards which were repaid by minimum automatic repayment at least once (Some-Min-Auto Cards). In the simulation the Some-Min-Auto Cards were counterfactually repaid over time as if the cards were not switched to automatic minimum repayment: At each time-step in the simulation, the spending amount was drawn from the whole data period of Some-Min-Auto Cards but the fraction of the balance repaid was drawn from card-months before Some-Min-Auto Cards had a first automatic minimum repayment. The sampling methods are identical to those used in the Spending-and-Repayment Simulation, and were based on the specific the credit limit, the merchant APR, and the cash APR for each card. The balance, interest, and fees were then calculated for the month. The simulation continued up to the number of observations of the card in the data.

The simulation results showed that Some-Min-Auto cards could save about 27%, 95% CI [20, 34] of total interest and fees if they were repaid as if they did not switch to an automatic minimum repayment. Considering that the proportion of interest and fees for Some-Min-Auto Cards among total interest and fees for all 10,000 cards is about 44%, we estimate that 12% (95% CI [8.7%, 15.0%]) of the total interest and fees for all cards is due to automatic minimum repayment.

Table A1. *Coefficients for Equation 1 with the Alternative Definition of Automatic Minimum Repayments*

IV	Estimate	LL	UL	Clustered SE	z value	Pr(>|z|)
Intercept × Minimum	3.304	2.470	4.138	0.426	7.8	0.00000
Intercept × Large1	2.222	1.401	3.042	0.419	5.3	0.00000
Intercept × Large2	2.542	1.715	3.368	0.422	6.0	0.00000
Intercept × Large3	2.327	1.488	3.166	0.428	5.4	0.00000
Intercept × Large4	2.485	1.605	3.365	0.449	5.5	0.00000
Intercept × Full	6.112	5.320	6.904	0.404	15.1	0.00000
Balance × Minimum	0.000	0.000	0.000	0.000	-3.8	0.00017
Balance × Large1	0.000	0.000	0.000	0.000	-2.7	0.00663
Balance × Large2	0.000	0.000	0.000	0.000	-6.6	0.00000
Balance × Large3	0.000	0.000	0.000	0.000	-6.9	0.00000
Balance × Large4	0.000	0.000	0.000	0.000	-7.3	0.00000
Balance × Full	-0.001	-0.001	-0.001	0.000	-18.6	0.00000
Credit Limit × Minimum	0.000	0.000	0.000	0.000	7.4	0.00000
Credit Limit × Large1	0.000	0.000	0.000	0.000	8.0	0.00000
Credit Limit × Large2	0.000	0.000	0.000	0.000	4.7	0.00000
Credit Limit × Large3	0.000	0.000	0.000	0.000	4.4	0.00001
Credit Limit × Large4	0.000	0.000	0.000	0.000	4.7	0.00000
Credit Limit × Full	0.000	0.000	0.000	0.000	2.0	0.05061
Utilization × Minimum	1.139	0.909	1.369	0.117	9.7	0.00000
Utilization × Large1	1.235	0.998	1.472	0.121	10.2	0.00000
Utilization × Large2	-0.148	-0.466	0.169	0.162	-0.9	0.35996
Utilization × Large3	-0.422	-0.820	-0.025	0.203	-2.1	0.03742
Utilization × Large4	-0.741	-1.113	-0.369	0.190	-3.9	0.00009
Utilization × Full	-2.222	-2.501	-1.944	0.142	-15.6	0.00000
Spending Amount × Minimum	0.000	0.000	0.000	0.000	-3.6	0.00035
Spending Amount × Large1	0.000	0.000	0.000	0.000	4.6	0.00001
Spending Amount × Large2	0.001	0.001	0.001	0.000	13.4	0.00000
Spending Amount × Large3	0.001	0.001	0.001	0.000	15.7	0.00000
Spending Amount × Large4	0.001	0.001	0.001	0.000	15.7	0.00000
Spending Amount × Full	0.002	0.001	0.002	0.000	23.4	0.00000
Merchant APR × Minimum	1.338	0.009	2.668	0.678	2.0	0.04843
Merchant APR × Large1	0.803	-0.531	2.137	0.681	1.2	0.23827
Merchant APR × Large2	1.478	0.034	2.922	0.737	2.0	0.04489
Merchant APR × Large3	0.593	-1.020	2.205	0.823	0.7	0.47116
Merchant APR × Large4	-0.207	-1.995	1.580	0.912	-0.2	0.82004
Merchant APR × Full	-5.132	-6.498	-3.765	0.697	-7.4	0.00000
Cash APR × Minimum	-2.906	-5.861	0.050	1.508	-1.9	0.05396
Cash APR × Large1	-5.583	-8.505	-2.660	1.491	-3.7	0.00018
Cash APR × Large2	-7.770	-10.866	-4.673	1.580	-4.9	0.00000
Cash APR × Large3	-7.653	-10.888	-4.419	1.650	-4.6	0.00000
Cash APR × Large4	-8.160	-11.335	-4.984	1.620	-5.0	0.00000
Cash APR × Full	-6.065	-9.013	-3.117	1.504	-4.0	0.00006
Charge-off Rate × Minimum	-7.629	-9.114	-6.144	0.758	-10.1	0.00000
Charge-off Rate × Large1	-11.062	-12.887	-9.238	0.931	-11.9	0.00000
Charge-off Rate × Large2	-20.589	-25.634	-15.544	2.574	-8.0	0.00000
Charge-off Rate × Large3	-21.111	-28.811	-13.410	3.929	-5.4	0.00000
Charge-off Rate × Large4	-12.282	-17.494	-7.071	2.659	-4.6	0.00000
Charge-off Rate × Full	-28.189	-34.007	-22.371	2.968	-9.5	0.00000
Before Min-Auto × Minimum	-2.850	-2.996	-2.704	0.075	-38.3	0.00000
Before Min-Auto × Large1	-0.823	-0.970	-0.675	0.075	-11.0	0.00000
Before Min-Auto × Large2	-1.255	-1.445	-1.065	0.097	-13.0	0.00000
Before Min-Auto × Large3	-1.402	-1.599	-1.206	0.100	-14.0	0.00000
Before Min-Auto × Large4	-1.440	-1.683	-1.198	0.124	-11.6	0.00000
Before Min-Auto × Full	-1.477	-1.639	-1.315	0.083	-17.9	0.00000
R^2 = .221						
Number of observations = 190,882						

Note. The standard errors were corrected by clustering by card and month.

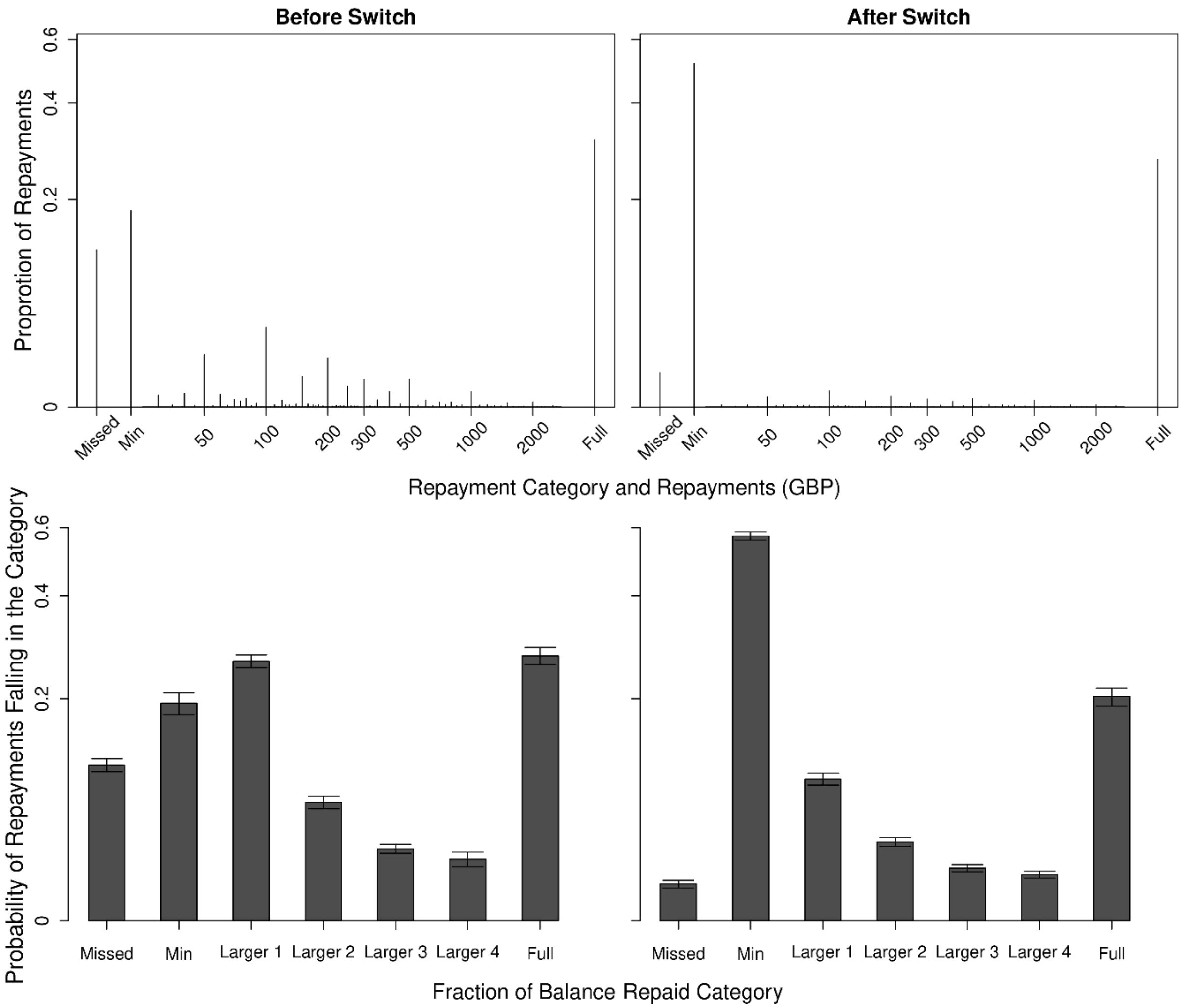

Figure A1. Repayments before and after cards switch to an automatic minimum repayment with the alternative definition of cards with automatic minimum repayments. This figure corresponds to the top panels of Figure 1 and Figure 2 with the alternative definition of cards with automatic minimum repayments. The top panels show dist0072ibution of repayment categories and amounts for each month before and after switching to an automatic minimum repayment. The bottom panels show predicted probabilities from a multinomial logit model repayments falling in categories of fraction repaid from missed (no payment made) to full (balance cleared in full). Values are predicted at the medians of covariates. The error bars are 95% confidence intervals.