How Do Consumers Avoid Penalty Fees? Evidence From Credit Cards

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Abstract

We use detailed data from multiple card issuers to show that credit card late payment fees decline sharply over the first few months of card life. This may suggest that consumers learn to remember to repay on time, but we show that memory does not drive this decline in fees. Instead, it is wholly due to consumers switching to automatic payments – thereby avoiding the need to remember to repay altogether. Not all consumers make this switch. Those who continue with manual payments, relying on memory to repay on time, see the likelihood of future fees unchanged at 20% per month. We conclude that heterogeneity in adopting account management features of financial products, such as automatic repayments, is important for understanding who avoids financial mistakes.

Keywords: credit cards, penalty fees, automatic payments, direct deposit

JEL Codes: D10, D12, D4, G21

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1 Introduction

Responding to feedback is a fundamental feature of rational consumer behavior. Positive and negative feedback leads rational consumers to adapt their behavior (Becker, 1976). For many products and services negative feedback is received in the form of a penalty fee or unexpectedly high bill. Studies based on field data show that contingent fees and charges commonly reduce with experience, suggesting consumers learn from their early mistakes (Miravete, 2003; DellaVigna and Malmendier, 2006; Ater and Landsman, 2013; Allcott and Rogers, 2014; Stango and Zinman, 2014; Grubb and Osborne, 2015).[1] However, responses to negative feedback can take different forms, from remembering to avoid the same mistake to changing a product or contract feature so that the mistake is automatically avoided in future.[2]

In this paper, we investigate how consumers avoid contingent fees and charges on their credit cards arising due to late payment. For credit cards, negative feedback takes the form of a penalty fee which appears on a credit card statement and deprives the consumer of marginal utility. Credit cards are the most common consumer unsecured borrowing product and late payment fees are the most common type of penalty fee.[3] How consumers respond to these fees, and the mechanisms consumers use to avoid future fees, are important issues (Agarwal et al., 2008). Fees could represent significant rents for credit card issuers, especially as card providers target products to consumers based on their behavioral characteristics (Ru and Schoar, 2016).[4]

We shed new light on consumer responses to credit card fees using individual level

[1] Recent papers using laboratory and field experiments to examine learning behaviors include Godlonton and Thornton (2013), Hanna et al. (2014), Palley and Kremer (2014) and Miravete and Palacios-Huerta (2014).

[2] Take the example of smartphone data contracts. An individual who exceeds their data limit in a given month and incurs excess charges could respond by either i) trying to monitor their future behavior to keep data usage below the limit in subsequent months or, ii) setting an automatic buffer on excess data usage fees.

[3] Approximately 75% of US consumers and 60% of UK consumers hold at least one credit card (Sources: Federal Reserve Bank of Boston Survey of Consumer Payment Choice 2014; Office for National Statistics Wealth and Assets Survey 2012–2014).

[4] Prior to the CARD Act in 2009, fee revenue accrued *per month* on US non-business credit cards was approximately $900m in late payment fees, $300m in over-limit fees and $150m in cash advance fees. The CARD Act limited fees, with over-limit fees essentially disappearing, but late payment fees continue to yield approximately $600m in revenue per month (Source: OCC Credit Card Metrics). Agarwal et al. (2015) estimate that overall the CARD Act saved consumers $11.9bn per year by lowering fees and charges.

account data on 250,000 new card openings across five card providers from the United Kingdom, a market with very similar characteristics to that in the United States. Our data span a two-year period. A feature of our data is that we observe rich information on how consumers manage their card repayments, such as whether they pay their account manually each month or instead use an automatic instruction ("autopay") for the bill to be paid.[5] We show that this additional information on how consumers manage their repayments is crucial for explaining whether and how consumers avoid late payment fees. Our data cover approximately 2.6 million account-cycles, and includes granular account level information.

Our analysis proceeds as follows. First, we show that late payment fees are front-loaded, peaking in the first month of account life and then declining sharply over the following months. We show that these patterns are not attributable to survivorship bias, i.e. accounts closing or falling dormant following the occurrence of a fee. The decline in late payment fees with tenure is also predicted from a rich multivariate regression model that includes a broad range of time-varying account level controls plus account and calendar time fixed-effects.

Why do fees decline over time? A previous study by Agarwal et al. (2008) focused on the dynamics of forgetting and remembering as the explanation for this decline. In their view, fees decline because forgetful consumers subsequently remember to repay on time. In this study we use information on how consumers manage their card repayments to show that fees decline not due to consumers remembering to repay in future. We see no evidence at all of fees improving memory to repay. Instead, the decline in fees is entirely due to consumers switching their mode of repayment to automatic payments such that they avoid the need to remember to repay in future.

First, we show that consumer responses to late payment fees differ substantially across consumers by whether or not they switch to an autopay facility. The *average* decline in late payment fees across all consumers over time is wholly attributable to a subset of

[5] Autopay was widely introduced in the UK from the 1990s onwards. All card issuers in our sample offer autopay on all of their products. Autopay is a more recent innovation in the United States credit card market.

consumers who switch their default repayment mode from manual repayment to autopay in response a late payment fee. While switching to autopay all but eliminates the likelihood of future fees, we find that among non-switchers the probability of fee payment remains as high as it was before these consumers incurred their first fee, at approximately 20% *per month*.

Hence, those consumers who react to the fee by changing their default mode of repayment using the autopay instruction find an effective facility to insure themselves against future forgetting. However, those who do not (and instead continue to rely on memory to pay their bill on time) remain just as likely to pay a late payment fee again in future. In essence, consumers only avoid future fees when they react by adopting autopay, acknowledging that they need a facility to avoid future failure to repay.[6] This result demonstrates the importance of consumer choices in adopting 'add-on' product features for avoiding future mistakes.

Examining the timing of fees and switching behavior, we show that the vast majority of consumers who switch following a late payment fee do so in the months immediately following the late payment fee. This suggests that the late payment fee acts as a call to action for consumers, and some consumers respond while the fee event is at the top of the mind. Because the switch to automatic payments creates a new default for these consumers, there is no ongoing need for them to remember to repay. By contrast, those who fail to switch must rely on remembering to repay in the following month, by which time the fee is no longer at the top of the mind, hence they tend to repeat the same mistake.

These results raise the question why *some* consumers switch to autopay in response to late payment fees while others do not. This result does not arise due to selection into products with differing autopay options, as all cards in our sample offer the autopay facility. Nor does this result arise due to selection into products with heterogeneity in fee levels across consumers, as fee levels are uniform across card providers, set at regulatory limits.

[6] Throughout this paper we distinguish between consumers who react to the late payment fee by changing their repayment mode, from purely manual to also include an automatic component, compared to consumers who do not. Consumers who do not change to include an automatic component have to rely on remembering to manually repay their card again in future – which we find is futile in learning to avoid future fees.

One possible reason for not switching to autopay is that a card holder is purely unable to repay (whether manually or automatically) due to liquidity constraints, and switching to automatic payments would therefore not solve the problem. However, non-switchers in our data have lower levels of debt, lower utilization and slightly *higher* average repayments compared with switchers, indicating that their failure to switch to autopay does not arise due to liquidity constraints.

We explore the relationship between switching behavior and individual characteristics. Drawing first on the credit card account data, we show that consumers who respond to late payment fees by switching appear to be on average financially more sophisticated. Switchers are more likely to have obtained a low-cost promotional card, often with 0% APR, reducing the interest payments on borrowing. They are also more likely to hold a low APR balance-transfer facility, allowing them to refinance higher-APR debt from other cards onto a lower-APR card.

We match in geographically granular census microdata to our credit card panel. Using this, we show that switchers to autopay appear to be on average more sophisticated. Switchers are disproportionately drawn from local populations with higher incomes, home values and education, lower unemployment and lower social insurance dependency when compared with non-switchers. Our results are in line with the notion that more sophisticated consumers react optimally in response to negative feedback (i.e. the late payment fee), while less sophisticated consumers fail to respond.[7] Recent studies show that mistakes of omission in other domains (not acting when it is optimal to do so), such as missed mortgage refinancing opportunities, are also less common among more sophisticated consumers (Andersen et al., 2015; Agarwal et al., 2016).[8]

In additional analysis we also consider two other common contingent fees on credit cards: cash advance fees and over-limit fees. In our data, cash advance fees decline with account tenure. Our analysis suggests this arises due to liquidity constraints, with cash

[7] Some sophisticated consumers might strategically default on their credit card repayments. However, the incentives for strategic default are weak in the UK consumer credit market as consumer bankruptcy fees are high (a minimum of £750) and the period of discharge can be lengthy, up to three years.

[8] Studies in the mortgage refinancing literature draw a contrast between mistakes of omission (failure to refinance) and mistakes of commission (failure to optimally refinance, which typically arise due to refinancing too early).

advances concentrated among higher risk customers in periods of high card utilization and high purchase volumes that coincide with card openings. We also show that over-limit fees tend to occur during periods of persistently high purchases and low repayments, with consumers responding to over-limit fees by making one-time balloon repayments and subsequent lowering in month-on-month purchase volumes. Hence, heterogeneity in incurring these fee types appears to be explained by economic fundamentals.

Our paper is closest to Agarwal et al. (2008), who use data from a US credit card issuer, while drawing very different conclusion as to how consumers avoid penalty fees. Our findings relate more broadly to the growing literature on the role of 'reminders' or 'prompts' to improve behavior (Karlan et al., 2016; Carlin et al., 2017). To some extent, automating flows – such as bill payment, debt payment or savings – do not require reminders to bring a financial need to the 'top of the mind' and prompt a manual action. However, at the same time, automating payments may result in lower-bound default effects, whereby consumers no longer pay attention to their accounts. In the case of credit cards, if consumers choose to set up automatic payments at the minimum payment amount (instead of automatic intermediate or full payments), they may reduce average payments. Hence, switching to autopay may increase interest charges while reducing late payment fees. Recent papers emphasize that minimum payments may give rise to default effects in debt repayment (Keys and Wang, 2018; Sussman and Bartels, 2018), including a suppressing effect on average repayments over time (Sakaguchi et al., 2018).[9]

In many settings additional product features also allow consumers to set automatic actions to changing states of the world, such as automatic rebalancing of passive mutual funds, or raising pension contributions with income increases. We focus on credit cards because they offer a rich environment for studying consumer responses to negative feedback. As a high frequency product, credit cards provide fast feedback on recent behavior. Fees

[9] Sakaguchi et al. (2018) examine repayment behavior of credit card holders before and after switching to direct debit. They show that card holders typically set a direct debit that reflects their model repayment behavior, e.g. paying in full, or minimum, or a set amount. After switching to direct debit, card holders' amodal repayments become much less frequent. Hence, if individuals switch to minimum payment direct debit, they tend not to make occasional balloon payments as they did before the switch. In this way, direct debit can act to delay time to repayment. Without natural experiments, however, it is difficult to establish causality between setting a direct debit and subsequent repayment behavior.

are prominently displayed on credit card statements, so the negative feedback from failing to repay on time is made salient to the consumer.[10] Also, the introduction of automatic payments offers an example of an insurance mechanism against future forgetting available to all consumers. This contrasts with other settings where consumers make decisions at low frequency, such as mortgage refinancing, portfolio rebalancing or pension fund allocation (Madrian and Shea, 2001; Choi et al., 2002; Agnew et al., 2003; Choi et al., 2004; Brunnermeier and Nagel, 2008; Calvet et al., 2009; Bilias et al., 2010; Andersen et al., 2015).

The response of consumers to credit card fees has been an important issue for regulation, including fee limits introduced by the 2009 US CARD Act. Autopay is a relatively new innovation in the US credit card market, but has existed in the UK credit card market since the early 1990s (where it is typically known as 'direct debit'). Views differ on the relative benefits of automatic repayment as a means of avoiding late payment fees against the possibility that consumers who use autopay neglect to pay attention to their account balances. Recently, this has provoked regulatory interest of the UK financial regulator, but has attracted surprisingly little academic research.[11]

This paper contributes to the growing literature on consumer behavior in the credit card market. A large literature documents that consumer choices in the credit card market appear sub-optimal (Agarwal et al., 2009; Gross and Souleles, 2002; Stango and Zinman, 2009; Meier and Sprenger, 2010; Ponce et al., 2017; Gathergood et al., 2017; Jorring, 2018). Credit card companies also exploit consumer inertia and naivete (Ausubel, 1991; Ru and Schoar, 2016). However, recent studies show that some consumers respond to incentives to improve their creditworthiness and reduce the cost of credit, consistent with our findings on consumer responses to late payment fees (Alan et al., 2017; Liberman, 2016).

[10] Credit card penalty fees and charges are also salient on account statements, and the card issuers in our UK data all write to consumers separately to notify them of charged fees. Consumers may be more likely to learn in settings where feedback is salient, such as credit card fees highlighted on account statements, compared with scenarios where the consequences of mistakes are not made salient to consumers, such as borrowing or repaying on the wrong credit card (Ponce et al., 2017). Our data also allow us to observe mechanisms by which consumers change their behavior in response to fees, such as switching to autopay.

[11] In the UK, the Financial Conduct Authority's (FCA) current 'Credit Card Market Study' has focused upon automatic credit card repayment, in particular automatic credit card repayment of the minimum payment only, as a potential source of detriment to consumers (Financial Conduct Authority, 2016). We are not aware of any academic research on how consumers use autopay facilities.

The structure of the remainder of our paper is as follows. In Section 2, we describe the credit card data we use in this study and present summary data. We introduce our main results in Section 3 by showing the decline in credit card fees with tenure. In Section 4 we show how the decline is entirely attributable to switching to automatic payments. In Section 5 we show that those who switch are financially more sophisticated. In Section 6 we explore the decline in cash advance fees and over limit fees and show that this is due to liquidity constraints. The final section concludes the paper.

2 Data

The data we use are provided by five UK credit card issuers who together comprise 40% of the UK credit card market by number of cards. The UK credit card market has many similarities with the US credit card market with cards offering the same features and fee structures. Some UK card issuers are subsidiaries of US firms and card issuance is dominated by the mainstream networks Mastercard and Visa. The credit card market mostly comprises general purpose credit cards, often with purchases rewards programs, teaser rate deals and balance transfer facilities. The issuers in our sample serve a broad range of market segments from 'prime' low-APR cards which are designed to focus on revenue accrual through interchange fees to 'sub-prime' cards issued with high APRs. We source the data via Argus Information and Advisory Services, who collate and harmonize data from credit card issuers.[12] Argus provided us with account level data for a 10% random sample of consumers who held at least one card among the five credit card issuers in the period between January 2013 and December 2014. Our data are an unbalanced panel in which we observe account openings and closures.

The total data sample comprises 1.4 million customers, 1.8 million individual credit cards, and approximately 48 million account cycles. The data include transaction level records (categorized spending and repayments) alongside account-cycle summary records (e.g. credit limits, purchases and repayments, average daily balances, revolving balances,

[12] Argus specializes in providing 'wallet view' databases of multiple cards held by individual consumers. They collate data from individual credit card issues into common data fields and synchronized payment cycles, allowing researchers to compare individual behavior across cards within consumer panels.

interest and charges). We also observe the opening date of each account in the sample which allows us to calculate account tenure. In addition, Argus provides geocodes in the form of 4-digit UK postcodes.[13]

Our focus in this paper is on patterns in fee payments early in the life of new cards. We therefore restrict the sample to cards that open within our sample period. This sample restriction gives us approximately 243,000 accounts and 2.7 million account cycles of data. Summary statistics for this sample are shown in Table 1. The mean credit limit among cards in our sample is approximately £4,600, and the mean balance is £1,700. This implies a mean utilization rate of close to 40% (median utilization rate is 32%). We focus our analysis on cards that open in the sample period, and many of those open with short-term discount 'teaser' rate deals. Hence, the mean annual percentage rate of charge (APR) is low at 9.3%, with approximately half of individual account-cycle observations having an APR of 0%. Figure A1 illustrates slight growth in new account openings over the data period, with some evidence of seasonality in account openings.

2.1 Credit Card Fee Types

Our analysis focuses on the three most common fee types: late payment fees, cash advance fees and over-limit fees.[14] Fee levels in the UK are uniform across products and card issuers within each fee type, with card issuers setting fees at the regulatory limits. This offers us the advantage that we do not need to be concerned that our results on patterns in fee payment arise due to consumers selecting into card types with differing fee levels or structures, or that card issuers target products with different fee regimes to customers based on their behavioral types (as in Ru and Schoar, 2016). While this is an attractive feature of our setting, one implication is that our data do not offer variation in fee types which could potentially be used to understand whether larger fees encourage greater or faster learning responses on the part of consumers.

Incurring a fee implies two negative outcomes for the card holder, i) an immediate

[13] UK postcodes are the equivalent to US Zip codes. To preserve anonymity of individual card holders, Argus provides the 4-digit 'outer' part of the postcode. There are approximately 3,000 UK 4-digit postcodes, which each contain on average 9,000 individual addresses, or 0.03% of UK addresses.

[14] Other, less common penalty fees exist, such as fees for paying a card into credit.

financial penalty and, ii) a marker on the card holder's credit file that reduces access to credit in the future. Late payment fees are incurred when the consumer fails to make at least the required minimum repayment on the account by the statement bill due date. The required minimum payment is typically £10 or 1% of the card balance, whichever is greater. Late payment fees are capped by regulation at a maximum £12 per month with no limit on the number of successive months in which a consumer can incur the fee. All card issuers in our dataset set the fee at the £12 regulatory limit.

Cash advance fees are incurred when a customer borrows cash on their credit card (including foreign currency advances) or transfers monies from their credit card account to their deposit account. Cash advances incur a fixed fee typically of 3%, with a £3 minimum charge per transaction. The APR for cash advances is also considerably higher than that on purchases – in our sample around 25%. Furthermore, interest is charged on cash advances from the day of the advance, even if the consumer repays the cash advance by their next payment due date. Cash advances are also reported on credit files.

Over-limit fees are incurred when a consumer exceeds their credit limit. These fees can be incurred at any point in the billing cycle and are also subject to a regulatory maximum of £12 per limit breach. A consumer may accrue several over-limit charges in a single billing cycle if additional purchases are made on the account. Over-limit events are also reported on credit files.

While the direct monetary fees might seem modest, all fee types we observe generate indirect costs through the impact on future credit availability via credit reporting flags. These fee payments affect behavioral credit scores used by the card company and may negatively impact the cost of current or future credit. The negative effects of fee payments therefore extend beyond the immediate fee. Hence, the fee amounts we observe understate the total economic costs of incurring fees.[15]

Table 2 summarizes fees in our sample, with summary data at the card level. Fees are quite common within our sample, with 34% of accounts incurring a fee at least once

[15] We do not consider these indirect penalties arising from fees in our analysis, in part because it is difficult to accurately evaluate the monetary or utility value of the indirect penalty arising through an impaired credit history. In the UK setting, lenders compute proprietary credit scores, hence the impact of a late payment fee on a consumer's credit file will differ by credit issuer.

within the sample period. Late payment fees are most common with 24% of accounts incurring a late payment fee at least once. Cash advance and over-limit fees are less common with 13% of accounts incurring a cash advance fee and 7% of accounts incurring an over-limit fee in the sample.

3 Credit Card Late Payment Fees Decline With Tenure

We begin our results by showing that credit card late payment fees decline with account tenure.[16] Figure 1 plots the decline in late payment fees with tenure in the raw data and the predicted decline in late payment fees with tenure from a rich multivariate model. Panel A shows the raw data plot. The proportion of accounts incurring late payment fees falls from 6% in the first month to 2.8% by month 23. The decline in fees is fastest over the first few months of account tenure, then slows in subsequent months.

The sample used in Figure 1 Panel A is an unbalanced panel. Therefore, the observed pattern of fee decline could potentially arise due to selective attrition, or 'survivorship bias', if accounts which incur a fee are more likely to close or fall dormant after the fee event. For this reason, in Figure A2 (see Web Appendix) we restrict the sample to accounts that open within our sample period and remain open and active for at least 15 months, though results are not sensitive to changing this cut-off value.[17] This balanced panel includes 46% of observations in the main sample. Figure A2 shows a very similar pattern of fee decline over tenure as that seen in the unbalanced panel. Summary statistics for this balanced panel sample can be found in Tables A1 and A2.

Figure 1 Panel B shows predicted fees from a multivariate model. We show these estimates because the pattern of fee decline we observe could potentially be caused by time-varying account characteristics, or strong calendar time events which might dominate a period within our two-year panel. To the extent that fee events change subsequent

[16] In doing so, we corroborate the main finding from Agarwal et al. (2008).

[17] We choose 15 months instead of the full panel length of 24 months as i) restricting the data to a 24-month panel reduces sample size considerably to only a few thousand accounts and ii) restricting to 24 months implies a panel of accounts all of which open in January 2013, which might highlight calendar month effects, though we see no strong seasonality in account openings. We see identical patterns of fee decline if we further shorten the panel length to 12 months or 10 months.

behavior, account usage might be negatively autocorrelated over time with fee events. To control for time-varying account characteristics, card fixed effects and calendar time fixed effects, we estimate a linear probability model, similar to Agarwal et al. (2008). We then plot the predicted probability of incurring a fee over tenure. The equation we estimate is:

$$P(fee = 1)^{j}_{i,t} = \alpha + \phi_i + \psi_{month} + \Omega_t Tenure_{i,t} + \beta(X)_{i,t} + \epsilon_{i,t} \tag{1}$$

Fee type j (here late payment fees, but later cash advance and over-limit fees) is a dummy variable that is 1 if a fee is paid on account i at tenure t. The probability of incurring a fee is modelled as a function of vectors of tenure dummies (Ω_t), month dummies (ψ_{month}), account fixed effects (ϕ_i) and time-varying account level controls ($\beta(X)_{i,t}$).[18] Standard errors are clustered by account. Predictions are shown at covariate medians. Table A3 reports the model estimates.[19]

The prediction plot in Figure 1 Panel B shows very similar patterns to those in the raw data. The likelihood of late payment fees falls steeply over the first few months of account tenure. Figure A2 plots predictions for the balanced panel sample, in which the decline in late payment fees is sharper, confirming again that the modelled patterns we see in the prediction plots are not attributable to attrition. The patterns in the model plots (Panel B) are not sensitive to extending or shortening the time window out from 15 months. We also see identical patterns from estimates of Equation 1 in which we include a dummy variable to control for whether the card carries a balance, and therefore has a non-zero minimum payment due. This shows that selective card inactivity does not account for our results.[20]

Before exploring the reasons why these patterns exist, we note one implication of these patterns in fee behavior: revenue streams from fees are front-loaded for card issuers. This might present another incentive for card issuers to acquire new customer accounts,

[18] Late payment fees appear in the data one month after the account is paid late, hence we lag tenure by one month in the model of late payment fees.

[19] Due to data restrictions we are unable to control for credit card issuer fixed effects. However, as fees are uniform in the UK, borrower self-selection into cards with different fees is not a concern in our setting.

[20] Throughout the remainder of the analysis presented in the paper, we find no difference in econometric estimates when including this dummy variable or not.

especially if initial fees are the result of mistakes by 'good' credit types and not due to high credit risk (which would make accounts less attractive to card issuers). In the UK credit card market, as in the US, credit card issuers aggressively compete for customers via initial incentives such as teaser rate deals (zero or low APR promotional periods), cash-back rewards and other joining incentives. One reason for this strong competition over acquisition may be the initial fee concentration captured by the card issuer.

4 Late Payment Fees and Autopay

Our main interest is in understanding why late payment fees decline with tenure. In this section we show that the tenure-profile of late payment fees differs markedly across account types by their manual vs. autopay repayment mode. Strikingly, we find *all* of the decline in late payment fees is concentrated among accounts that open with manual repayment regime and then switch to an autopay regime. Accounts that fail to switch from manual repayment to automatic repayment illustrate no decline in fees.

Before showing these results in detail, we describe how the autopay facility functions with a credit card. Autopay is a new concept in the academic literature on credit cards. A credit card will have one of two repayment regimes: a purely manual repayment regime or a regime which also includes automatic payments and can even be entirely automatic. Under manual repayment, a customer receives a bill each payment cycle, either electronically or in the mail, which must be repaid manually for example by electronic bank transfer, by mailing a depositor's check, or by making a payment via the telephone. Under the autopay regime, the customer authorizes his or her bank to automatically settle the account by direct debit without manual instruction from the customer each month. Thus, part, and sometimes all, of the bill is paid automatically, whilst additional manual repayments can still be made. That is, autopay does not prevent the customer from also making (additional) manual repayments. Autopay is setup via a one-time instruction to the credit card company, often on the telephone or internet. Under UK law, an autopay instruction requires the consumer's consent. Autopay is guaranteed by the government against failure of the payments system to clear the transaction.[21]

In the UK, autopay instructions are commonly used for a range of recurring payments, including mortgage payments, utility bills, cell phone bills and municipal taxes. In the case of a credit card, an autopay instruction also specifies the amount to be paid each month. The option to use autopay is available on all credit cards in the UK by law.[22] This is important in our analysis, as we can rule out the possibility that fee patterns differ across consumers due to selection into cards with or without the autopay option. At any time, consumers can choose to set autopay at the minimum payment due, a higher level in percent or specified monetary value, or the balance in full. Once an autopay instruction is set up on a credit card account, at each billing cycle the amount will be automatically paid from the consumer's deposit account. Autopay therefore removes the need for the customer to be attentive to their bill and repayment (at least for the avoidance of late payment fees), conditional upon having sufficient funds in their deposit account.

To show the importance of autopay, Figure 2 illustrates the patterns in late payment fee decline for three account types: accounts that from inception open with an autopay regime and remain on that regime through the data period (Panel A, 14.4% of accounts); accounts that open with a manual repayment regime and keep this regime through at least the first 15 months of account life (Panel B 64.1% of accounts); and accounts that open with a manual repayment regime but switch to the autopay regime within the first 15 months of account life (Panel C, 21.4% of accounts).[23] These plots are obtained by estimating Equation 1 separately for each account type.[24]

The late payment fee patterns differ markedly across the panels of Figure 2. Unsurprisingly, among accounts which have an autopay instruction from inception, shown

[21] In the UK, autopay is commonly referred to as "Direct Debit". To make a direct debit instruction, the customer has to complete a paper or online form detailing their deposit account details and providing their consent. Direct debit cannot be set up by proxy or as a trigger within a contingent contract. The direct debit mandate guarantees the customer against failed payments in the event of electronic of other failure of the payments system. It does not guarantee the payment in case of insufficient funds in the customer's deposit account.

[22] Fewer than 0.5% of UK deposit accounts do not offer an autopay facility as an option to a consumer (Source: British Bankers Association).

[23] We use 15 months here to avoid calendar month effects which would arise from using a 24-month time period, implying all accounts opened in January 2013. We also exclude from the sample a smaller number of accounts that switch autopay status multiple times during the period.

[24] We show corresponding scatter plots of fees in Figure A3. Tables A4 to A6 report the model estimates.

in Panel A, the probability of a late payment fee is close to zero throughout the life of these accounts (because at least the minimum amount is automatically repaid on time). Hence, a late payment fee is incurred only when the customer's deposit account has insufficient funds, a very rare event. Among accounts which never have an autopay instruction, by contrast, the probability of late payment fees is consistently around 7%, with no decline over account tenure. All of the decline in fees with tenure is seen among accounts that switch from manual repayment to autopay, in Panel C. Among these switching accounts, the probability of incurring a fee is close to 18% at the point of opening, but quickly declines and reaches 0% after a few months.

We show the sensitivity of these model estimates to variation in the set of controls, set of fixed effects, regression functional form and panel length in Figure A4. The figure shows a "specification curve" suggested by Simonsohn et al. (2015). A specification curve is a visualization of how coefficient magnitudes and precision vary across specifications of econometric models. In Figure A4, each dot represents an estimate of the coefficient on the dummy variable for tenure at value of month 10 from Equation 1. This month is chosen as there are clear differences in fee likelihoods at this month across the panels in Figure 2. The unfilled dots show estimates for always non-autopay accounts and the filled dots show estimates for the switched to autopay accounts. Each column presents estimates for a separate equation, with the rows in the bottom panel indicating the combination of sample, control variables, fixed effects and functional forms used in the models. Results show that across the wide variety of models the coefficient estimate on the tenure = Month 10 dummy among the sample of switched-to-autopay accounts is always below that in the non-autopay accounts, and both sets of estimates are stable across specifications.[25]

4.1 Switching to Autopay Following a Late Payment Fee

Adopting autopay appears to be the driver of declining late payment fees with tenure. To further explore this, we conduct an event-study analysis to examine the relationship between late payment fees and switching repayment mode to autopay. The event-study

[25] In both samples the coefficient estimates are biased upwards when the set of time-varying control variables is omitted, shown by the right-hand set of estimates in each column panel.

approach allows us to focus on changes in behavior which are close to the timing of the first late payment fee incurred on an account. We estimate an event study model, given by Equation 2 below, which incorporates a set of time-varying card characteristics to capture changes in purchase or repayment behavior, or changes in credit risk, which might occur at the same time as a late payment fee. We estimate the following event-study equation:

$$P(fee=1)^{j}_{i,t} = \alpha + \phi_i + \psi_{month} + \Omega_t Distance^{\text{1st fee type } j}_{i,t} + \beta(X)_{i,t} + \epsilon_{i,t} \tag{2}$$

where the probability of account i incurring a fee of type j (here late payment fees) at time t is a function of the distance in time since the first fee event of type j, controlling for time-varying account characteristics, individual fixed effects and calendar month fixed effects. Note that in this model the distinction between calendar time and account tenure is immaterial as fee events are modelled in distance in months from the month of the first fee.

In Figure 3 we show plots of the predicted probability of incurring a late payment fee, where the x-axis is event-time elapsed since the first fee, for all accounts that are manually repaid throughout (Panel A, approximately two-thirds of all accounts that incur a first late payment fee) and those that switch to autopay (Panel B approximately one third of accounts that incur a first late payment fee).[26] The total sample size is 18,100 accounts that incur a first fee during the sample period. By construction, the plots only show months after the first late payment fee event.

Panel A illustrates that among non-switching accounts (i.e. accounts that do not switch away from manual repayment regime in the 10 months following the first fee) the fee likelihood is persistently 20% per month in the months following the first fee event. Among accounts that switch repayment regime, shown in Panel B, the fee likelihood reduces immediately in the month after incurring the first fee to 10%, and falls to 0% in the following months.[27]

[26] We show corresponding scatter plots in Figure A5. Tables A7 and A8 report the model estimates. Less than 1% of accounts incur a late payment fee while already being repaid by autopay, an additional small number of accounts switch autopay status more than once in the sample period.

[27] The decline in fees is not immediately to zero as i) not all accounts that switch to autopay following a late payment fee do so in the month immediately following the first fee event; ii) accounts may continue

To show fee dynamics around the switch to autopay, Figure 4 plots the proportion of accounts incurring a late payment fee, where the x-axis is event time since the first autopay payment. The figure confirms that late payment fees are a strong trigger of switching to autopay. In the months before switching the fee rate among accounts that switch is approximately 8%, this spikes to 15% in the month before the switch. Following the setup of an autopay instruction, the proportion of accounts incurring a late payment fee falls to nearly 0%.

These results illustrate that the decline in late payment fees over tenure occurs due to a subset of customers changing their repayment behavior by adopting autopay. The sharp decline in subsequent fees also strongly suggests that the late payment fees incurred by these customers were one-time mistakes. If late payment fees were due to persistent liquidity constraints, then switching to automatic payments would not reduce the late payment fee. It is more plausible that switching to autopay reflects a decision by customers to insure themselves against future forgetting. Remarkably, customers who do not switch to autopay show a persistently high likelihood of future fees. For these customers – who need to remember each month to make their card payments in order to avoid late payment fees – purely "remembering" to pay in future appears to be an ineffective strategy for reducing the likelihood of future fees.

We again use a specification curve to show the sensitivity of these model estimates to variation in the set of controls, set of fixed effects, regression functional form and panel length in Figure A6. Each dot shows an estimate of the coefficient on the dummy variable for 5 months after the first fee from Equation 2. This month is chosen as there are clear differences in fee likelihoods at this month in Figure 3. The unfilled dots show estimates for always non-autopay accounts and the filled dots show estimates for the switched to autopay accounts. Results show that the coefficient estimate on the dummy variable among the sample of switched-to-autopay accounts is always below that in the non-autopay accounts, and both sets of estimates are persistently different across specifications. The estimates are slightly sensitive to the inclusion of combinations of account and calendar month fixed

to incur late payment fees due to insufficient funds in the consumer's deposit account.

effects (which are all included in our main estimates of Equation 2).

4.2 Timing of the Switch to Autopay

Our main result suggests that the late payment fee acts as a "call to action" for consumers to switch their repayment status from manual payment to automatic payment. The late payment fee appears effective at preventing future fees only insofar as consumers respond to this call to action through switching to autopay. Examining the timing of fees and switching behavior, we show that the vast majority of consumers who switch following a late payment fee do so in the months immediately following the late payment fee.

Figure 5 takes the sample of all accounts which incur at least one fee and illustrates the probability that an account switches to autopay over the months after the first fee is incurred. Switches occur soon after the fee, either in the same month as the fee (month 0 for individuals who switch to autopay and bring their account up-to-date with the first autopay payment), or in the following month. The switching rate in subsequent months falls sharply to zero. Hence, it appears that late payment fees prompt immediate action, or the result is no action at all. Because the switch to automatic payments creates a new default for these consumers, there is no ongoing need for them to take any further action once they respond to the immediate call to action. By contrast, those who fail to switch must rely on remembering to repay in the following month, by which time the fee is no longer at the top of the mind, hence they tend to repeat the same mistake.

4.3 Responses to Second Time Late Payment Fees

In this sub-section we examine consumer responses to second fees. The patterns of responses to second fees may differ from those to first fees if, for example, second fees have a strong reinforcement effect on memory, attenuating the benefits of auto payment repayment. Among those accounts that incur a first fee, 34.3% of accounts incur a second fee within the sample period. To show how consumers respond to second late payment fees, Figure 6 replicates the analysis of first-fees by showing responses to late payment fees among accounts that do and do not switch to autopay after the incursion of a *second* fee. The pattern in the figure is the same as in the first fee analysis, with no evidence of learning among consumers who do not respond to the second fee by switching to autopay. Of those incurring a second late payment fee, approximately one quarter switch to autopay while three-quarters persist with manual repayment. The month-by-month likelihood of incurring a second fee remains high at approximately 20% through the ten months following the second fee. That the pattern for second late payment fees so strongly resembles the pattern for first late payment fees indicates that even subsequent fees do not help people to learn to remember to repay their bill but do act, just as first fees, to prompt some people to switch to autopay.

5 Who Switches to Autopay?

The results on late payment fees raise the question why *some* card holders switch to autopay after incurring a fee while others do not. This distinction is important because differences in subsequent fees between switchers and non-switchers are substantial. Among non-switchers, the fee probability persisting at 20% per month implies that an account will incur a £12 late payment fee every five months; while among switchers this likelihood is approximately 2%, implying an account will incur a late payment fee every 50 months. Hence, over reasonable time periods, non-switching accounts will incur 10 times more late payment fees compared to switching accounts. While these direct fee costs are moderate, this is an underestimate of the total difference in the economic costs of fees, which also includes the indirect costs arising from markers added to credit files.[28]

We consider a variety of explanations for why some individuals choose to switch repayment mode, but others do not. In Table 3, we compare account characteristics for individuals who do and do not switch following the incursion of a first late payment fee using information from the Argus data and also match data on consumer characteristics using geocodes. In Panel A we compare switchers and non-switchers by their card usage and in Panel B by their card characteristics. The availability of geocodes also allows us

[28] Credit markers indicate increased risks to lenders, and result in consumers facing higher interest costs and reduced credit supply across a range of credit products.

to match-in a rich set of socio-economic covariates, by which we compare switchers and non-switchers in Panel C. Other recent studies using matched census data, based on US zip codes, include Mian and Sufi (2009) and Chetty et al. (2013).[29] This allows us to understand more about differences across the groups which might drive their different responses to a late payment fee.

We now discuss three explanations for the differences between switchers and non-switchers:

Occasional Usage. One potential reason for not switching to autopay is that customers have low levels of account activity, so the need to repay in the future is low and hence late payment fees are occasional events. However, a comparison of account characteristics suggests that non-switchers do not avoid switching because they have low card activity (and hence low likelihood of future fees). On average, non-switchers carry more than £1,900 of balances. Non-switchers also have higher monthly purchases compared with switchers (£170 compared to £150) and also have higher monthly repayments (£260 compared to £190).

Liquidity Constraints. Consumers might not switch to autopay if they are financially constrained and cannot make repayments. Autopay does not provide perfect insurance against failure to pay if the consumer's deposit account contains insufficient funds to meet the repayment due, and the consumer would incur penalty charges on the deposit account as well as on the credit card. However, non-switchers do not appear liquidity constrained in the data. First, card utilization among non-switchers is actually lower than among non-switchers compared with switchers (48% compared with 59%). Monthly purchases are also only approximately 10% of the spare capacity on the card, suggesting that non-switchers are not moving towards a liquidity constraint on their credit card. Second, non-switchers make *higher* average repayments each month compared to

[29] We draw upon detailed census records from the UK National Census for 2011. The UK national census has been conducted every ten years since 1801 and is a very detailed of household information, costing approximately £500 million to administer. The 2011 census had a 94% response rate. Summary data and a 5% sample of raw data are made available to researchers via the UK Office for National Statistics. In the Argus data consumers are spread across 2994 different postcode districts. The census statistical unit is smaller, covering 8,436 Middle-super output areas (MSOA). We take a weighted average of to-be-matched variables across MSOAs within postcode districts.

switchers (despite being more likely to miss payments) also suggesting that lack of available funds in their deposit account does not drive this behavior.[30] While we cannot observe the deposit account position of card holders in our sample, the higher average repayments among non-switchers suggest that they are not constrained by low available funds in other accounts.

Financial Sophistication. Differences in the adoption of autopay might reflect differences in sophistication across consumers. Less sophisticated consumers may not realize their need to automate payments, naively relying on remembering to repay manually in future. Differences in card characteristics between switchers and non-switchers show that switchers have a higher propensity to hold cards with 0% introductory merchant APR and are also more likely to hold cards with a balance transfer facility. Other characteristics also suggest that switchers are on average more sophisticated. The matched geodata indicates that switchers are drawn from localities with higher median house prices, lower jobless claimants, higher weekly incomes, higher proportions of individuals in the locality with post-high school educational qualifications and a lower proportion of children in the locality entitled to free school meals. They also have lower ACORN scores, a postcode-level affluence score constructed by the UK statistics authority, indicating a higher degree of affluence.[31]

Overall, these differences in characteristics of accounts and consumers who switch, compared to those who do not switch, suggest that differences in behavior arise due to difference in the characteristics of card holders, with no differences in balances or indicators of liquidity constraints. For robustness, in Table A10 replicates Table 3 for the sample of consumers that incur a second late payment fee. In keeping with our results from the analysis of first fee events non-switchers do not appear to be only occasional card users or more likely liquidity constrained: they have lower utilization, higher purchases and higher payments than non-switchers. Instead, switchers have a range of indicators of being more

[30] Figure A8 illustrates mean payment amounts by non-switchers in the months before and after their first late payment fee.

[31] The differences in means across groups are all statistically significant at the 1% level. These differences should be interpreted relative to the standard deviation of the data (which is lower than the population average due to averaging within geocode areas)

financial sophisticated than non-switchers: switchers are more likely to have introductory 0% APR deals and balance transfer facilities, plus are drawn from localities with higher median house prices, lower jobless claimants, higher weekly incomes, higher proportions of individuals in the locality with post-high school educational qualifications and a lower proportion of children in the locality entitled to free school meals.

6 Cash Advance Fees and Over-Limit Fees

In this final results section we explore the dynamics of cash advance fees and over-limit fees, the two most common fee types after late payment fees. Understanding the dynamics of these fees is important in itself, as they also represent significant flows of revenues for card issues, though below revenues accrued from late payment fees.[32] Also, in contrast with late payment fees, credit cards do not offer consumer's management features analogous to automatic payments that could provide an automatic facility for avoiding these fee types.

6.1 Cash Advance Fees

Figure 7 illustrates the evolution of cash advances with account tenure, showing analogous illustrations to those shown for late payment fees in Figure 1. As with late payment fees, we observe a sharp decline in the proportion of accounts incurring cash advance fees over the first few months of account life. This pattern is also predicted from estimates of Equation 1, shown in Panel B of Figure 7.[33]

Why do cash advance fees decline with tenure? The use of this high-cost cash borrowing facility might reflect a customer facing a binding liquidity constraint. With other sources of cash unavailable (e.g. deposit account balances) and present consumption needs requiring cash payments, customers might draw upon this alternative source of funds by taking a new credit card. If so, we would expect cash advances to be concentrated among higher risk, liquidity constrained customers. These patterns appear to be at play in our data.

[32] As described in Footnote 4, prior to the introduction of the CARD ACT over-limit fees and cash advance fees together summed to approximately half of the revenues received from late payment fees.

[33] Figure A9 further shows identical patterns when we restrict the data to be a balanced panel.

First, we show that the decline in cash advance fees with tenure is concentrated in higher risk accounts. The riskiest 10% of accounts incur 38% of all cash advance fees in our sample. In the Argus data, the credit risk of an account is measured by the probability of charge-off (six consecutive missed payments). The probability variable is provided by the card issuers on a harmonized scale common across issuers in the Argus dataset. Figure 8 illustrates predicted probability plots from estimates of Equation 1, in which models are fitted separately for accounts with high and low probability of charge-off (split at the median).[34] The figure illustrates that among high probability of charge-off accounts the likelihood of fee incursion drops from approximately 7% at account opening to 3% after 15 months, whereas for low probability of charge-off accounts the likelihood is steady at 2% throughout the first 15 months of account life.

Second, we also find that cash advances appear much more common among customers who appear liquidity constrained. We cannot directly observe liquidity constraints in our data. Instead, we use proxy measures of card balances and card utilization. Figure 9 shows the average balance among accounts in the months before, during and after the account incurs consecutive cash advance fees. Each account contributes to one of the panels in the figure, depending on the number of consecutive cash advance fees within the first spell of the account's history in which a cash advance is incurred.[35] Accounts that never incur a cash advance fee are omitted from the figure. The panels illustrate that the onset of a spell of cash advance months sees average balances increase, continue to rise through the spell of cash advances, and then plateau or fall slightly at the end of the spell. Figure 10 confirms that higher balances translate to higher utilization.

This effect could, of course, occur mechanically through cash advances adding to balances and so raising account utilization. However, Figure 11 illustrates that the onset of a spell of cash advances occurs in the same month as an upswing in card purchases, which remain persistently high through the spell of cash advances. The panels illustrate

[34] The corresponding scatter plots of fees over tenure for each group are shown in Figure A10. Tables A12 and A13 report the model estimates. Sample sizes are smaller in these estimates because not all accounts in the data include values for the probability of charge-off.

[35] We restrict the data to accounts that have at least one month of observations before and after the spell. The sample size is lower among panels with longer spells of cash advances. We exclude accounts with multiple consecutive spells of cash advance fees.

that most spells of cash advances show large average increases in purchases in the month in which the spell of cash advances begins. Purchases tend downwards through the spell of cash advances.

These patterns in card usage behavior indicate that the onset of cash advances occurs predominantly among higher-risk accounts around the time at which purchase behavior and utilization increase, indicating the customer is more likely to be liquidity constrained. These patterns are also inconsistent with the alternative hypothesis that consumers are simply more likely to use their cards for cash advances when purchases increase, as we see increases in borrowing (not transacting) during spells of cash advances.[36]

Of course, these patterns in cash advances over time do not rule out the possibility that learning dynamics maybe at play for some customers, as suggested by Agarwal et al. (2008). We expect that in some cases customers begin using their credit card incognizant of the high costs of cash advances, subsequently changing their behavior once fees are reported on credit card statements. However, in our data the use of cash advances appears linked to the fundamental economic drivers of credit risk and liquidity, suggesting these are the main driver of cash advance fees.

6.2 Over-Limit Fees

Figure 12 illustrates the evolution of over-limit fees with account tenure, showing analogous illustrations to those shown for late payment fees in Figure 1. Here we see that over-limit fees steadily increase in the first few months of account life.[37] In our data, accounts take time after opening to accrue balances. Among accounts that incur an over-limit fee, the first fee is on average incurred at 8 months after opening. Very few accounts immediately accrue a balance after opening that exceeds the account limit (fewer than 0.5% of accounts in our sample). This pattern is unsurprising, as purchase levels are typically low relative

[36] This behavior among accounts in our sample also differs from that in the sample used by Agarwal et al. (2008), who find no clear patterns in card usage correlating with the incursion of any fee type, suggesting consumers make unpredictable mistakes in their data.

[37] The data also show that the proportion of accounts incurring over-limit fees increases through the first months of tenure among both high and low risk of charge-off accounts (see Figure A14). Hence, the pattern in fees over tenure in our data suggests that consumers on average *do not* open credit cards and put them straight over limit, as if ignorant of the existence of a credit limit, even among higher risk accounts that are likely to be held by less sophisticated consumers and have lower credit limits.

to credit limits. However, our result here contrasts with that seen in Agarwal et al. (2008), who find in their US data the same pattern in over-limit fees as that seen in late payment fees and cash advance fees.[38]

The pattern seen in Figure 12 does not mean that consumers do not respond to over-limit fee events. We do observe a decline in over-limit fees with tenure when we look at a set of accounts incurring their first over-limit fee *at a given tenure*, illustrated in Figure A13. We examine how consumers respond to a first over-limit fee. To do so, we estimate Equation 2 for over-limit fees and illustrate the predicted probability plots in Panel A of Figure 13.[39] In the months after the first fee event, the likelihood of a subsequent fee drops sharply. Panel A illustrates that in the month following the first fee the probability of a second fee is 40%, but this falls to less than 20% after two further months. Hence, there is low persistence in over-limit fees at the account level. This suggests that consumers on average adjust their behavior relatively quickly after an over-limit event. This pattern is consistent with the increase in the proportion of accounts exhibiting over-limit fees over the first months of tenure.

What drives customer responses to over-limit fees? In subsequent panels of Figure 13, we show the pattern of purchases (Panel B) and repayments (Panel C) around the time that the first over-limit fee is incurred. We observe that the period before the over-limit fee sees accounts exhibit successive months of higher purchases and declining repayments, with a spike in purchases in the month in which the fee is incurred. By contrast, in the period after the incursion of the over-limit fee, purchase volumes drop sharply, by approximately 55%, which persists over the 10 months following the first fee event.

Hence, the observed pattern of responses to an over-limit fee is that consumers on average take action to avoid future fees by cutting purchase volumes sharply, while leaving repayments unchanged. This is also consistent with the existence of individual liquidity constraints, as the reduction in balances when faced with a binding credit limit

[38] Agarwal et al. (2008) find that over-limit fees peak at the first month of card life, declining subsequently. This difference might reflect differences in card usage between the UK and US, with possibly a subset of US customers opening accounts with large balance transfers that may push the account over limit soon after opening.

[39] The corresponding scatter plots of fees over tenure for each group are shown in Figure A12 Tables A15 to A17 report the model estimates.

is concentrated in the current period through lower consumption purchases instead of higher repayments. As in the conclusions we draw from our analysis of cash advance fees, we expect that in the very few cases we observe in which customers open accounts and immediately put the account over-limit, learning dynamics may be at play. However, our data suggest that this is not the main driver of the dynamics of over-limit fees.

7 Conclusion

In this paper, we examine patterns in credit card fees among newly opened credit card accounts. In a large sample of accounts from five credit card providers, we show that the proportion of accounts incurring late payment fees peaks in the first month of account life, then declines sharply. While a decline in fees is often attributed to consumers learning from experience, we show that the decline in fees on average is wholly attributable to a subset of customers who switch to automatic repayments. That is, without using automatic repayments, late payment fees appear not to help card holders learn to remember to repay their bill on time. Our analysis of switchers and non-switchers suggests that switchers are more likely to be sophisticated, with switching behavior not appearing to be driven by occasional borrowing needs or liquidity constraints.

Our findings may have important implications for understanding how consumers respond to feedback – in the most general sense of the word – in financial markets. With their prominent fees and short time cycles, credit cards are a very promising financial product for adapting behavior. Our core finding, that people only avoid fees when either they act to change their ongoing repayment behavior by setting an automatic payment is important for understanding which consumers gain from financial innovations (such as automatic payments) and the costs to consumers who do not embrace additional features of financial products. The heterogeneous responses across customers in our data also implies that losses from incurring fees are unevenly distributed among consumers. While some consumers take action to insure themselves against the effects of future failure to make a payment, other consumers remain exposed to future mistakes and appear not to "learn". The role of autopay in these responses to fees also suggests that only some consumers are more likely to realize the benefits from technological innovation in payments technology, such as automatic repayment, while others may fail to realize the benefits of these new technologies.

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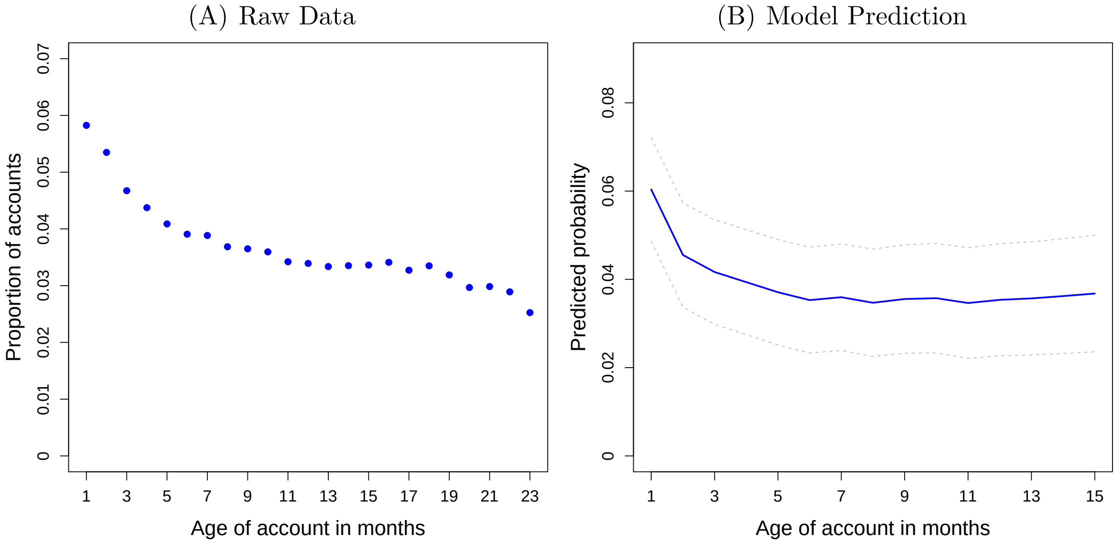
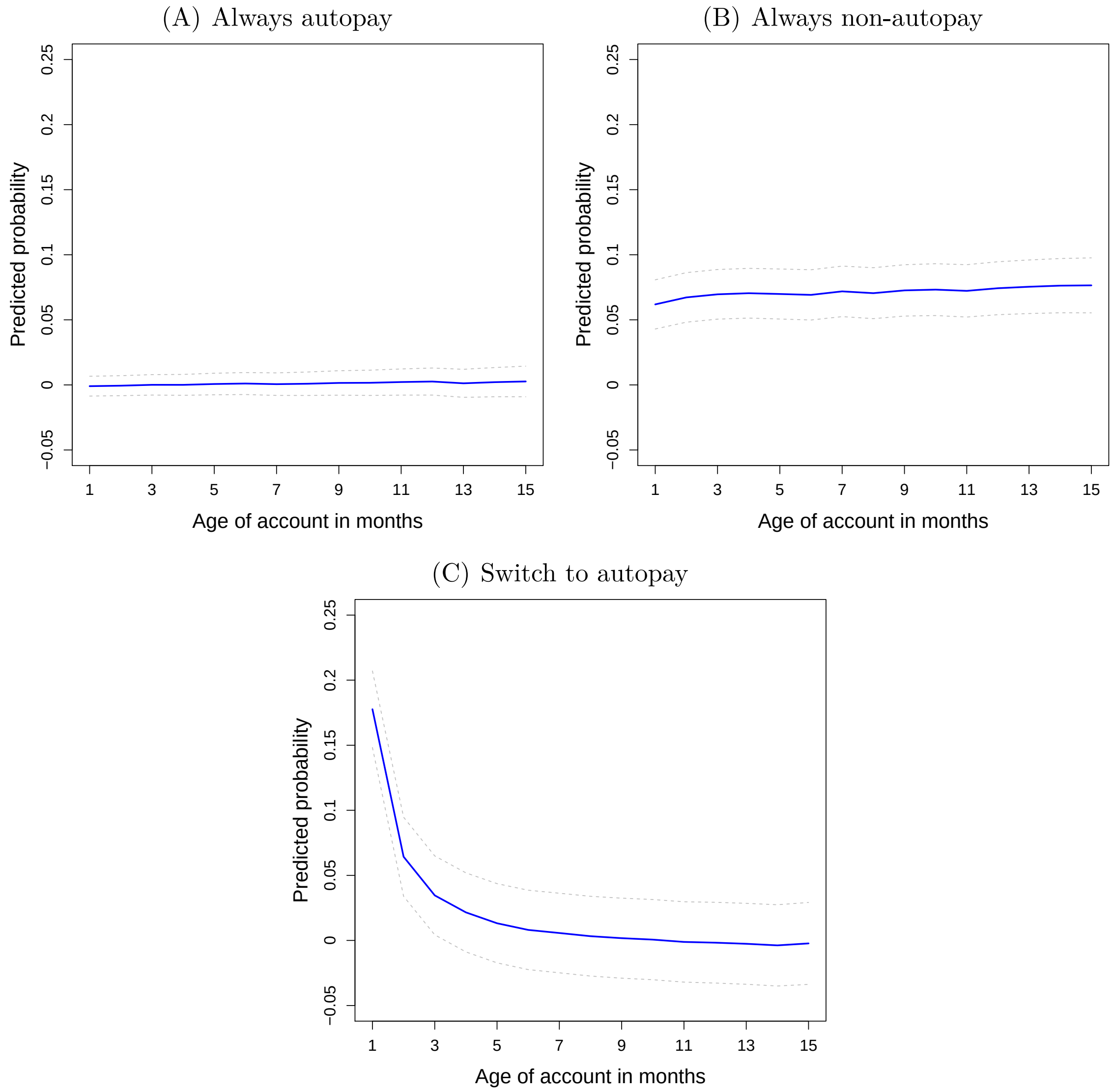
Figure 1: Late Payment Fees and Account Tenure



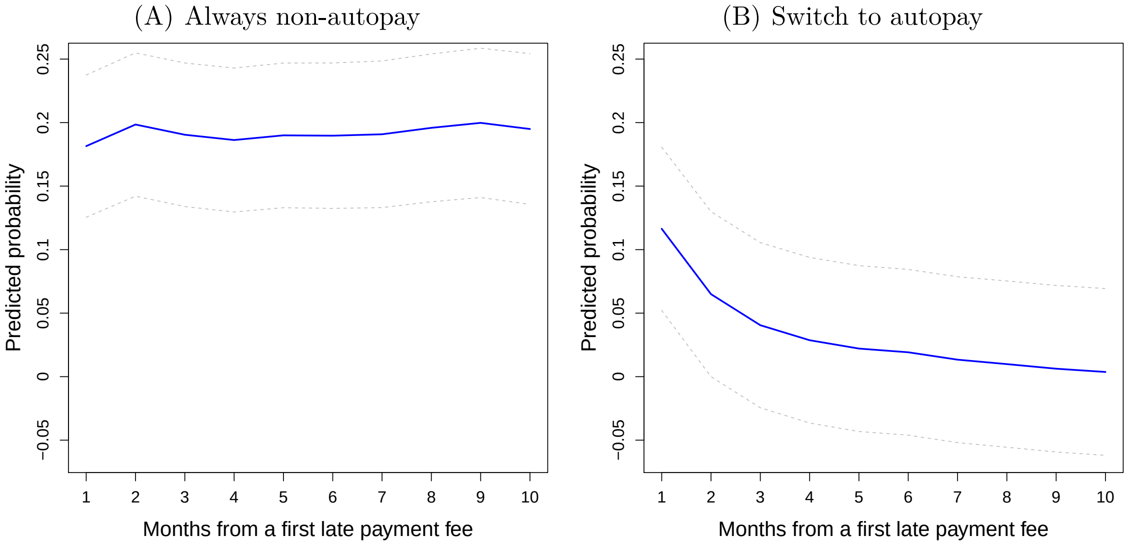
Note: Panel A plots the mean of the y-axis variable (dummy variable indicating whether the account incurred a late payment fee) by units of the x-axis variable (age of the account in months). The x-axis variable is adjusted one month forward as late payment fees are incurred in the next account cycle (the cycle in which payment is due). The sample comprises all accounts in the sample opened at or after January 2013. Panel B plots the predicted probability of an account incurring a late payment fee within the month based on estimates of Equation 1. Predictions are from a linear probability model at covariate medians with clustered standard errors at account level. Full model estimates are reported in Table A3. 95% confidence intervals are illustrated by dashed lines.

Figure 2: Probability of Late Payment Fee by Autopay Status



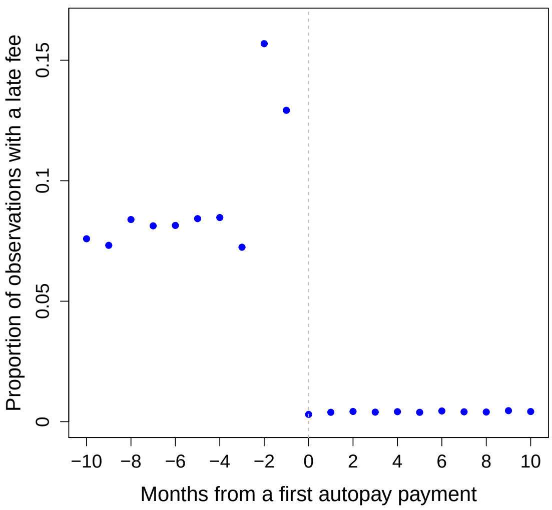
Note: Figure plots the predicted probability of accounts incurring a late payment fee in the next period by the age of the account in months. Predictions are from a linear probability model at covariate medians (Equation 1). The panels show three mutually exclusive groups of accounts: accounts which were subject to an autopay instruction from account opening onwards; accounts which were never subject to an autopay instruction; and accounts which switched from manual to autopay after account opening. 95% confidence intervals are illustrated by the dashed lines. The corresponding scatter plots of fees over tenure for each group are shown in Figure A3. Tables A4 to A6 report the model estimates.

Figure 3: Probability of Late Payment Fee in Months After First Fee, by Autopay Status



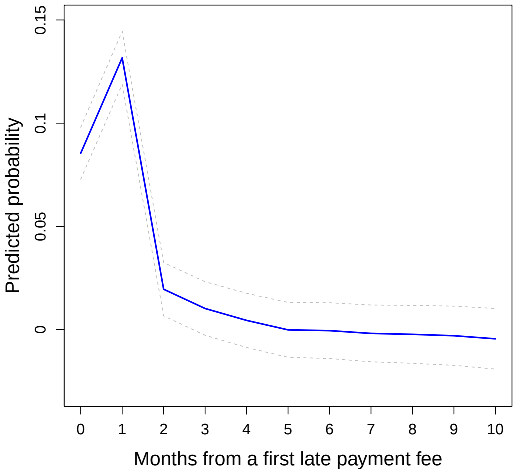
Note: Figure plots the predicted probability of accounts incurring a late payment fee in months after the first late payment fee is incurred (month zero). Predictions are from a linear probability model at covariate medians (Equation 2). The panels show two mutually exclusive groups: accounts which were never subject to an autopay instruction throughout the sample period; and accounts which switched from manual to autopay within the sample period. All accounts incurred a late payment fee at month 0 (not plotted on figure). 95% confidence intervals are illustrated by the dashed lines. The corresponding scatter plots of fees over tenure for each group are shown in Figure A5. Tables A7 and A8 report the model estimates.

Figure 4: Late Payment Fees in Months Before and After Switch to Autopay



Note: Figure plots the proportion of accounts switching from manual repayment to automatic repayment in the months following the first late payment fee incurred on the account.

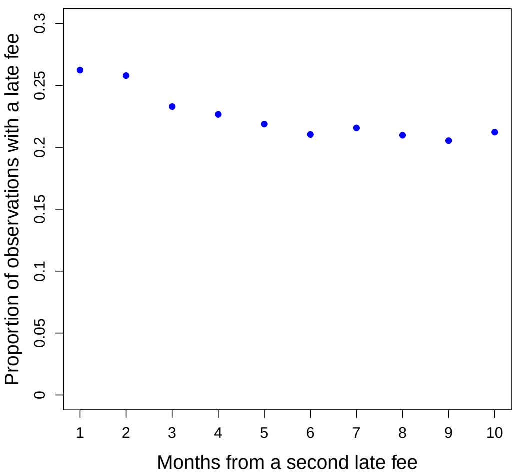
Figure 5: Probability of Accounts Switching to Autopay by Month After First Late Payment Fee



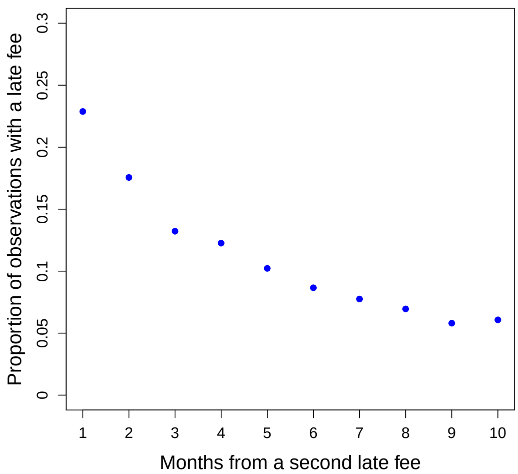
Note: Figure plots the probability of accounts switching to autopay by months from the first late payment fee (month zero). Sample is all accounts with at least one late payment fee. The corresponding scatter plot of proportion of accounts switching by month after late payment fee shown in Figure A7. Table A9 reports the model estimates.

Figure 6: Late Payment Fees in Months Following a Second Fee, by Autopay Status

(A) Always non-autopay

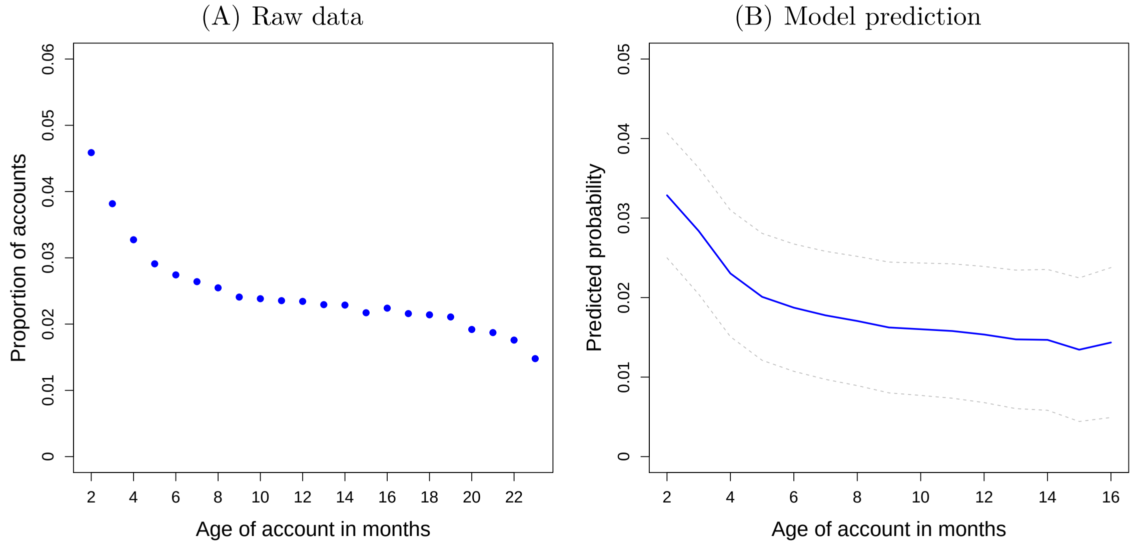


(B) Switch to autopay



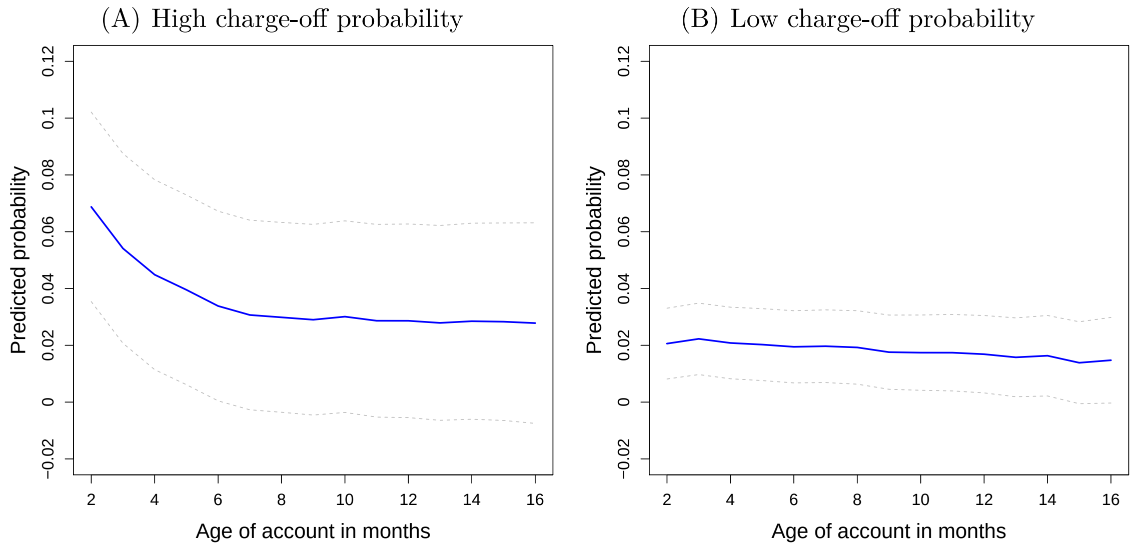
Note: Figures plot the proportion of accounts incurring a late payment fee in months after the second late payment fee incurred (month zero). Sample comprises accounts that incurred a first late payment fee and did not switch to autopay before incurring a second late payment fee (at least one month after the first fee). The panels show two mutually exclusive groups: accounts which were never subject to an autopay instruction throughout the sample period; and accounts which switched from manual repayment to autopay within the sample period.

Figure 7: Cash Advance Fees and Account Tenure



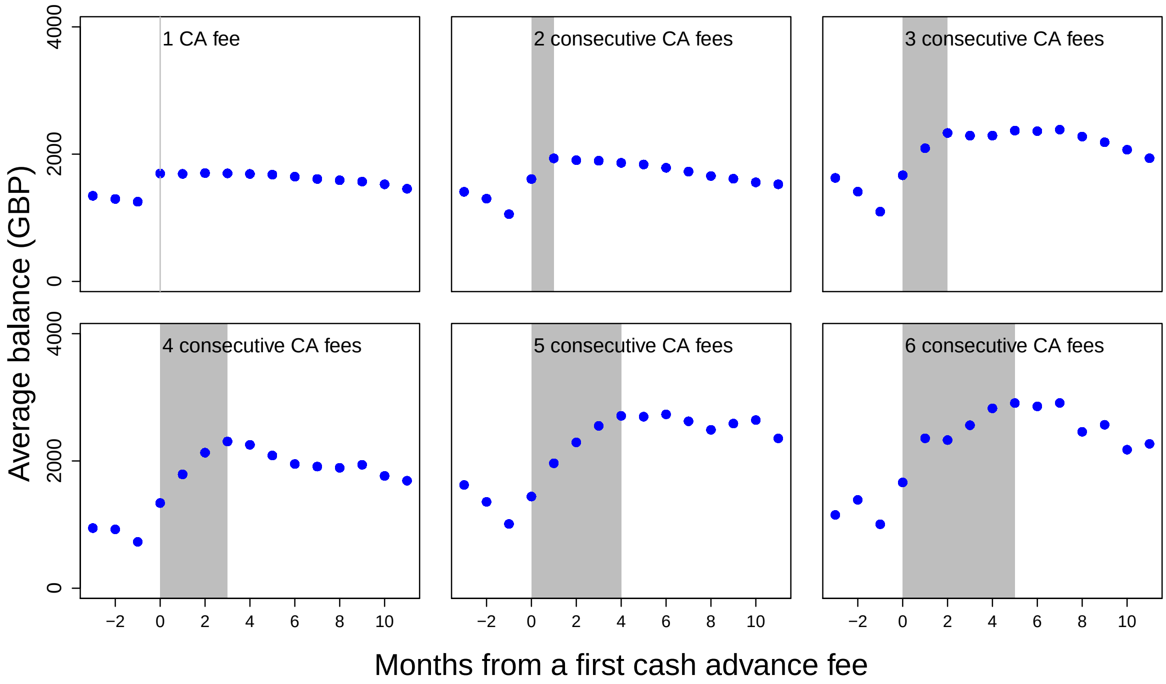
Note: Panel A plots the mean of the y-axis variable (dummy variable indicating whether the account incurred a cash advance fee) by units of the x-axis variable (age of the account in months). The sample comprises all accounts in the sample opened at or after January 2013. Panel B plots the predicted probability of an account incurring a cash advance fee within the month based on estimates of (Equation 1). Predictions are from a linear probability model at covariate medians with clustered standard errors at account level. Full model estimates are reported in Table A11. 95% confidence intervals are illustrated by dashed lines.

Figure 8: Probability of Cash Advance Fees for High / Low Risk Accounts



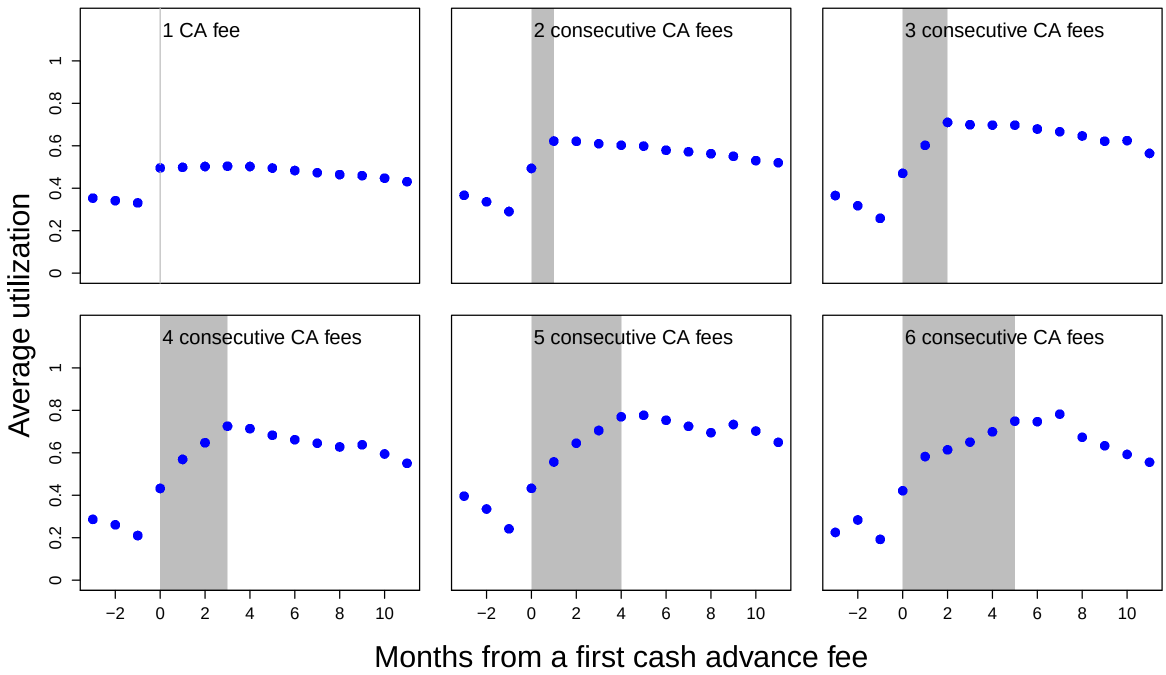
Note: Figure plots the predicted probability of accounts incurring a cash advance fee by age of account. Predictions are from a linear probability model at covariate medians (Equation 1). The panels show plots from models estimated separately for accounts with high (Panel A) and low (Panel B) probability of charge-off at account opening (median split). 95% confidence intervals are illustrated by the dashed lines. The corresponding scatter plots of fees over tenure for each group are shown in Figure A10. Tables A12 to A13 report the model estimates.

Figure 9: Credit Card Balances Through Spells of Cash Advance Fees



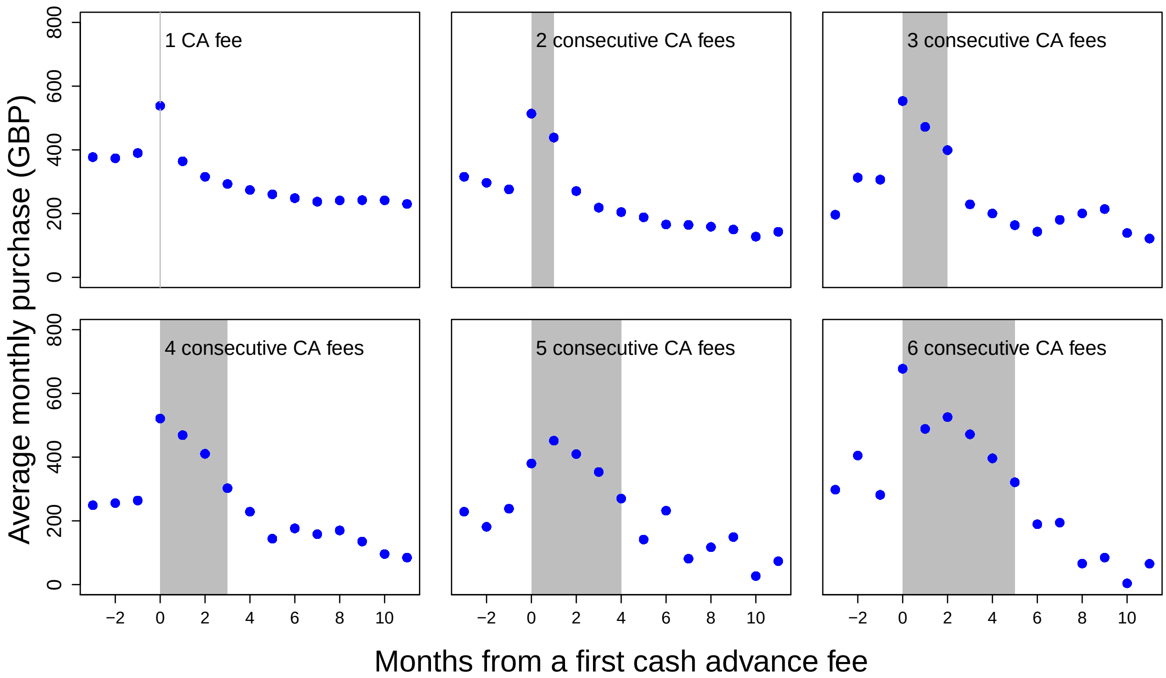
Note: Figure plots average credit card balances in each month by length of spell of consecutive months with at least one cash advance recorded on the account in each month. The x–axis ranges from three months before the first cash advance on the account through 11 months after.

Figure 10: Credit Card Utilization Through Spells of Cash Advance Fees



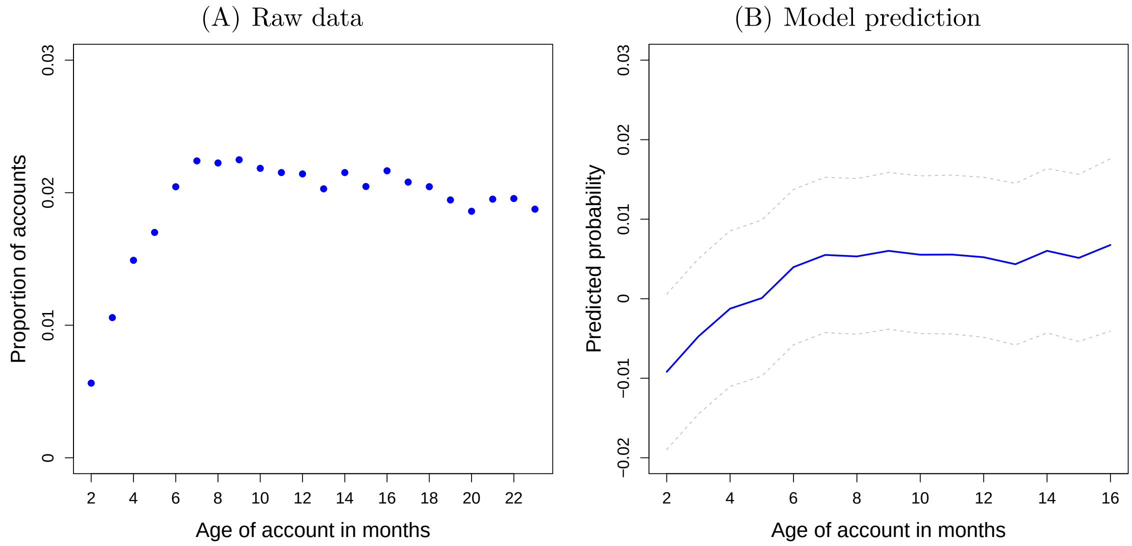
Note: Figure plots average utilization among accounts by length of spell of consecutive months with at least one cash advance recorded on the account in each month. The x–axis ranges from three months before the first cash advance on the account through 11 months after.

Figure 11: Credit Card Purchases Through Spells of Cash Advance Fees



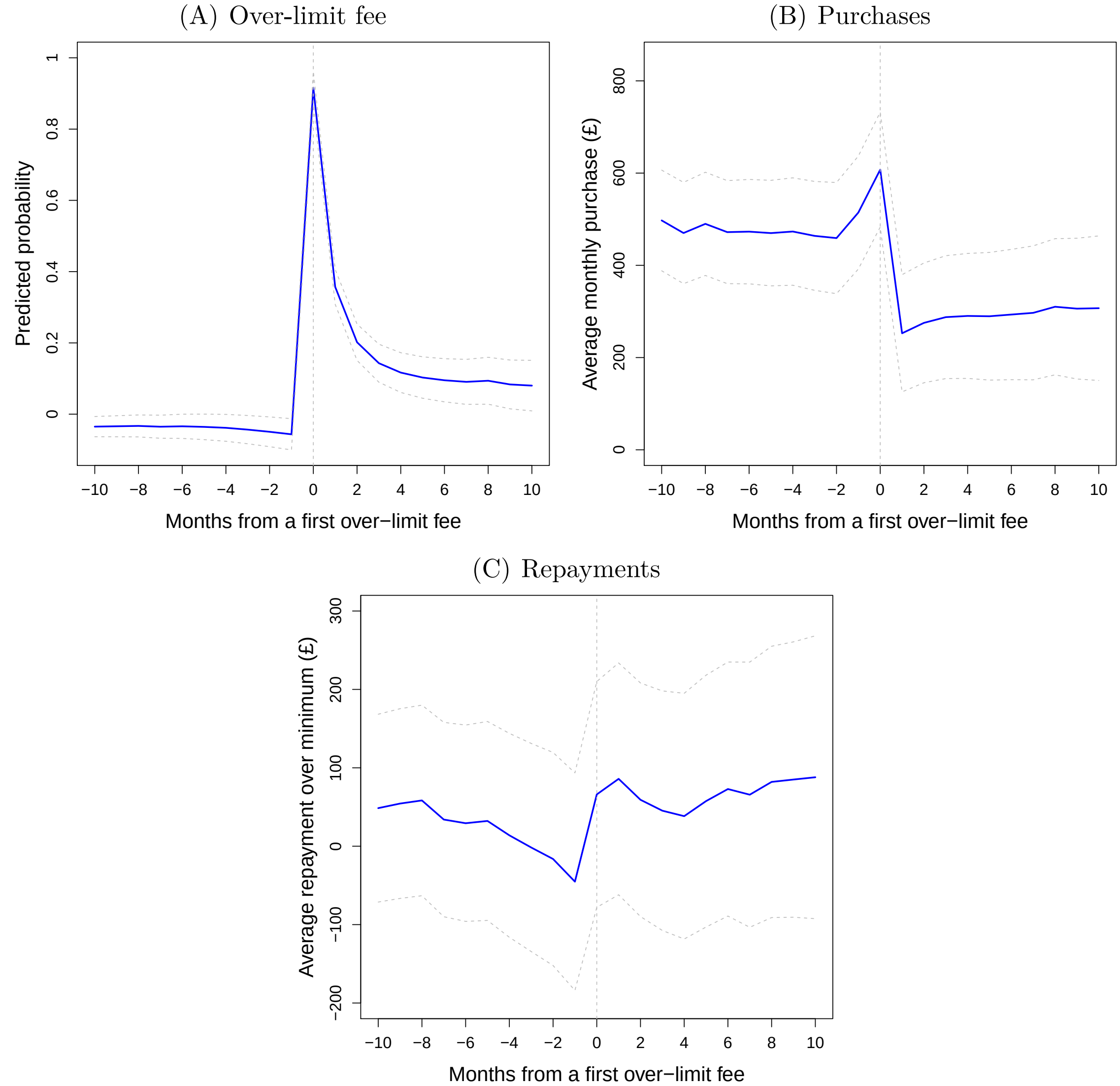
Note: Figure plots value of all credit card purchases within the month by length of spell of consecutive months with at least one cash advance recorded on the account in each month. The x–axis ranges from three months before the first cash advance on the account through 11 months after.

Figure 12: Over-Limit Fees and Account Tenure



Note: Panel A plots the mean of the y-axis variable (dummy variable indicating whether the account incurred an over-limit fee) by units of the x-axis variable (age of the account in months). The sample comprises all accounts in the sample opened at or after January 2013. Panel B plots the predicted probability of an account incurring an over-limit fee within the month based on estimates of (Equation 1). Predictions are from a linear probability model at covariate medians with clustered standard errors at account level. Full model estimates are reported in Table A14. 95% confidence intervals are illustrated by dashed lines.

Figure 13: Predicted Fees, Purchases and Repayments Around First Over-Limit Fee



Note: Figure plots the predicted probability of accounts incurring an over-limit fee in months before and after the over-limit fee is incurred (Panel A) and predicted average values of purchases and repayments (Panels B and C). Predictions are from a linear probability model at covariate medians (Equation 2). 95% confidence intervals illustrated by dashed lines. The corresponding scatter plots are shown in Figure A12. Tables A15 to A17 report the model estimates.

Table 1: Summary Statistics

	Mean	SD	10th%tile	25th%tile	Median	75th%tile	90th%tile
Merchant APR (%)	9.28	0.09	0	0	6.89	17.95	19.94
Merchant APR|given %>0	18.25	0.03	15.75	16.94	17.95	18.94	21.94
Cash APR (%)	24.79	0.04	17.95	24.89	24.93	27.95	27.95
Credit Limit (£)	4,645.32	3,126.98	1,250.00	2,250.00	4,050.00	6,300.00	8,900.00
Monthly Purchase (£)	226.41	605.37	0.00	0.00	0.00	194.57	688.97
Monthly Purchase|given £>0	542.56	837.13	34.49	97.57	278.98	660.66	1,302.62
Monthly Cash Advance (£)	7.74	117.18	0.00	0.00	0.00	0.00	0.00
Monthly Cash Advance|given £>0	240.68	608.87	20.00	49.05	100.00	260.00	510.00
Repayment (£)	236.92	648.97	0.00	19.50	50.00	170.00	564.41
Repayment|given balance>0 (£)	286.51	703.12	20.00	33.91	80.00	210.29	700.00
Balance (£)	1,692.55	2,033.93	0.00	120.51	1,005.06	2,529.46	4,413.41
Utilization (%)	39.830	36.123	0.000	3.477	31.739	75.048	93.392
Charge-off Rate (%)	1.246	3.331	0.140	0.210	0.400	1.200	2.920
Number of accounts	242,899						
Number of account-months	2,669,259						

Note: Table shows summary data for sample of new card openings. Unit of data is an account-month. Charge-off Rate is the predicted probability of charge-off within the next sixth months

Table 2: Fee Summary Statistics

	Share of accounts incurring fee (%)
Any fee	33.63
Late payment fee	24.17
Cash advance fee	13.05
Over-limit fee	7.26

Note: Table shows card-level summary data for fees incurred by fee type.

Table 3: Matched Card and Census Characteristics: Autopay Switchers and Non-Switchers

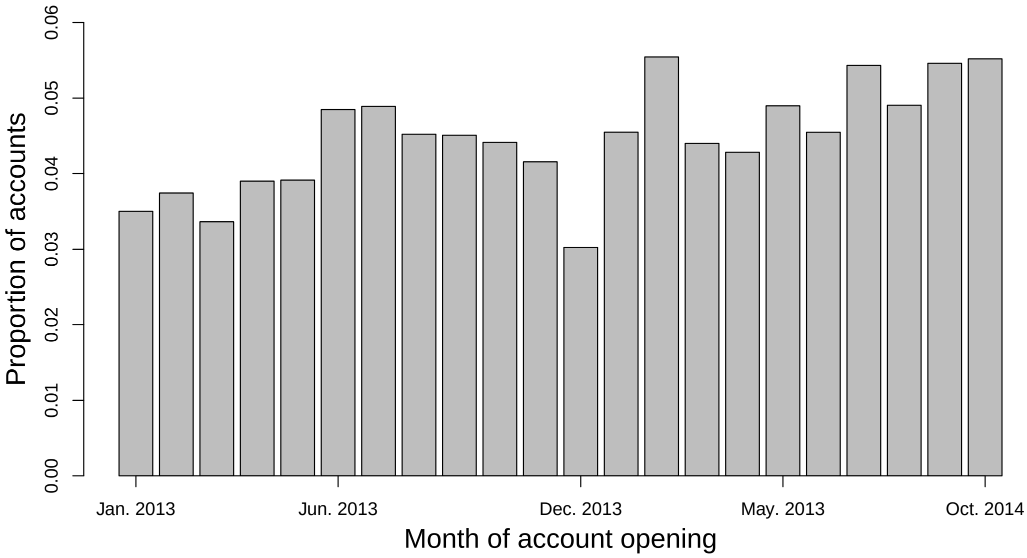
Variable name	All Mean	All S.D.	Non-Autopay Mean	Switch Mean	t score	p value
Panel A						
Card Usage						
Mean balance (£)	1,842.59	1,920.89	1,553.33	2,406.46	-134.03	0.0000
Mean utilization (%)	51.32	37.26	47.61	58.57	-96.32	0.0000
Mean monthly purchase (£)	162.20	451.52	170.38	146.27	16.58	0.0000
Mean repayment|given balance>0 (£)	234.43	620.42	261.87	185.97	38.27	0.0000
Panel B						
Card Characteristics						
Has 0% intro APR (0/1)	0.79	0.40	0.76	0.88	-36.60	0.0000
Mean Merchant APR (%)	7.85	9.62	9.08	4.85	48.28	0.0000
Mean Cash APR (%)	25.11	3.12	25.05	25.27	-7.70	0.0000
Has Balance Transfer (0/1)	0.60	0.49	0.57	0.67	-21.19	0.0000
Panel C						
Socio-Economic Characteristics (Postcode)						
Mean house price (£)	206,490	112,899	204,718	211,194	-4.69	0.0000
Jobless claimants (%)	2.626	1.445	2.664	2.528	6.36	0.0000
Mean weekly income (£)	744.69	160.61	740.63	755.46	-7.53	0.0000
Educational level 4+ (%)	28.294	8.756	28.110	28.782	-6.31	0.0000
Mean Acorn category	3.246	0.681	3.264	3.197	8.43	0.0000
Free-school meal (%)	13.036	7.150	13.225	12.535	7.84	0.0000

Note: Sample sizes are as follows. Card usage (Panel A) and characteristics (Panel B) are measured at the month level. Sample size for card characteristics: Non-Autopay 288,977; Switch 148,237. Socio-economic characteristics are measured at the card holder level. The match rate of socio-economic data to card holder identifiers differs by variable. For house price, weekly income and educational level: Non-Autopay 24,677; Switch 9,299. For jobless claimants: Non-Autopay 15,846; Switch 6,054. For Acorn category: Non-Autopay 26,400; Switch 9,921; For free school meals: Non-Autopay 23,338; Switch 8,818.

Appendix

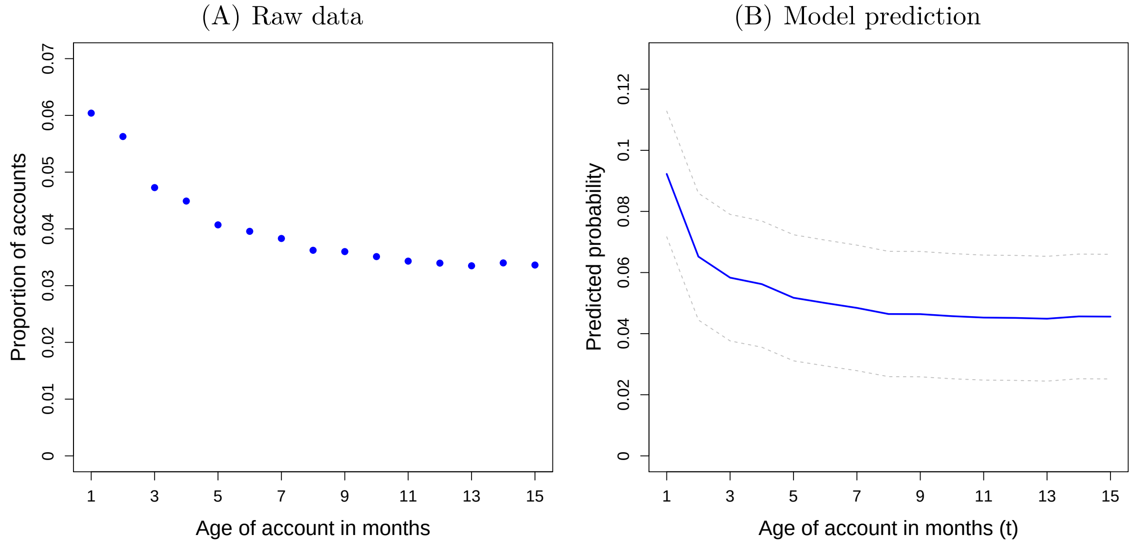
WEB APPENDIX – FOR ONLINE PUBLICATION ONLY

Figure A1: Account Openings by Calendar Month



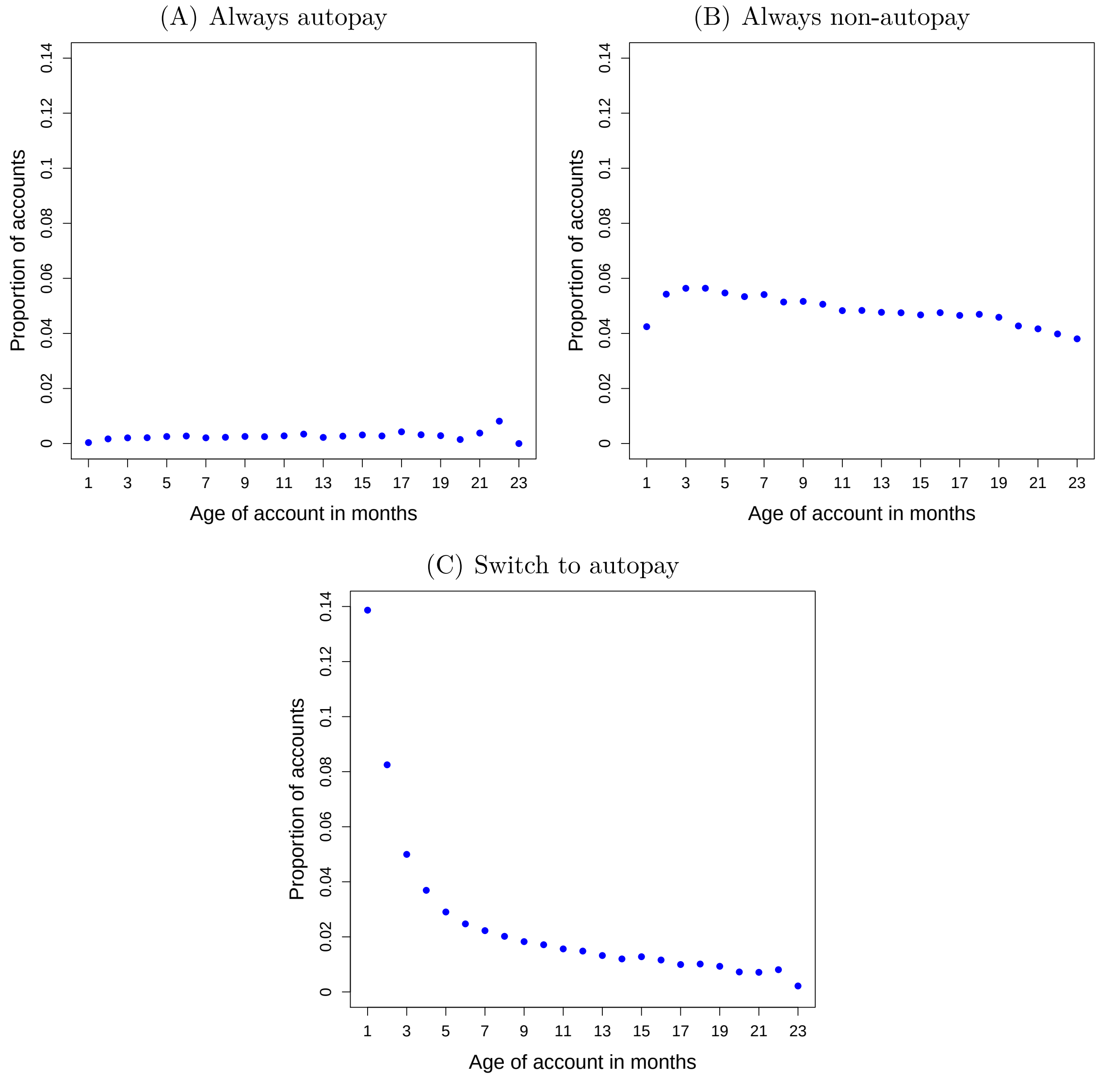
Note: Figure illustrates bar plot of proportion of total sample of new account openings that open in each calendar month.

Figure A2: Late Payment Fees and Account Tenure, Balanced Panel



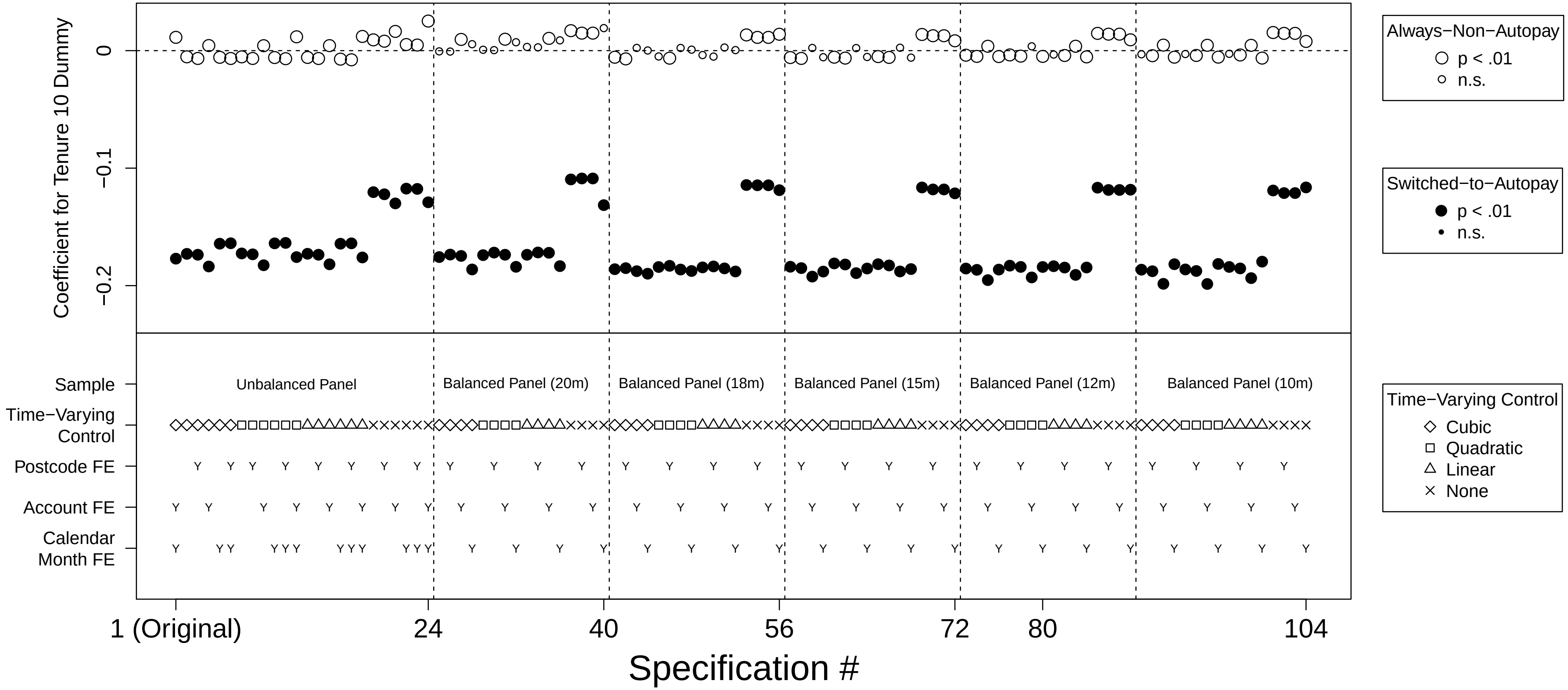
Note: Figure reproduces the plots in Figure 1 when the data is restricted to a balanced panel of accounts which open within the sample period and remain open for at least the following 15 months.

Figure A3: Late Payment Fees and Account Tenure by Autopay Status



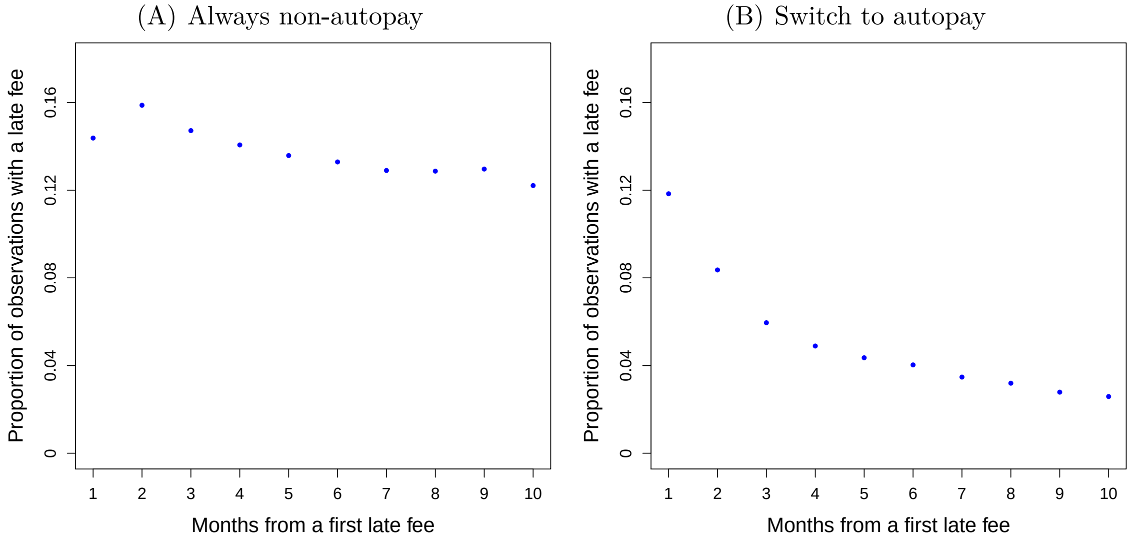
Note: Figure plots the proportion of accounts incurring a late payment fee in the next period by age of account in months. The panels show three mutually exclusive groups: accounts which were always subject to an autopay instruction from account opening onwards; accounts which were never subject to an autopay instruction; and accounts which switched from manual to autopay within the sample period.

Figure A4: Specification Curve Illustrating Estimates from Equation 1 (Fee Decline With Tenure)



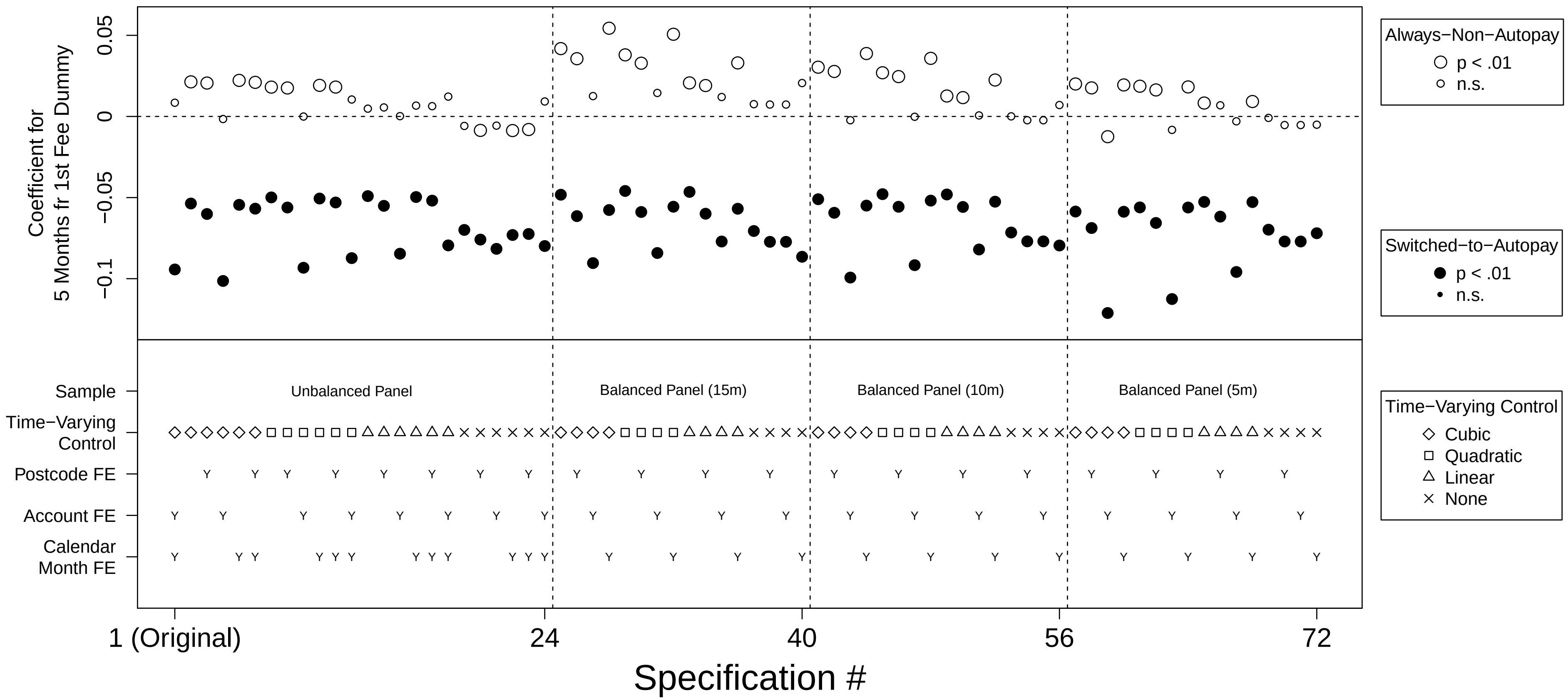
Note: Figure shows coefficient estimates (dots) and p-values (dot sizes) of the account tenure = 10 months dummy from estimates of Equation 1 for accounts that were always subject to an autopay instruction from account opening onwards and accounts which switched from manual repayments to autopay within the sample. Each column shows estimates from a separate regression, with the combination of control variables and fixed effects indicated in the bottom rows and panel sample length indicated on the x-axis. See Simonsohn et al. (2015) for an explanation of the specification curve methodology.

Figure A5: Late Payment Fees in Months Following a First Fee, by Autopay Status



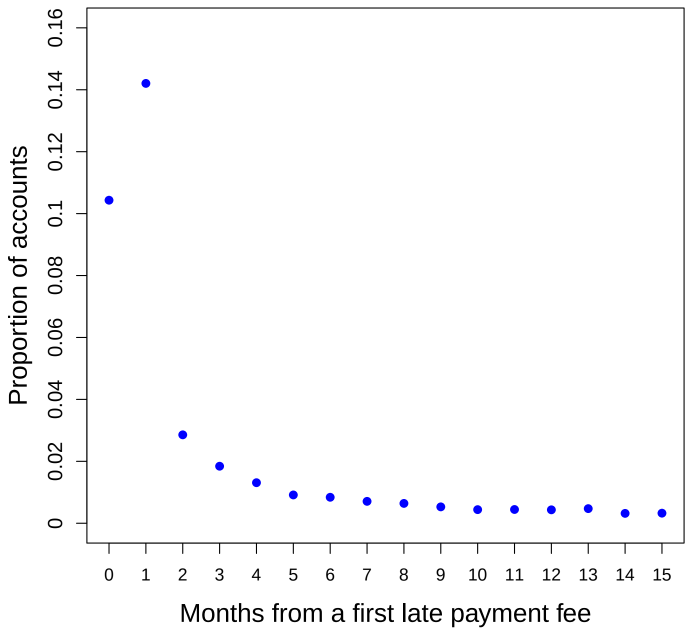
Note: Figures plot the proportion of accounts incurring a late payment fee in months after the first late payment fee incurred (month zero). The panels show two mutually exclusive groups: accounts which were never subject to an autopay instruction throughout the sample period; and accounts which switched from manual repayment to autopay within the sample period.

Figure A6: Specification Curve Illustrating Estimates from Equation 2 (Fees After First Late Fee)



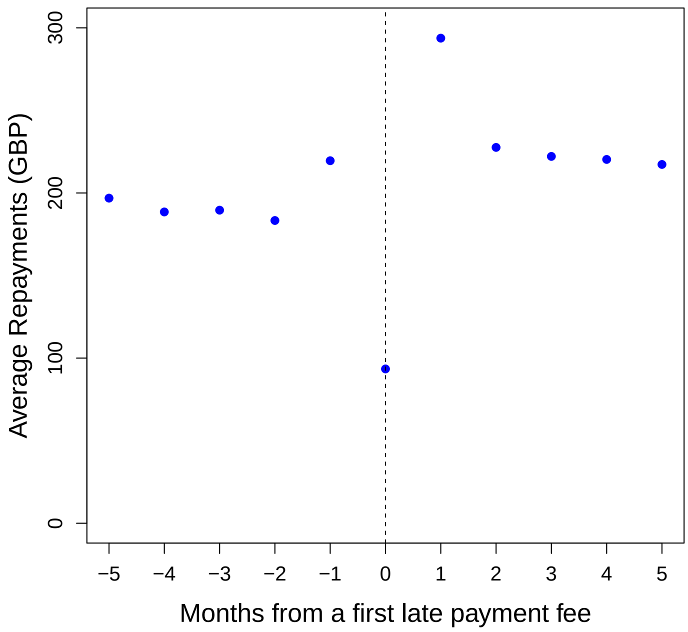
Note: Figure shows coefficient estimates (dots) and p-values (dot sizes) of the time dummy for month = 5 months after 1st late fee from estimates of Equation 2 for accounts that were always subject to an autopay instruction from account opening onwards and accounts which switched from manual repayments to autopay within the sample. Each column shows estimates from a separate regression, with the combination of control variables and fixed effects indicated in the bottom rows and panel sample length indicated on the x-axis. See Simonsohn et al. (2015) for an explanation of the specification curve methodology.

Figure A7: Proportion of Accounts Switching to Autopay by Month After First Late Payment Fee



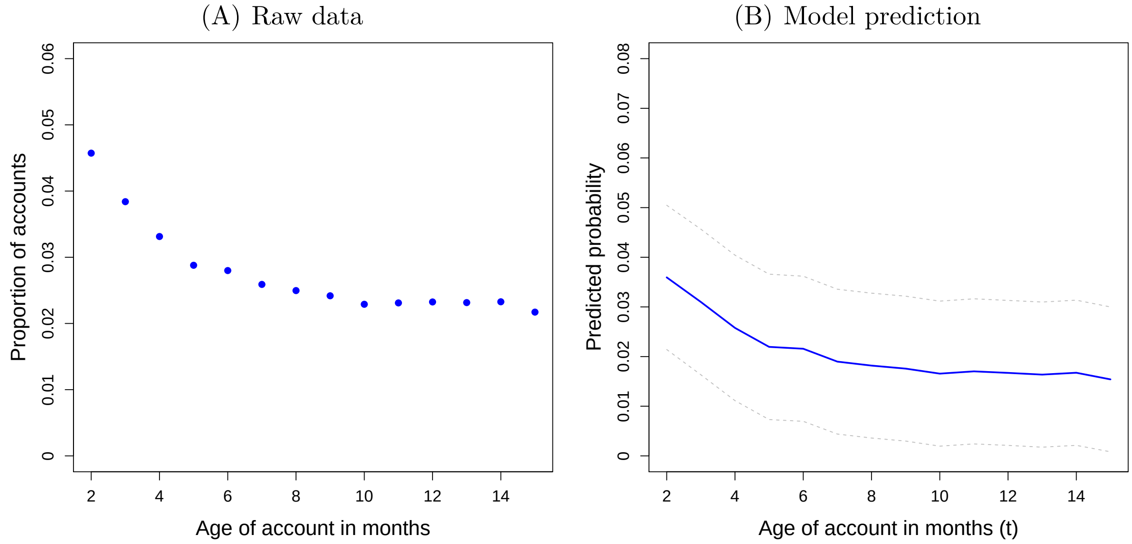
Note: Figure plots the proportion of accounts incurring a late payment fee in months before and after the accounts switch from manual repayment to automatic repayment.

Figure A8: Repayments by Non-Autopay Accounts in Months Before and After First Late Payment Fee



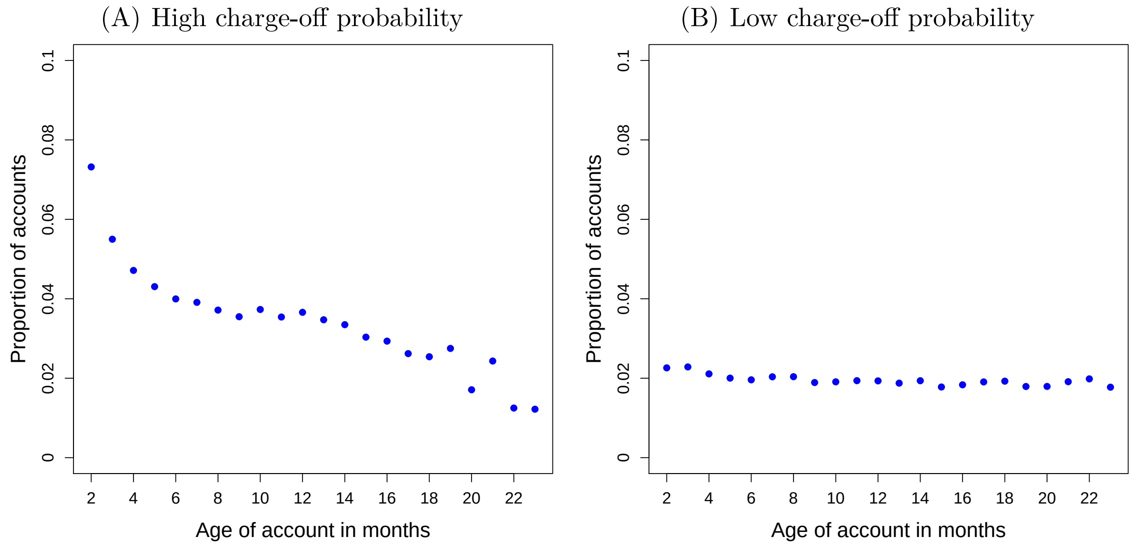
Note: Figure plots the mean monthly repayment among accounts that do not switch to autopay in the months before and after the account incurs a first late payment fee.

Figure A9: Cash Advance Fees and Account Tenure, Balanced Panel



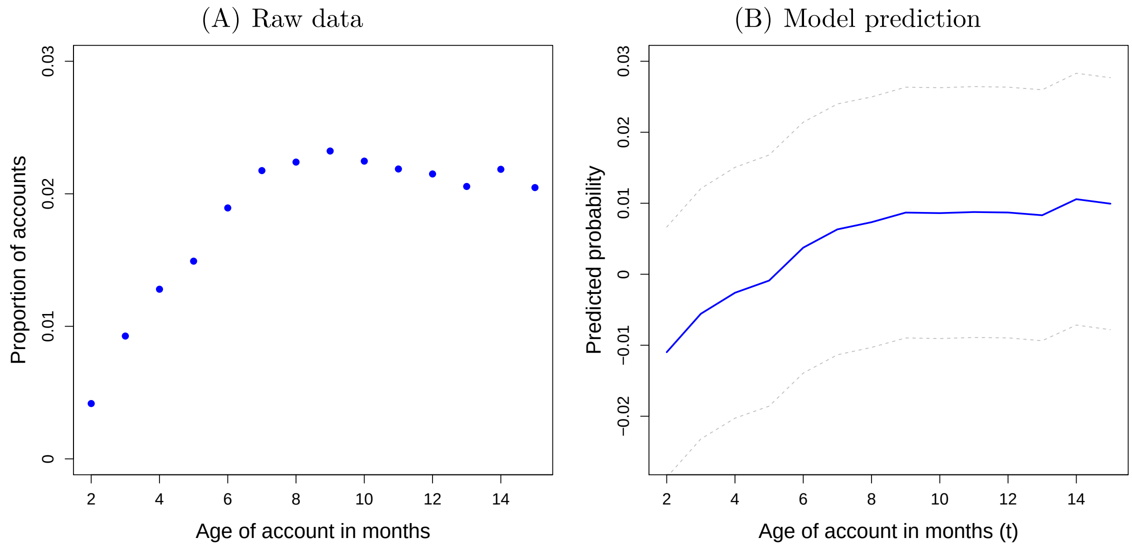
Note: Figure reproduces the plots in Figure 7 when the data is restricted to a balanced panel of accounts which open within the sample period and remain open for at least the following 15 months.

Figure A10: Cash Advance Fees by Tenure, High/Low Charge-Off Probability Accounts



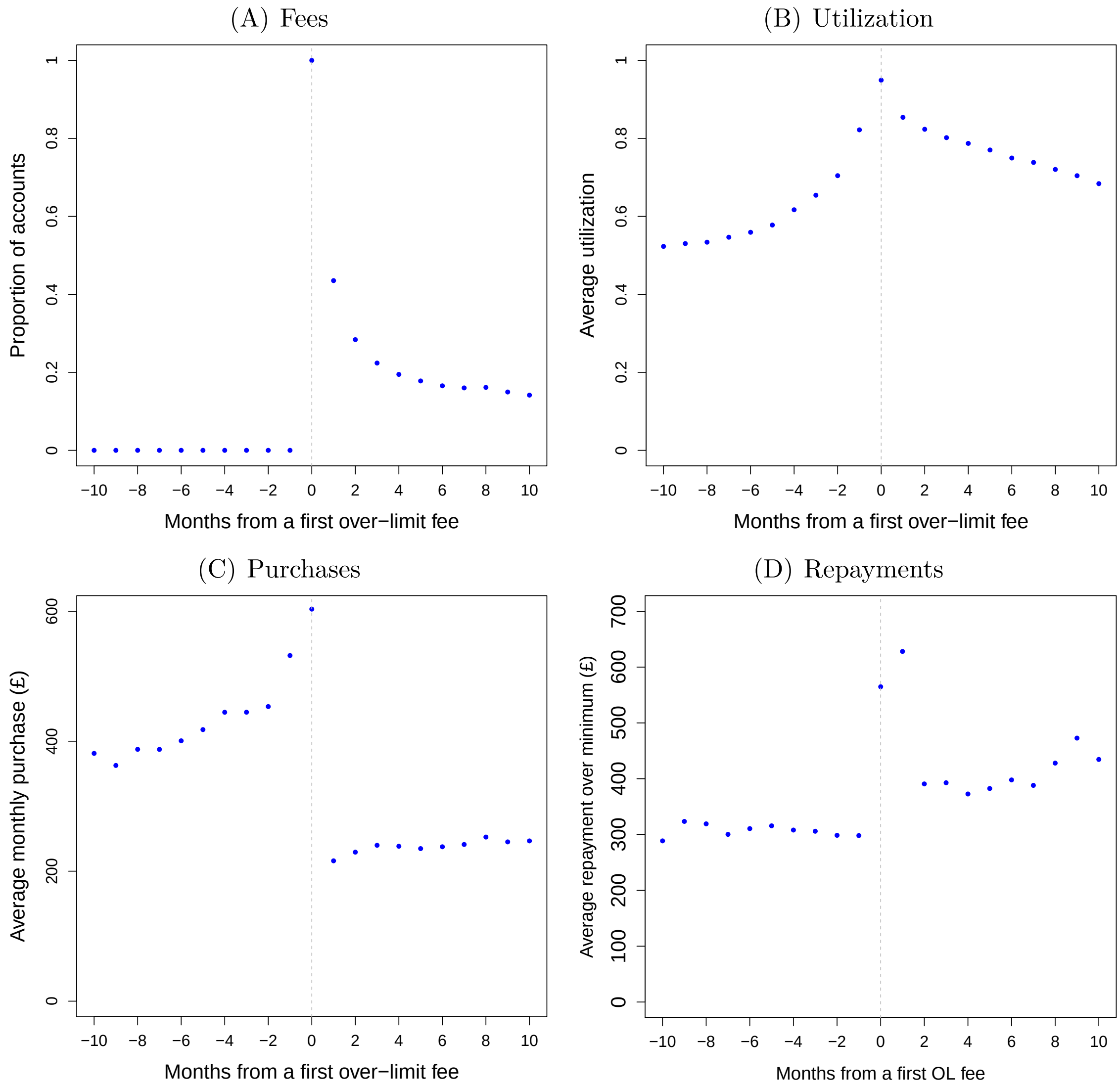
Note: Figure plots the proportion of accounts incurring a cash advance fee by age of account. The panels show plots from models estimated separately for accounts with high (Panel A) and low (Panel B) probability of charge-off at account opening (median split).

Figure A11: Over-Limit Fees and Account Tenure, Balanced Panel



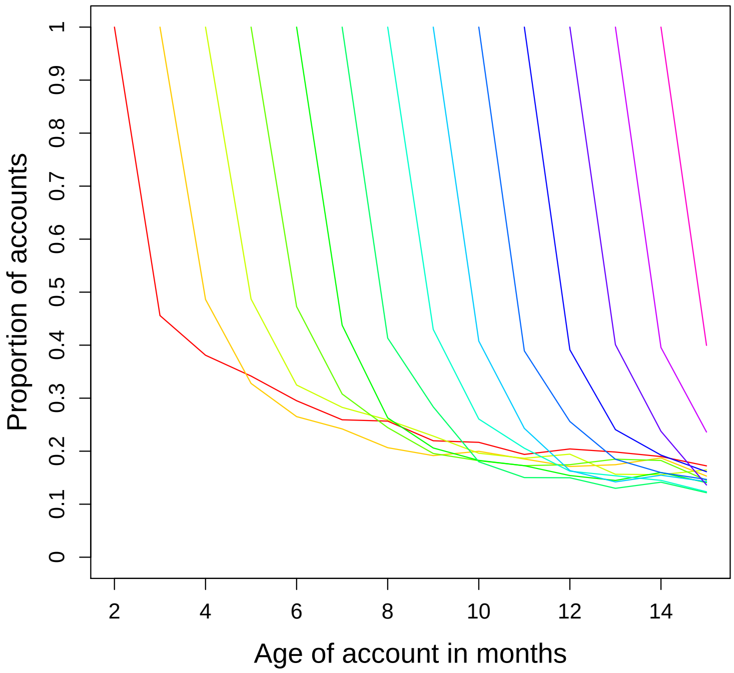
Note: Figure reproduces the plots in Figure 12 when the data is restricted to a balanced panel of accounts which open within the sample period and remain open for at least the following 15 months. 95% confidence intervals are illustrated by the dashed lines.

Figure A12: Purchases, Repayments and Utilization in Months Following First Over-Limit Fee



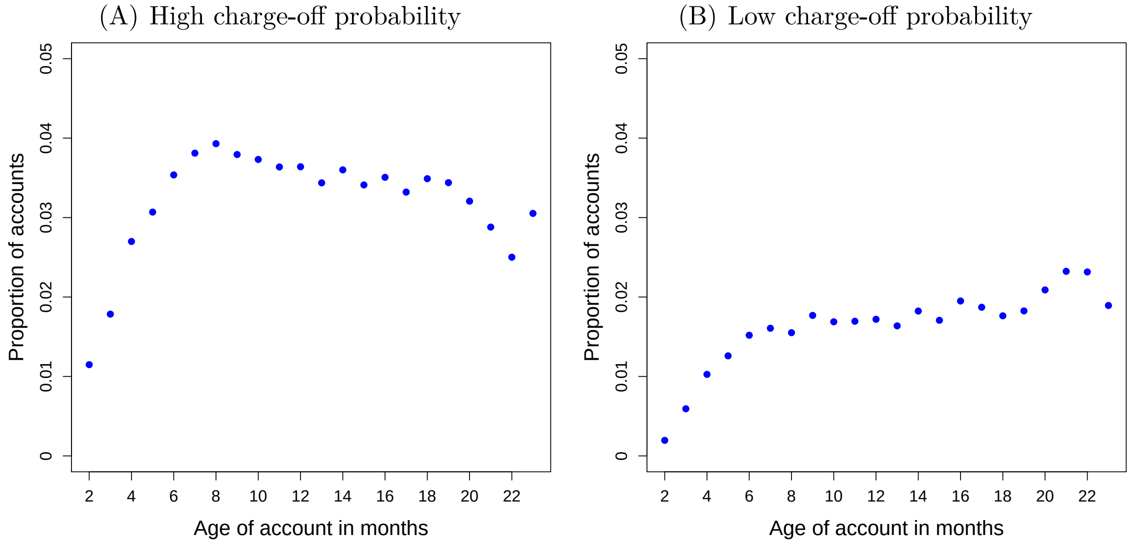
Note: Figures plot in Panel A average purchases (in £), in Panel B average repayment (in £) and in Panel C average utilization (balance expressed as a fraction of the credit limit) by number of months since the account first incurred an over-limit fee.

Figure A13: Over-Limit Fees and Tenure, by Tenure of First Over-Limit Fee



Note: Figure plots the proportion of accounts incurring an over-limit fee by age of account in months. Each line represents a set of accounts by month in which they incurred a first over-limit fee.

Figure A14: Over-Limit Fees and Tenure for High and Low Charge-Off Probability Accounts



Note: Figures plots the proportion of accounts incurring over-limit fees by tenure for high and low charge-off probability accounts (median split)

Table A1: Summary Statistics – Balanced Panel

	Mean	SD	10th%tile	25th%tile	Median	75th%tile	90th%tile
Merchant APR (%)	8.5	0.09	0	0	0	17.95	18.94
Merchant APR|given %>0	18.51	0.03	15.9	16.94	17.95	18.94	21.94
Cash APR (%)	25.41	0.03	21.94	24.93	24.93	27.95	27.95
Credit Limit (£)	4,683.1	3,108.2	1,250.0	2,300.0	4,100.0	6,300.0	8,700.0
Monthly Purchase (£)	225.39	591.65	0.00	0.00	0.00	193.94	691.88
Monthly Purchase|given £>0	540.21	814.39	34.35	97.40	279.00	663.59	1,300.59
Monthly Cash Advance (£)	6.93	118.45	0.00	0.00	0.00	0.00	0.00
Monthly Cash Advance|given £>0	231.62	645.82	20.00	40.00	100.00	250.00	500.00
Repayment (£)	246.60	663.35	0.00	22.65	50.00	182.41	600.00
Repayment|given balance>0 (£)	295.16	713.36	23.11	35.00	80.00	223.00	725.00
Balance (£)	1,749.15	2,030.11	0.00	169.66	1,090.96	2,635.00	4,474.16
Utilization (%)	40.816	35.971	0.000	4.702	33.785	76.001	93.277
Charge-off Rate (%)	1.194	3.071	0.130	0.190	0.360	1.200	2.920
Number of accounts	82,661						
Number of account-months	1,239,915						

Note: Table shows summary data for sample of new card openings. Unit of data is an account-month. Charge-off Rate is the predicted probability of charge-off within the next sixth months.

Table A2: Fee Summary Statistics – Balanced Panel

	Share of accounts incurring fee (%)
Any fee	41.76
Late payment fee	30.65
Cash advance fee	15.73
Over-limit fee	10.01

Note: Table shows card-level summary data for fees incurred by fee type.

Table A3: Fixed Effects OLS Estimates of Equation 1, Late Payment Fees

	β	S.E.	t-value	p-value
Tenure 2	-0.015	0.001	-15.234	0.000
Tenure 3	-0.019	0.001	-18.409	0.000
Tenure 4	-0.021	0.001	-18.661	0.000
Tenure 5	-0.023	0.001	-18.475	0.000
Tenure 6	-0.025	0.001	-17.796	0.000
Tenure 7	-0.024	0.002	-15.461	0.000
Tenure 8	-0.026	0.002	-14.707	0.000
Tenure 9	-0.025	0.002	-12.920	0.000
Tenure 10	-0.025	0.002	-11.685	0.000
Tenure 11	-0.026	0.002	-11.188	0.000
Tenure 12	-0.025	0.002	-10.037	0.000
Tenure 13	-0.025	0.003	-9.198	0.000
Tenure 14	-0.024	0.003	-8.379	0.000
Tenure 15	-0.024	0.003	-7.602	0.000
Tenure 16+	-0.022	0.004	-6.187	0.000
Balance^3	0.000	0.000	-0.549	0.583
Balance^2	0.000	0.000	1.061	0.289
Balance	0.000	0.000	-7.609	0.000
Credit Limit^3	0.000	0.000	7.868	0.000
Credit Limit^2	0.000	0.000	-12.744	0.000
Credit Limit	0.000	0.000	20.139	0.000
Utilization^3	0.000	0.000	-5.616	0.000
Utilization^2	-0.007	0.002	-4.350	0.000
Utilization	0.047	0.003	15.739	0.000
Charge-off Rate^3	-1.304	0.200	-6.524	0.000
Charge-off Rate^2	1.202	0.174	6.888	0.000
Charge-off Rate	-0.119	0.037	-3.203	0.001
Monthly Purchase^3	0.000	0.000	-1.455	0.146
Monthly Purchase^2	0.000	0.000	1.293	0.196
Monthly Purchase	0.000	0.000	-1.630	0.103
R^2	0.254			
Number of observations	2,392,275			
Number of accounts	230,531			

Note: OLS regression estimates of Equation 1 in which late payment fee dummy is dependent variable. Standard errors are clustered by account. The baseline for the tenure dummies is Tenure 1. Prediction plot from the model is illustrated in Figure 1, Panel B.

Table A4: Fixed Effects OLS Estimates Late Payment Fees and Tenure, Always-Autopay Accounts

	β	S.E.	t-value	p-value
Tenure 2	0.000	0.000	0.797	0.425
Tenure 3	0.001	0.001	1.486	0.137
Tenure 4	0.001	0.001	1.046	0.296
Tenure 5	0.002	0.001	1.325	0.185
Tenure 6	0.002	0.002	1.308	0.191
Tenure 7	0.002	0.002	0.843	0.399
Tenure 8	0.002	0.002	0.873	0.382
Tenure 9	0.002	0.002	1.018	0.309
Tenure 10	0.003	0.003	0.955	0.339
Tenure 11	0.003	0.003	1.054	0.292
Tenure 12	0.004	0.003	1.071	0.284
Tenure 13	0.002	0.004	0.611	0.541
Tenure 14	0.003	0.004	0.789	0.430
Tenure 15	0.004	0.004	0.851	0.395
Tenure 16+	0.004	0.005	0.813	0.416
Balance^3	0.000	0.000	-0.411	0.681
Balance^2	0.000	0.000	0.440	0.660
Balance	0.000	0.000	-0.838	0.402
Credit Limit^3	0.000	0.000	1.328	0.184
Credit Limit^2	0.000	0.000	-1.436	0.151
Credit Limit	0.000	0.000	1.720	0.085
Utilization^3	0.004	0.003	1.258	0.209
Utilization^2	0.000	0.003	-0.027	0.978
Utilization	0.003	0.005	0.609	0.543
Charge-off Rate^3	-1.432	0.643	-2.225	0.026
Charge-off Rate^2	1.259	0.550	2.290	0.022
Charge-off Rate	0.098	0.070	1.409	0.159
Monthly Purchase^3	0.000	0.000	0.473	0.636
Monthly Purchase^2	0.000	0.000	-0.607	0.544
Monthly Purchase	0.000	0.000	0.991	0.322
R^2	0.252			
Number of observations	273,532			
Number of accounts	31,735			

Note: OLS regression of Equation 1 in which late payment fee is the dependent variable, model estimates for sample of always-autopay accounts only. Standard errors are clustered by account. The baseline for the tenure dummies is Tenure 1. Prediction plot from the model is illustrated in Figure 2, Panel A

Table A5: Fixed Effects OLS Estimates Late Payment Fees and Tenure, Non-Autopay Accounts

	β	S.E.	t-value	p-value
Tenure 2	0.005	0.001	4.296	0.000
Tenure 3	0.008	0.001	5.788	0.000
Tenure 4	0.009	0.002	5.607	0.000
Tenure 5	0.008	0.002	4.493	0.000
Tenure 6	0.007	0.002	3.587	0.000
Tenure 7	0.010	0.002	4.303	0.000
Tenure 8	0.009	0.003	3.309	0.001
Tenure 9	0.011	0.003	3.710	0.000
Tenure 10	0.011	0.003	3.541	0.000
Tenure 11	0.010	0.004	2.951	0.003
Tenure 12	0.012	0.004	3.249	0.001
Tenure 13	0.014	0.004	3.278	0.001
Tenure 14	0.014	0.004	3.237	0.001
Tenure 15	0.015	0.005	3.050	0.002
Tenure 16+	0.018	0.006	3.184	0.001
Balance^3	0.000	0.000	3.757	0.000
Balance^2	0.000	0.000	-3.369	0.001
Balance	0.000	0.000	-0.506	0.613
Credit Limit^3	0.000	0.000	6.095	0.000
Credit Limit^2	0.000	0.000	-8.099	0.000
Credit Limit	0.000	0.000	13.110	0.000
Utilization^3	-0.001	0.000	-2.315	0.021
Utilization^2	-0.010	0.005	-1.883	0.060
Utilization	0.059	0.007	8.549	0.000
Charge-off Rate^3	-1.602	0.253	-6.334	0.000
Charge-off Rate^2	1.601	0.228	7.021	0.000
Charge-off Rate	-0.339	0.054	-6.328	0.000
$\text{Monthly Purchase}^3$	0.000	0.000	-3.479	0.001
$\text{Monthly Purchase}^2$	0.000	0.000	4.128	0.000
Monthly Purchase	0.000	0.000	-8.353	0.000
R^2	0.268			
Number of observations	1,338,862			
Number of accounts	131,318			

Note: OLS regression of Equation 1 in which late payment fee is the dependent variable, model estimates for sample of non-autopay accounts only. Standard errors are clustered by account. The baseline for the tenure dummies is Tenure 1. Prediction plot from the model is illustrated in Figure 2, Panel B

Table A6: Fixed Effects OLS Estimates Late Payment Fees and Tenure, Switch to Autopay Accounts

	β	S.E.	t-value	p-value
Tenure 2	-0.113	0.004	-29.447	0.000
Tenure 3	-0.143	0.004	-38.717	0.000
Tenure 4	-0.156	0.004	-41.586	0.000
Tenure 5	-0.164	0.004	-42.918	0.000
Tenure 6	-0.170	0.004	-43.332	0.000
Tenure 7	-0.172	0.004	-42.552	0.000
Tenure 8	-0.174	0.004	-41.839	0.000
Tenure 9	-0.176	0.004	-40.898	0.000
Tenure 10	-0.177	0.004	-39.758	0.000
Tenure 11	-0.179	0.005	-38.811	0.000
Tenure 12	-0.179	0.005	-37.327	0.000
Tenure 13	-0.180	0.005	-36.212	0.000
Tenure 14	-0.181	0.005	-34.932	0.000
Tenure 15	-0.180	0.005	-33.027	0.000
Tenure 16+	-0.180	0.006	-30.486	0.000
Balance^3	0.000	0.000	2.354	0.019
Balance^2	0.000	0.000	-2.570	0.010
Balance	0.000	0.000	-0.138	0.890
Credit Limit^3	0.000	0.000	8.062	0.000
Credit Limit^2	0.000	0.000	-10.377	0.000
Credit Limit	0.000	0.000	13.455	0.000
Utilization^3	-0.001	0.000	-8.122	0.000
Utilization^2	-0.006	0.001	-5.970	0.000
Utilization	0.041	0.005	8.562	0.000
Charge-off Rate^3	-3.704	0.937	-3.955	0.000
Charge-off Rate^2	3.482	0.622	5.595	0.000
Charge-off Rate	-0.520	0.089	-5.874	0.000
Monthly Purchase^3	0.000	0.000	2.169	0.030
Monthly Purchase^2	0.000	0.000	-3.128	0.002
Monthly Purchase	0.000	0.000	4.845	0.000
R^2	0.218			
Number of observations	501,489			
Number of accounts	47,188			

Note: OLS regression of Equation 1 in which late payment fee is the dependent variable, model estimates for sample of switch-to-autopay accounts only. Standard errors are clustered by account. The baseline for the tenure dummies is Tenure 1. Prediction plot from the model is illustrated in Figure 2, Panel C

Table A7: Fixed Effects OLS Estimates Late Payment Fees in Months Following a First Fee, Non-Autopay Accounts

	β	S.E.	t-value	p-value
Months fr 1st Late Fee 2	0.017	0.003	5.826	0.000
Months fr 1st Late Fee 3	0.009	0.003	2.572	0.010
Months fr 1st Late Fee 4	0.005	0.004	1.112	0.266
Months fr 1st Late Fee 5	0.008	0.005	1.644	0.100
Months fr 1st Late Fee 6	0.008	0.006	1.361	0.174
Months fr 1st Late Fee 7	0.009	0.007	1.316	0.188
Months fr 1st Late Fee 8	0.014	0.008	1.783	0.075
Months fr 1st Late Fee 9	0.018	0.009	2.011	0.044
Months fr 1st Late Fee 10	0.013	0.010	1.331	0.183
Months fr 1st Late Fee 11	0.024	0.011	2.178	0.029
Months fr 1st Late Fee 12	0.023	0.012	1.897	0.058
Months fr 1st Late Fee 13+	0.028	0.015	1.912	0.056
Balance^3	0.000	0.000	-0.411	0.681
Balance^2	0.000	0.000	0.645	0.519
Balance	0.000	0.000	-1.576	0.115
Credit Limit^3	0.000	0.000	2.307	0.021
Credit Limit^2	0.000	0.000	-3.769	0.000
Credit Limit	0.000	0.000	7.778	0.000
Utilization^3	-0.020	0.006	-3.339	0.001
Utilization^2	-0.072	0.023	-3.154	0.002
Utilization	0.171	0.034	5.046	0.000
Charge-off Rate^3	-1.509	0.280	-5.385	0.000
Charge-off Rate^2	1.673	0.280	5.974	0.000
Charge-off Rate	-0.702	0.076	-9.234	0.000
Monthly Purchase^3	0.000	0.000	-1.458	0.145
Monthly Purchase^2	0.000	0.000	2.126	0.034
Monthly Purchase	0.000	0.000	-4.871	0.000
R^2	0.326			
Number of observations	284,857			
Number of accounts	35,095			

Note: OLS Regression with clustered standard errors clustered by account. Prediction plot from the model is illustrated in Figure 3, Panel A.

Table A8: Fixed Effects OLS Estimates Late Payment Fees in Months Following a First Fee, Switch-to-Autopay Accounts

	β	S.E.	t-value	p-value
Months fr 1st Late Fee 2	-0.051	0.004	-13.776	0.000
Months fr 1st Late Fee 3	-0.076	0.004	-19.216	0.000
Months fr 1st Late Fee 4	-0.088	0.004	-20.926	0.000
Months fr 1st Late Fee 5	-0.094	0.004	-21.231	0.000
Months fr 1st Late Fee 6	-0.097	0.005	-20.852	0.000
Months fr 1st Late Fee 7	-0.103	0.005	-20.746	0.000
Months fr 1st Late Fee 8	-0.107	0.005	-19.787	0.000
Months fr 1st Late Fee 9	-0.110	0.006	-19.317	0.000
Months fr 1st Late Fee 10	-0.113	0.006	-18.448	0.000
Months fr 1st Late Fee 11	-0.112	0.007	-16.838	0.000
Months fr 1st Late Fee 12	-0.115	0.007	-16.051	0.000
Months fr 1st Late Fee 13+	-0.119	0.008	-14.687	0.000
Balance^3	0.000	0.000	-0.859	0.390
Balance^2	0.000	0.000	0.997	0.319
Balance	0.000	0.000	-1.223	0.221
Credit Limit^3	0.000	0.000	3.840	0.000
Credit Limit^2	0.000	0.000	-5.646	0.000
Credit Limit	0.000	0.000	9.126	0.000
Utilization^3	-0.004	0.002	-2.877	0.004
Utilization^2	0.035	0.016	2.178	0.029
Utilization	-0.013	0.019	-0.714	0.476
Charge-off Rate^3	-5.741	0.918	-6.255	0.000
Charge-off Rate^2	5.936	0.673	8.816	0.000
Charge-off Rate	-1.419	0.116	-12.219	0.000
$\text{Monthly Purchase}^3$	0.000	0.000	0.193	0.847
$\text{Monthly Purchase}^2$	0.000	0.000	0.145	0.885
Monthly Purchase	0.000	0.000	-0.666	0.505
R^2	0.279			
Number of observations	147,715			
Number of accounts	14,420			

Note: OLS regression with clustered standard errors clustered by account. Prediction plot from the model is illustrated in Figure 3, Panel B.

Table A9: OLS Estimates Probability of Accounts Switching to Autopay by Month After First Late Payment Fee

	β	S.E.	t-value	p-value
Tenure 2	-0.113	0.004	-29.447	0.000
Tenure 3	-0.143	0.004	-38.717	0.000
Tenure 4	-0.156	0.004	-41.586	0.000
Tenure 5	-0.164	0.004	-42.918	0.000
Tenure 6	-0.170	0.004	-43.332	0.000
Tenure 7	-0.172	0.004	-42.552	0.000
Tenure 8	-0.174	0.004	-41.839	0.000
Tenure 9	-0.176	0.004	-40.898	0.000
Tenure 10	-0.177	0.004	-39.758	0.000
Tenure 11	-0.179	0.005	-38.811	0.000
Tenure 12	-0.179	0.005	-37.327	0.000
Tenure 13	-0.180	0.005	-36.212	0.000
Tenure 14	-0.181	0.005	-34.932	0.000
Tenure 15	-0.180	0.005	-33.027	0.000
Tenure 16+	-0.180	0.006	-30.486	0.000
Balance^3	0.000	0.000	2.354	0.019
Balance^2	0.000	0.000	-2.570	0.010
Balance	0.000	0.000	-0.138	0.890
Credit Limit^3	0.000	0.000	8.062	0.000
Credit Limit^2	0.000	0.000	-10.377	0.000
Credit Limit	0.000	0.000	13.455	0.000
Utilization^3	-0.001	0.000	-8.122	0.000
Utilization^2	-0.006	0.001	-5.970	0.000
Utilization	0.041	0.005	8.562	0.000
Charge-off Rate^3	-3.704	0.937	-3.955	0.000
Charge-off Rate^2	3.482	0.622	5.595	0.000
Charge-off Rate	-0.520	0.089	-5.874	0.000
$\text{Monthly Purchase}^3$	0.000	0.000	2.169	0.030
$\text{Monthly Purchase}^2$	0.000	0.000	-3.128	0.002
Monthly Purchase	0.000	0.000	4.845	0.000
R^2	0.218			
Number of observations	501,489			
Number of accounts	47,188			

Note: OLS regression with clustered standard errors clustered by account. Prediction plot from the model is illustrated in Figure 5

Table A10: Matched Characteristics of Autopay Switchers and Non-Switchers After Second Fee

Variable name	All Mean	All S.D.	Non-Autopay Mean	Switch Mean	t score	p value
Panel A						
Card Usage						
Mean balance (£)	1,788.73	1,843.86	1,635.58	2,290.14	-50.87	0.0000
Mean utilization (%)	58.99	39.24	56.73	66.36	-39.85	0.0000
Mean monthly purchase (£)	123.92	381.69	130.14	103.55	11.40	0.0000
Mean repayment|given balance>0 (£)	204.35	576.80	221.68	151.86	20.52	0.0000
Panel B						
Card Characteristics						
Has 0% intro APR (0/1)	0.77	0.42	0.75	0.86	-15.29	0.0000
Mean Merchant APR (%)	10.54	9.83	11.09	8.19	15.77	0.0000
Mean Cash APR (%)	25.31	3.03	25.26	25.53	-5.29	0.0000
Has Balance Transfer (0/1)	0.60	0.49	0.60	0.63	-3.40	0.0007
Panel C						
Socio-Economic Characteristics (Postcode)						
Mean house price (£)	207,521	115,875	206,082	214,376	-2.78	0.0055
Jobless claimants (%)	2.635	1.451	2.662	2.506	3.76	0.0002
Mean weekly income (£)	743.06	161.52	740.48	755.38	-3.82	0.0001
Educationla level 4+ (%)	28.302	8.790	28.156	28.997	-4.01	0.0001
Mean Acorn category	3.259	0.682	3.269	3.208	3.93	0.0001
Free-school meal (%)	13.172	7.179	13.290	12.613	3.92	0.0001

Note: Table shows summary statistics for sample of accounts that incur a second fee. Non-Autopay sub-sample comprises accounts that did not switch to autopay following the second fee. Switch sample comprises accounts that switched to autopay following the second fee.

Table A11: Fixed Effects OLS Estimates of Equation 1, Cash Fees

	β	S.E.	t-value	p-value
Tenure 3	-0.004	0.001	-7.378	0.000
Tenure 4	-0.010	0.001	-14.078	0.000
Tenure 5	-0.013	0.001	-15.863	0.000
Tenure 6	-0.014	0.001	-15.210	0.000
Tenure 7	-0.015	0.001	-14.255	0.000
Tenure 8	-0.016	0.001	-13.159	0.000
Tenure 9	-0.017	0.001	-12.353	0.000
Tenure 10	-0.017	0.001	-11.248	0.000
Tenure 11	-0.017	0.002	-10.331	0.000
Tenure 12	-0.018	0.002	-9.648	0.000
Tenure 13	-0.018	0.002	-9.170	0.000
Tenure 14	-0.018	0.002	-8.487	0.000
Tenure 15	-0.019	0.002	-8.354	0.000
Tenure 16+	-0.019	0.003	-6.841	0.000
Balance^3	0.000	0.000	3.614	0.000
Balance^2	0.000	0.000	0.290	0.772
Balance	0.000	0.000	-4.595	0.000
Credit Limit^3	0.000	0.000	6.792	0.000
Credit Limit^2	0.000	0.000	-8.452	0.000
Credit Limit	0.000	0.000	13.739	0.000
Utilization^3	0.000	0.000	-2.828	0.005
Utilization^2	-0.008	0.003	-2.688	0.007
Utilization	0.017	0.004	4.427	0.000
Charge-off Rate^3	4.380	0.146	30.062	0.000
Charge-off Rate^2	-5.203	0.133	-39.193	0.000
Charge-off Rate	1.178	0.030	39.784	0.000
$\text{Monthly Purchase}^3$	0.000	0.000	4.447	0.000
$\text{Monthly Purchase}^2$	0.000	0.000	-5.176	0.000
Monthly Purchase	0.000	0.000	15.934	0.000
R^2	0.362			
Number of observations	2,273,923			
Number of accounts	222,956			

Note: OLS regression estimates of Equation 1 in which cash advance fee dummy is dependent variable. Standard errors are clustered by account. The baseline for the tenure dummies is Tenure 2. Prediction plot from the model is illustrated in Figure 7, Panel B

Table A12: Fixed Effects OLS Estimates Cash Advance Fees and Tenure, High Probability of Charge-Off Accounts

	β	S.E.	t-value	p-value
Tenure 3	-0.015	0.001	-10.460	0.000
Tenure 4	-0.024	0.002	-14.144	0.000
Tenure 5	-0.029	0.002	-14.411	0.000
Tenure 6	-0.035	0.002	-14.932	0.000
Tenure 7	-0.038	0.003	-14.175	0.000
Tenure 8	-0.039	0.003	-12.857	0.000
Tenure 9	-0.040	0.003	-11.937	0.000
Tenure 10	-0.039	0.004	-10.444	0.000
Tenure 11	-0.040	0.004	-9.807	0.000
Tenure 12	-0.040	0.004	-8.962	0.000
Tenure 13	-0.041	0.005	-8.497	0.000
Tenure 14	-0.040	0.005	-7.722	0.000
Tenure 15	-0.040	0.006	-7.221	0.000
Tenure 16+	-0.041	0.006	-6.373	0.000
Balance^3	0.000	0.000	0.618	0.537
Balance^2	0.000	0.000	0.121	0.904
Balance	0.000	0.000	-1.592	0.111
Credit Limit^3	0.000	0.000	2.408	0.016
Credit Limit^2	0.000	0.000	-3.547	0.000
Credit Limit	0.000	0.000	5.627	0.000
Utilization^3	-0.001	0.001	-1.542	0.123
Utilization^2	-0.029	0.019	-1.531	0.126
Utilization	0.035	0.024	1.488	0.137
Charge-off Rate^3	4.758	0.281	16.944	0.000
Charge-off Rate^2	-5.234	0.247	-21.204	0.000
Charge-off Rate	1.057	0.055	19.135	0.000
Monthly Purchase^3	0.000	0.000	1.995	0.046
Monthly Purchase^2	0.000	0.000	-2.363	0.018
Monthly Purchase	0.000	0.000	5.541	0.000
R^2	0.388			
Number of observations	499,526			
Number of accounts	53,534			

Note: OLS regression with standard errors clustered by account. The baseline for the tenure dummies is Tenure 2. Prediction plot from the model is illustrated in Figure 8.

Table A13: Fixed Effects OLS Estimates Cash Advance Fees and Tenure, Low Probability of Charge-Off Accounts

	β	S.E.	t-value	p-value
Tenure 3	0.002	0.001	1.925	0.054
Tenure 4	0.000	0.001	0.217	0.828
Tenure 5	0.000	0.001	-0.292	0.771
Tenure 6	-0.001	0.001	-0.787	0.431
Tenure 7	-0.001	0.002	-0.547	0.584
Tenure 8	-0.001	0.002	-0.700	0.484
Tenure 9	-0.003	0.002	-1.385	0.166
Tenure 10	-0.003	0.002	-1.301	0.193
Tenure 11	-0.003	0.003	-1.180	0.238
Tenure 12	-0.004	0.003	-1.256	0.209
Tenure 13	-0.005	0.003	-1.480	0.139
Tenure 14	-0.004	0.004	-1.199	0.230
Tenure 15	-0.007	0.004	-1.756	0.079
Tenure 16+	-0.006	0.004	-1.314	0.189
Balance^3	0.000	0.000	1.237	0.216
Balance^2	0.000	0.000	-1.308	0.191
Balance	0.000	0.000	-0.754	0.451
Credit Limit^3	0.000	0.000	2.121	0.034
Credit Limit^2	0.000	0.000	-3.704	0.000
Credit Limit	0.000	0.000	7.516	0.000
Utilization^3	0.000	0.000	-2.437	0.015
Utilization^2	-0.002	0.002	-1.487	0.137
Utilization	0.016	0.003	4.519	0.000
Charge-off Rate^3	4.433	0.276	16.037	0.000
Charge-off Rate^2	-4.906	0.258	-19.015	0.000
Charge-off Rate	1.065	0.054	19.555	0.000
$\text{Monthly Purchase}^3$	0.000	0.000	2.890	0.004
$\text{Monthly Purchase}^2$	0.000	0.000	-3.235	0.001
Monthly Purchase	0.000	0.000	10.429	0.000
R^2	0.301			
Number of observations	740,566			
Number of accounts	57,243			

Note: OLS regression with standard errors clustered by account. The baseline for the tenure dummies is Tenure 2. Prediction plot from the model is illustrated in Figure 8.

Table A14: Fixed Effects OLS Estimates of Equation 1, Over-Limit Fees

	β	S.E.	t-value	p-value
Tenure 3	0.004	0.000	12.906	0.000
Tenure 4	0.008	0.000	15.999	0.000
Tenure 5	0.009	0.001	14.308	0.000
Tenure 6	0.013	0.001	16.103	0.000
Tenure 7	0.015	0.001	14.861	0.000
Tenure 8	0.015	0.001	12.491	0.000
Tenure 9	0.015	0.001	11.399	0.000
Tenure 10	0.015	0.002	9.733	0.000
Tenure 11	0.015	0.002	8.698	0.000
Tenure 12	0.014	0.002	7.683	0.000
Tenure 13	0.014	0.002	6.579	0.000
Tenure 14	0.015	0.002	6.800	0.000
Tenure 15	0.014	0.002	5.873	0.000
Tenure 16+	0.016	0.003	5.694	0.000
Balance^3	0.000	0.000	-5.317	0.000
Balance^2	0.000	0.000	8.054	0.000
Balance	0.000	0.000	-14.146	0.000
Credit Limit^3	0.000	0.000	4.694	0.000
Credit Limit^2	0.000	0.000	-9.851	0.000
Credit Limit	0.000	0.000	17.841	0.000
Utilization^3	0.002	0.001	1.616	0.106
Utilization^2	0.048	0.025	1.910	0.056
Utilization	0.102	0.025	4.115	0.000
Charge-off Rate^3	-0.165	0.173	-0.954	0.340
Charge-off Rate^2	-0.537	0.167	-3.213	0.001
Charge-off Rate	0.917	0.045	20.386	0.000
Monthly Purchase^3	0.000	0.000	-1.236	0.217
Monthly Purchase^2	0.000	0.000	1.006	0.314
Monthly Purchase	0.000	0.000	9.097	0.000
R^2	0.367			
Number of observations	2,273,923			
Number of accounts	222,956			

Note: OLS regression estimates of Equation 1 in which over-limit fee dummy is dependent variable. Standard errors are clustered by account. The baseline for the tenure dummies is Tenure 2. Prediction plot from the model is illustrated in Figure 12, Panel A

Table A15: Fixed Effects OLS Estimates Over-Limit Fees in Months Before and After First Over-Limit Fee

	β	S.E.	t-value	p-value
Months fr 1st OL Fee -11	-0.001	0.004	-0.138	0.890
Months fr 1st OL Fee -10	-0.002	0.005	-0.323	0.747
Months fr 1st OL Fee -9	-0.001	0.007	-0.104	0.917
Months fr 1st OL Fee -8	0.000	0.008	0.035	0.972
Months fr 1st OL Fee -7	-0.002	0.009	-0.204	0.838
Months fr 1st OL Fee -6	-0.001	0.011	-0.073	0.942
Months fr 1st OL Fee -5	-0.002	0.012	-0.198	0.843
Months fr 1st OL Fee -4	-0.005	0.014	-0.369	0.712
Months fr 1st OL Fee -3	-0.010	0.015	-0.672	0.502
Months fr 1st OL Fee -2	-0.016	0.016	-0.987	0.323
Months fr 1st OL Fee -1	-0.023	0.018	-1.306	0.192
Months fr 1st OL Fee 0	0.949	0.019	49.554	0.000
Months fr 1st OL Fee 1	0.391	0.021	18.635	0.000
Months fr 1st OL Fee 2	0.235	0.022	10.589	0.000
Months fr 1st OL Fee 3	0.176	0.024	7.480	0.000
Months fr 1st OL Fee 4	0.150	0.025	6.001	0.000
Months fr 1st OL Fee 5	0.136	0.026	5.161	0.000
Months fr 1st OL Fee 6	0.128	0.028	4.621	0.000
Months fr 1st OL Fee 7	0.124	0.029	4.242	0.000
Months fr 1st OL Fee 8	0.127	0.031	4.130	0.000
Months fr 1st OL Fee 9	0.117	0.032	3.623	0.000
Months fr 1st OL Fee 10	0.113	0.034	3.373	0.001
Months fr 1st OL Fee 11	0.129	0.035	3.656	0.000
Months fr 1st OL Fee 12+	0.122	0.038	3.250	0.001
Credit Limit^3	0.000	0.000	3.231	0.001
Credit Limit^2	0.000	0.000	-3.574	0.000
Credit Limit	0.000	0.000	2.035	0.042
Charge-off Rate^3	2.846	0.288	9.872	0.000
Charge-off Rate^2	-4.288	0.269	-15.968	0.000
Charge-off Rate	2.289	0.066	34.513	0.000
Monthly Purchase^3	0.000	0.000	0.503	0.615
Monthly Purchase^2	0.000	0.000	-0.755	0.450
Monthly Purchase	0.000	0.000	9.567	0.000
R^2	0.611			
Number of observations	234,232			
Number of accounts	17,606			

Note: OLS regression with clustered standard errors by account. Prediction plot from the model is illustrated in Figure 13.

Table A16: Fixed Effects OLS Estimates Account Purchases in Months Before and After First Over-Limit Fee

	β	S.E.	t-value	p-value
Months fr 1st OL Fee -11	-15.272	13.172	-1.159	0.246
Months fr 1st OL Fee -10	-17.791	14.749	-1.206	0.228
Months fr 1st OL Fee -9	-45.072	16.375	-2.753	0.006
Months fr 1st OL Fee -8	-25.193	18.872	-1.335	0.182
Months fr 1st OL Fee -7	-43.142	19.810	-2.178	0.029
Months fr 1st OL Fee -6	-42.070	22.228	-1.893	0.058
Months fr 1st OL Fee -5	-45.233	24.198	-1.869	0.062
Months fr 1st OL Fee -4	-41.833	26.632	-1.571	0.116
Months fr 1st OL Fee -3	-51.284	28.898	-1.775	0.076
Months fr 1st OL Fee -2	-56.075	31.316	-1.791	0.073
Months fr 1st OL Fee -1	-0.589	33.704	-0.017	0.986
Months fr 1st OL Fee 0	92.407	36.627	2.523	0.012
Months fr 1st OL Fee 1	-262.439	38.497	-6.817	0.000
Months fr 1st OL Fee 2	-239.912	40.964	-5.857	0.000
Months fr 1st OL Fee 3	-227.456	43.301	-5.253	0.000
Months fr 1st OL Fee 4	-224.859	45.552	-4.936	0.000
Months fr 1st OL Fee 5	-225.571	47.930	-4.706	0.000
Months fr 1st OL Fee 6	-221.846	50.442	-4.398	0.000
Months fr 1st OL Fee 7	-218.180	52.852	-4.128	0.000
Months fr 1st OL Fee 8	-204.942	55.764	-3.675	0.000
Months fr 1st OL Fee 9	-209.027	57.935	-3.608	0.000
Months fr 1st OL Fee 10	-208.088	60.788	-3.423	0.001
Months fr 1st OL Fee 11	-186.031	63.883	-2.912	0.004
Months fr 1st OL Fee 12+	-203.980	70.378	-2.898	0.004
Balance^3	0.000	0.000	5.613	0.000
Balance^2	0.000	0.000	-8.231	0.000
Balance	0.324	0.022	14.799	0.000
Credit Limit^3	0.000	0.000	2.140	0.032
Credit Limit^2	0.000	0.000	-0.407	0.684
Credit Limit	0.024	0.027	0.918	0.358
Utilization^3	-3.450	3.993	-0.864	0.388
Utilization^2	56.488	38.725	1.459	0.145
Utilization	-247.259	48.487	-5.099	0.000
Charge-off Rate^3	-8,881.306	422.107	-21.040	0.000
Charge-off Rate^2	11,430.993	411.814	27.758	0.000
Charge-off Rate	-3,909.626	111.212	-35.155	0.000
R^2	0.547			
Number of observations	234,232			
Number of accounts	17,606			

Note: OLS regression with clustered standard errors by account. Prediction plot from the model is illustrated in Figure 13.

Table A17: Fixed Effects OLS Estimates Account Repayments in Months Before and After First Over-Limit Fee

	β	S.E.	t-value	p-value
Months fr 1st OL Fee -11	-9.552	13.096	-0.729	0.466
Months fr 1st OL Fee -10	-3.713	16.199	-0.229	0.819
Months fr 1st OL Fee -9	0.276	18.927	0.015	0.988
Months fr 1st OL Fee -8	-24.107	20.554	-1.173	0.241
Months fr 1st OL Fee -7	-28.799	22.725	-1.267	0.205
Months fr 1st OL Fee -6	-25.901	25.525	-1.015	0.310
Months fr 1st OL Fee -5	-44.229	28.431	-1.556	0.120
Months fr 1st OL Fee -4	-59.750	31.023	-1.926	0.054
Months fr 1st OL Fee -3	-74.421	34.220	-2.175	0.030
Months fr 1st OL Fee -2	-103.317	37.500	-2.755	0.006
Months fr 1st OL Fee -1	7.923	41.043	0.193	0.847
Months fr 1st OL Fee 0	27.801	44.025	0.631	0.528
Months fr 1st OL Fee 1	1.111	46.502	0.024	0.981
Months fr 1st OL Fee 2	-12.807	49.207	-0.260	0.795
Months fr 1st OL Fee 3	-19.782	52.091	-0.380	0.704
Months fr 1st OL Fee 4	-0.584	55.251	-0.011	0.992
Months fr 1st OL Fee 5	14.811	57.545	0.257	0.797
Months fr 1st OL Fee 6	7.599	61.035	0.125	0.901
Months fr 1st OL Fee 7	23.915	64.303	0.372	0.710
Months fr 1st OL Fee 8	26.927	66.943	0.402	0.688
Months fr 1st OL Fee 9	29.846	70.004	0.426	0.670
Months fr 1st OL Fee 10	50.832	73.545	0.691	0.489
Months fr 1st OL Fee 11	44.161	77.397	0.571	0.568
Months fr 1st OL Fee 12+	29.420	83.981	0.350	0.726
Balance^3	0.000	0.000	1.596	0.110
Balance^2	0.000	0.000	-1.516	0.129
Balance	0.224	0.031	7.159	0.000
Credit Limit^3	0.000	0.000	0.647	0.518
Credit Limit^2	0.000	0.000	0.647	0.518
Credit Limit	-0.054	0.034	-1.611	0.107
Utilization^3	-1.465	4.712	-0.311	0.756
Utilization^2	-32.852	43.338	-0.758	0.448
Utilization	-80.675	60.346	-1.337	0.181
Charge-off Rate^3	-567.594	338.109	-1.679	0.093
Charge-off Rate^2	465.901	382.012	1.220	0.223
Charge-off Rate	-404.561	118.854	-3.404	0.001
$\text{Monthly Purchase}^3$	0.000	0.000	-1.059	0.290
$\text{Monthly Purchase}^2$	0.000	0.000	1.904	0.057
Monthly Purchase	0.178	0.018	9.823	0.000
R^2	0.452			
Number of observations	234,232			
Number of accounts	17,606			

Note: OLS regression with clustered standard errors by account. Prediction plot from the model is illustrated in Figure 13.