Learning With Your Credit Card: Evidence From Consumer Responses To Penalty Fees

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Abstract

Consumers commonly incur late payment fees in the first few months of using a new credit card. These fees subsequently decline, suggesting that consumers learn to repay on time. Using a quarter of a million new credit card openings, we investigate consumer responses to penalty fees. We find that following a late payment fee, some consumers react by switching to automatic repayments, thereby insuring themselves against future forgetting and eliminating future late payment fees. Other consumers, who appear on average to be less sophisticated, continue with manual payments, relying on remembering to repay on time in the future. But this proves to be completely ineffective, with an ongoing likelihood of future fees unchanged at 20% per month. We conclude that consumer heterogeneity in adopting additional features of financial products, such as automatic repayments, is crucial for understanding whether and how consumers learn from experience.

Keywords: learning, credit cards, automatic payments, direct deposit

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1 Introduction

Learning from experience is a fundamental feature of rational consumer behavior. Positive and negative feedback leads rational consumers to adapt their behavior as they learn (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]. Learning can take different forms, from remembering not to commit the same mistake (e.g. remembering to make the next mortgage payment on time) to changing a product or contract feature (e.g. setting a buffer on smartphone data usage).

In this paper, we investigate whether consumers learn to avoid contingent fees and charges on their credit cards. For credit cards, negative feedback takes the form of penalty fees, such as fees for late payments, which appear on credit card statements. Credit cards are the most common consumer unsecured borrowing product and late payment fees are the most common type of penalty fee.[2] Whether consumers learn from these fees, and whether learning is common across consumers, are important issues (Agarwal et al., 2013). 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).[3]

We shed new light on consumer responses to credit card fees using individual level account data on 250,000 new card openings across five card providers from the United Kingdom over a two-year period. A feature of our data is that we observe rich information

[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] 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).

[3] 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.

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.[4] We show that this additional information on how consumers manage their repayments is crucial for explaining whether and how consumers learn in response to late payment fees. Our data covers 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.

We then explore why these patterns in fee payment exist. Using information on how consumers manage their card repayments, we show that responses to late payment fees differ substantially across consumers. The average decline across all consumers is wholly attributable to a group of consumers who switch their default repayment mode from manual repayment to autopay in response to their first 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 repayments 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 remembering to pay their bill on time), remain just as likely to pay a late payment fee again in future. In essence, consumers only learn from the fee when they react by adopting autopay, acknowledging that they need a facility to avoid future forgetting.[5]

[4] 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.

[5] Throughout this paper we distinguish between consumers who react to the late payment fee by changing their repayment mode, from manual to automatic, compared to consumers who do not. Those consumers

This raises the question why *some* consumers adopt 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. One possible reason for not switching to autopay is that a card holder is purely unable to repay (whether manually or automatically) due to lack of funds, 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 *higher* average repayments compared with switchers, indicating that their failure to switch to autopay does not arise due to liquidity constraints.

Instead, using matched census geodata, 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. 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.[6] 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).[7]

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 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

have to rely on remembering to manually repay their card again in future – which we find is futile in learning to avoid future fees.

[6] 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.

[7] 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).

fees tend to occur during periods of 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 builds on earlier work by Agarwal et al. (2013) who data from a US credit card issuer. They show that the proportion of credit card accounts incurring penalty fees falls sharply over the first few months of account tenure. They attribute their results to consumers responding to a fee by learning to repay in the future. Our main contribution is to show the economic mechanisms at work in these responses and the heterogeneity in learning across consumers. Our contribution focuses on heterogeneity in adopting an additional product feature, designed to insure consumers against forgetting, but utilised by only a subset of consumers.

Our setting offers a rich environment for studying consumer responses to negative feedback. As a high frequency product credit cards provide fast feedback on recent behavior. 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).

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 fees they have incurred. 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 allows us to observe mechanisms by which consumers change their behavior in response to fees, such as switching to autopay.

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.[8] 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.

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). 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).

The structure of the remainder of our paper is as follows. In the next section, 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 for tenure. In Sections 4 and 5 we explore explanations for this decline by fee type: late payments fees, cash advance fees and over-limit fees. The final section concludes the paper.

2 Data

The data we use is 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, for example Barclaycard or Capital One, and card issuance is dominated by the mainstream networks Mastercard and Visa. The credit card market mostly comprises general purpose credit cards, often with

[8] 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.

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.[9] 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 is 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 includes transaction level records (categorized spending and repayments) alongside account-cycle summary records (e.g. credit limits, purchases and repayments, average daily balances, revolving balances, 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.[10]

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.

[9] 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.

[10] 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.

2.1 Credit Card Fee Types

Our analysis focuses on the three most common fee types[11]: late payment fees, cash advance fees and over-limit fees. 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 selection 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 does 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 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 data 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

[11] Other, less common penalty fees exist, such as fees for paying a card into credit. Penalty fees represent direct negative feedback to consumers. Indirect negative feedback also exists in the form of markers on credit files, which may reduce the supply of credit to consumers and potentially also worsen credit terms on existing products. Agarwal et al. (2013) also focus on these three fee types.

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.

All fee types we observe generate indirect costs through the impact on future credit availability via credit reporting. 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.[12]

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 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.[13] 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 data 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.

[12] 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.

[13] In doing so, we corroborate the main finding from Agarwal et al. (2013).

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.[14] 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 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 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. (2013). 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 ($\beta(X)_{i,t}$).[15] Standard errors are clustered by account. Predictions are shown at covariate medians. Table A3 reports the model estimates.[16]

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

[14] 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.

[15] 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.

[16] 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.

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.

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, 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. At any time, a credit card will have one of two repayment regimes: manual repayment or automatic repayment. 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 cheque, or by making a payment via the telephone. Under autopay, the customer authorizes his or her bank to automatically settle the account by direct debit without manual instruction from the customer each month.[17]

[17] This does not prevent the customer from also making (additional) manual repayments.

Autopay is setup via a one-time instruction to the credit card company. 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.[18] The results we present here are not sensitive to extending or shortening the time window out from 15 months.

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.[19] 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 at least the first 15 months of account life (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).[20]

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[18] 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 signature. 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.

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

[20] 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

These plots are obtained by estimating Equation 1 separately for each account type.[21]

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

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 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 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

of accounts that switch autopay status multiple times during the period.

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

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).[22] 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 5%, and falls to effectively 0% over the following 12 months.[23] These plots illustrate that accounts that switch to autopay see a sharply reduced likelihood of subsequent fees.

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

[22] We show corresponding scatter plots in Figure A4. 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.

[23] Not all accounts that switch to autopay following a late payment fee do so in the month immediately following the first fee event.

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.

4.2 Switchers and Non-Switchers

These results or late payment fees naturally give rise to the question of 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 switches 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.[24]

We now 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 switchers and non-switchers using information from the Argus data and also match data on consumer characteristics using geocodes. We have limited information on consumer characteristics in our data, but the availability of geocodes allows us to match-in a rich set of covariates. Other recent studies using matched census data, based on US zip codes, include Mian and Sufi (2009) and Chetty et al. (2013). We draw upon detailed census

[24] 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.

records from the UK National Census for 2011.[25] This allows us to understand more about differences across the groups which might drive their different responses to a late payment fee.

First, 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 £1,700 of balances and have monthly purchases over £200 per month, showing they are typically active card users with regular repayments. The level of purchases among non-switchers is very similar to that among switchers.

Second, consumers might not switch to autopay if they are financially constrained and cannot make repayments. Autopay does not provide perfect insurance against forgetting 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. Card utilization among non-switchers is lower than among switchers and non-switchers make *higher* average repayments each month compared to switchers, suggesting they do not avoid switching to autopay due to low liquidity.

Third, differences in the adoption of autopay might reflect differences in sophistication across customers. When we use the census data to compare the groups by their consumer characteristics, non-switchers appear less sophisticated compared to switchers. Consumers who switch to autopay 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,

[25] 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.

a postcode-level affluence score constructed by the UK statistics authority, indicating a higher degree of affluence. 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).

Overall, these differences in characteristics of accounts and consumers who switch, compared to those who do not switch, suggest that in response to a late payment fee, more sophisticated consumers are more likely to switch to an autopay regime to insure themselves against future forgetting. By contrast, less sophisticated consumers stick with a manual repayment regime, relying on memory to remember to repay in subsequent months. However, patterns in subsequent fee payment indicate that relying on memory is a very ineffective way of avoiding future fees.

4.3 Responses to Second Fees

It is possible that some consumers might respond to a first fee by deciding to switch to autopay should they incur a fee again in the future. We therefore also examine how consumers respond to a second late payment fee. Approximately 8.3% of all accounts incur a second late payment fee within the sample period, amounting to 34.3% of accounts that incurred a first fee. To show how consumers respond to second late payment fees, Figure A5 replicates the earlier analysis 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.

Table A9 shows that consumers who switch to autopay following a second late payment fee are, in keeping with our results from the analysis of first fee events, 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. Once again, we see that non-switchers actually have higher average monthly repayments compared to switchers, again suggesting that differences in adoption of autopay are unlikely to be related to lack of funds available to the customer.

5 Cash Advance Fees and Over-Limit Fees

In the remainder of the paper we examine the evolution of cash advance fees and over-limit fees with account tenure. For these fees, learning mechanisms might also be at work. After incurring a fee, consumers might learn that accessing cash via a credit card is particularly costly and then adjust their behavior, depending on the cost and availability of cash via other means. Similar dynamics might plausibly be at work in the evolution of over-limit fees.

5.1 Cash Advance Fees

Figure 5 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 5.[26]

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 the presence 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.

[26] Figure A6 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 6 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).[27] 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 7 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.[28] 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 8 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 9 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 that most spells of cash advances show large average increases in purchases in the month in

[27] The corresponding scatter plots of fees over tenure for each group are shown in Figure A7. Tables A11 and A12 report the model estimates.

[28] The sample size is lower among panels with longer spells of cash advances.

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.[29]

Of course, these patterns in cash advances over time do not rule out the possibility that learning dynamics maybe at play for some customers. We expect that in some cases customers begin using their credit card in-cognisant 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.

5.2 Over-Limit Fees

Figure 10 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. 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 to credit limits. However, our result here contrasts with that seen in Agarwal et al. (2013), who find in their US data the same pattern in over-limit fees as that seen in late payment

[29] This behavior among accounts in our sample also differs from that in the sample used by Agarwal et al. (2013), who find no clear patterns in card usage correlating with the incursion of any fee type, suggesting consumers make unpredictable mistakes in their data.

fees and cash advance fees.[30]

The pattern seen in Figure 10 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 A10.[31] 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 11.[32] 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.[33]

What drives customer responses to over-limit fees? In subsequent panels of Figure 11, 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

[30] Agarwal et al. (2013) 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.

[31] The data also shows 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 A11). 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.

[32] The corresponding scatter plots of fees over tenure for each group are shown in Figure A9 Tables A14 to A16 report the model estimates.

[33] Figure A10 shows that, by tenure, among accounts which incur an over-limit fee the likelihood of subsequent fees in the following months declines sharply.

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 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 suggests that this is not the main driver of the dynamics of over-limit fees.

6 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. Our analysis of switchers and non-switchers suggests that switchers are more likely to be sophisticated (as measured by socio-economic characteristics of the postcode in which they reside) compared with those who do not switch. Among non-switchers, the rate of late payment fees remains persistently high. That is, without using automatic repayments, late payment fees appear not to help card holders learn to repay their bill on time. Our results indicate that switchers who adapt their behavior by switching to automatic payment are more sophisticated (with higher income and education) compared to the non-switchers.

Our findings may have important implications for understanding how consumer learn – 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 learning. Our core finding, that people only “learn” 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 forgetting, 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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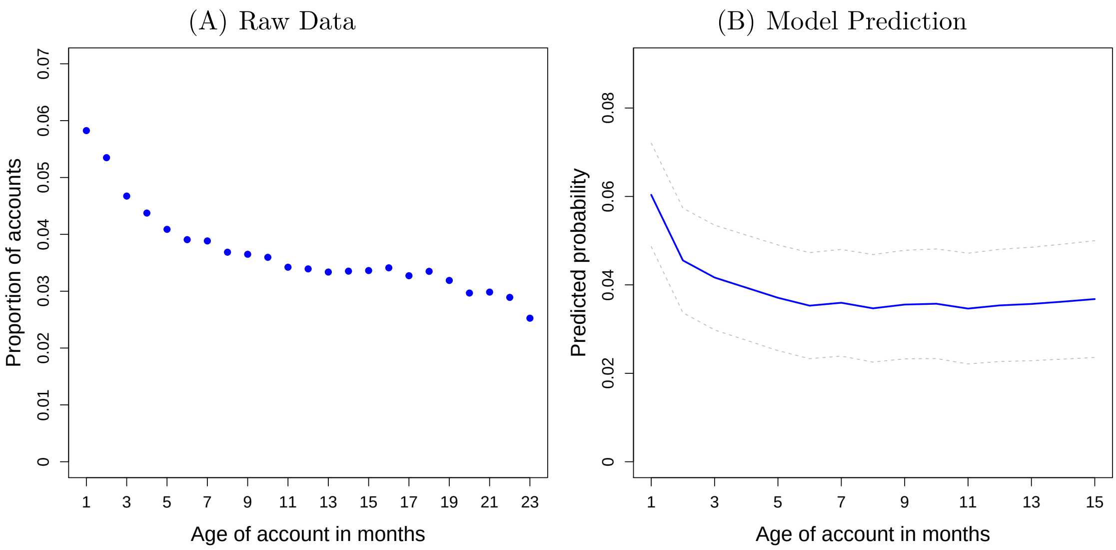
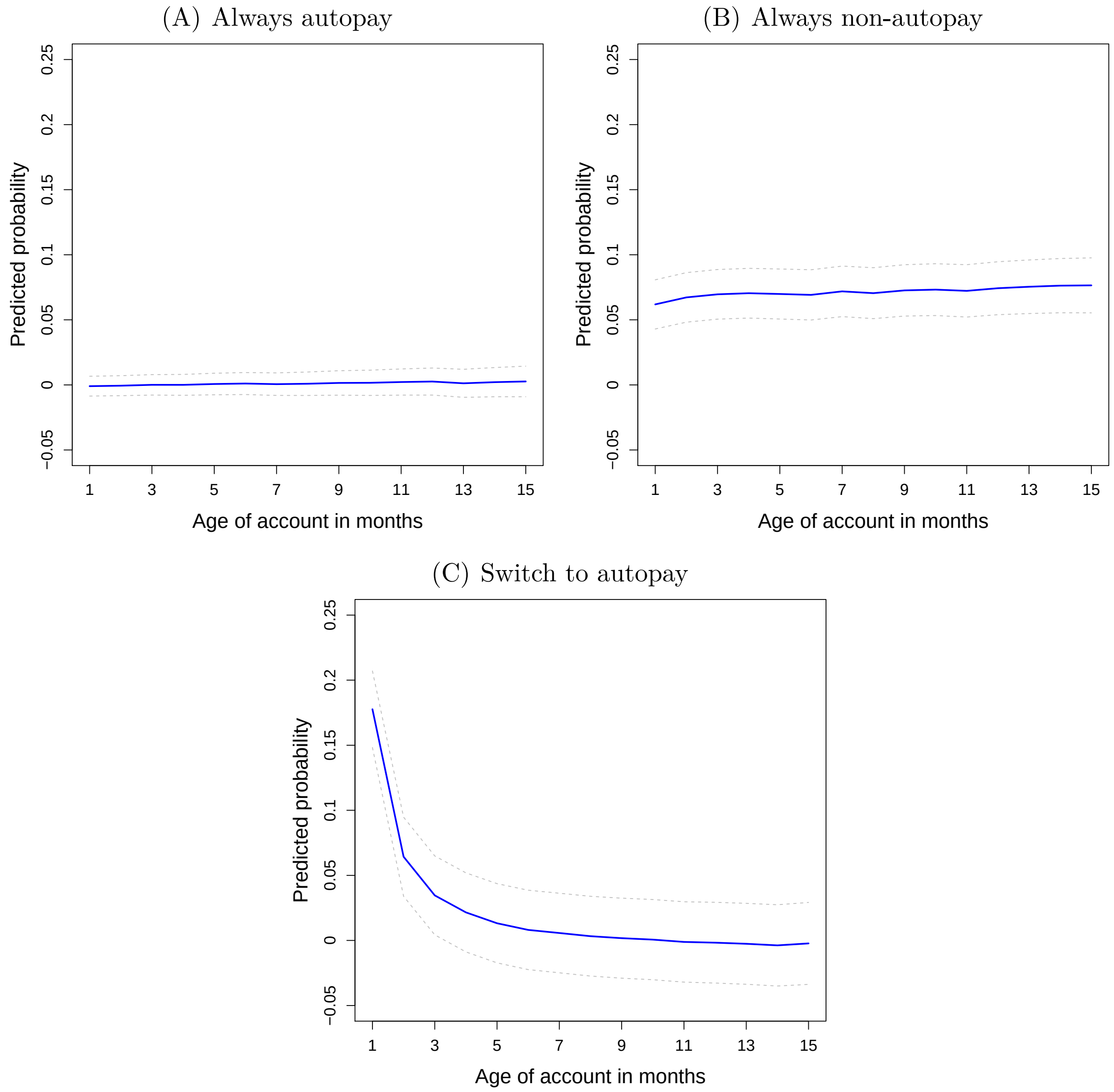
Figure 1: Late Payment Fees and Account Tenure



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.

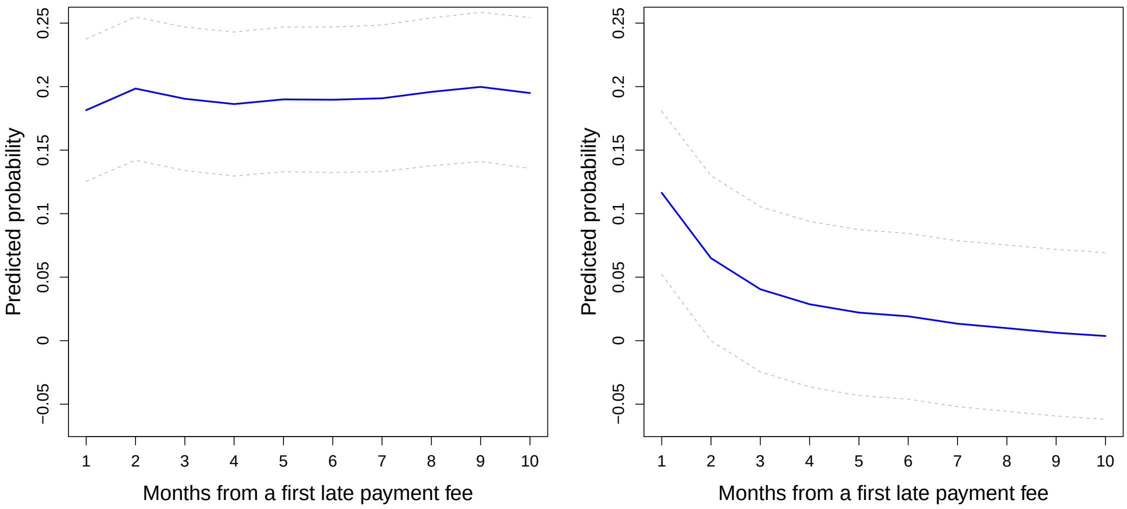
Figure 2: Probability of Late Payment Fee by Autopay Status



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 covariates 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.

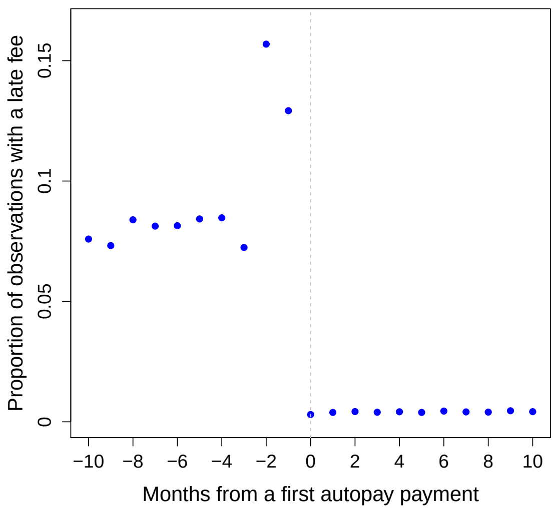
Figure 3: Probability of Late Payment Fee in Months After First Fee, by Autopay Status

(A) Always non-autopay (B) Switch to autopay



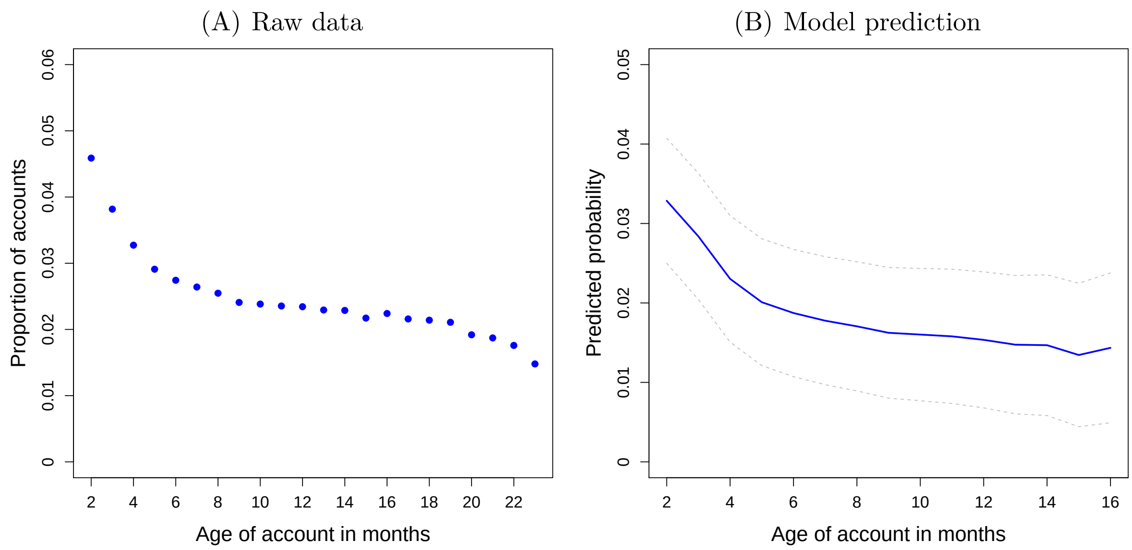
Note: Figure plots the predicted probability of accounts incurring a late payment fee in months after the first late payment fee is incurred (month zero). Predictions are from a linear probability model at covariates medians (Equation 2). The panels show two mutually exclusive groups: accounts which 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 A4. Tables A7 and A8 report the model estimates.

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



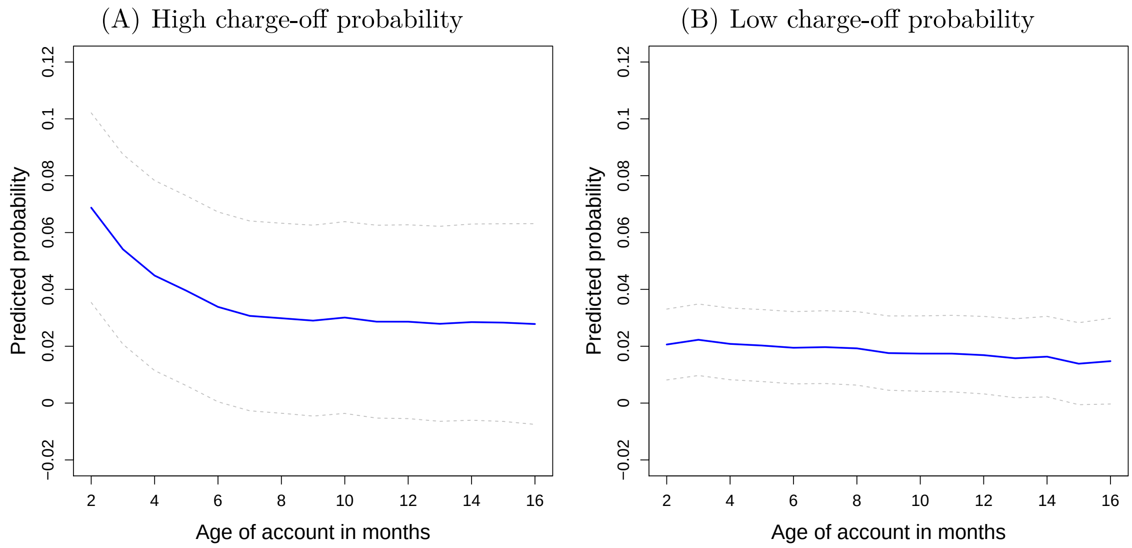
Note: Figure plots the proportion of accounts incurring a late payment fee in months before and after the accounts switch from manual repayment to automatic repayment.

Figure 5: Cash Advance Fees and Account Tenure



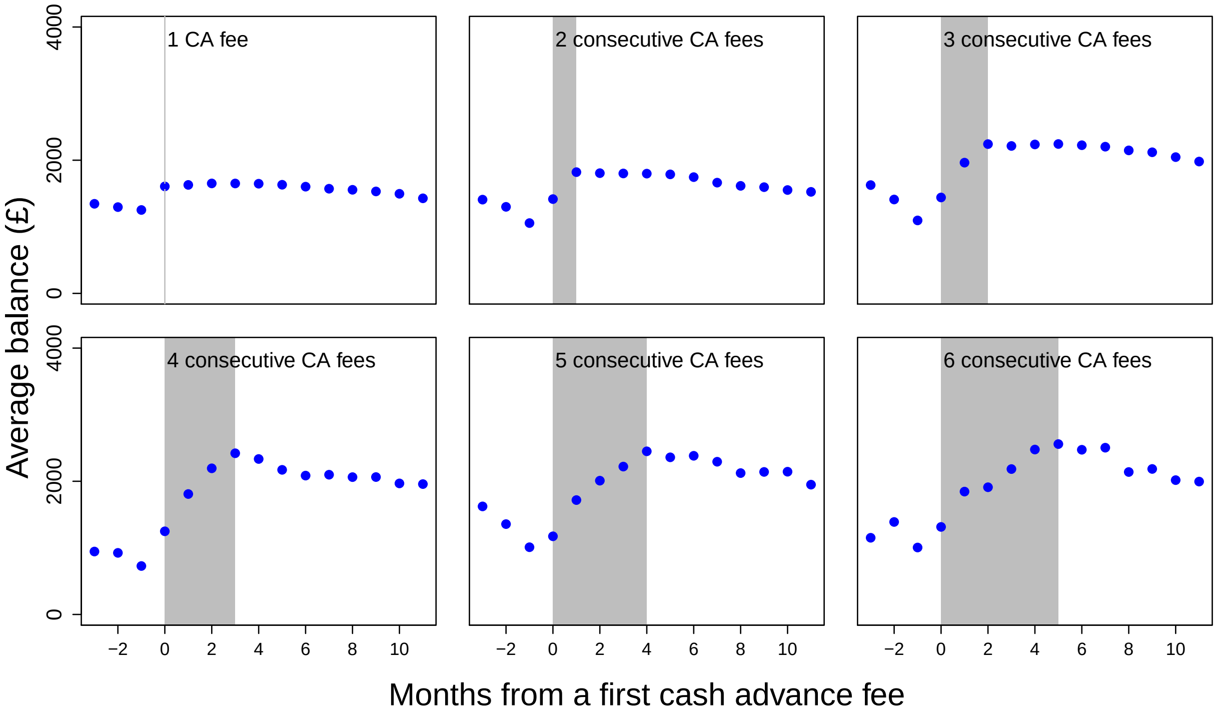
Note: Panel A plots the mean of the y-axis variable (dummy variable indicating whether the account incurred a cash advance fee) by units of the x-axis variable (age of the account in months). The sample comprises all accounts in the sample opened at or after January 2013. Panel B plots the predicted 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 A10. 95% confidence intervals are illustrated by dashed lines.

Figure 6: Probability of Cash Advance Fees for High / Low Risk Accounts



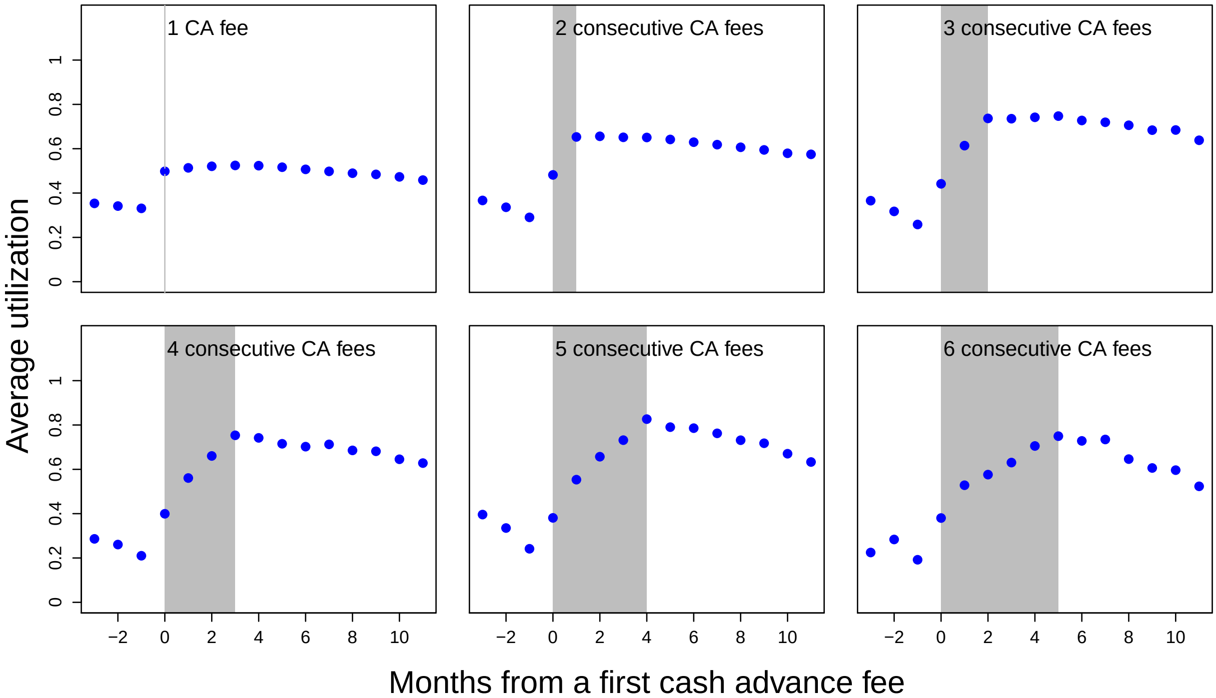
Note: Figure plots the predicted probability of accounts incurring a cash advance fee by age of account. Predictions are from a linear probability model at covariates medians (Equation 1). The panels show plots from models estimated separately for accounts with high (Panel A) and low (Panel B) probability 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 A7. Tables A11 to A12 report the model estimates.

Figure 7: Credit Card Balances Through Spells of Cash Advance Fees



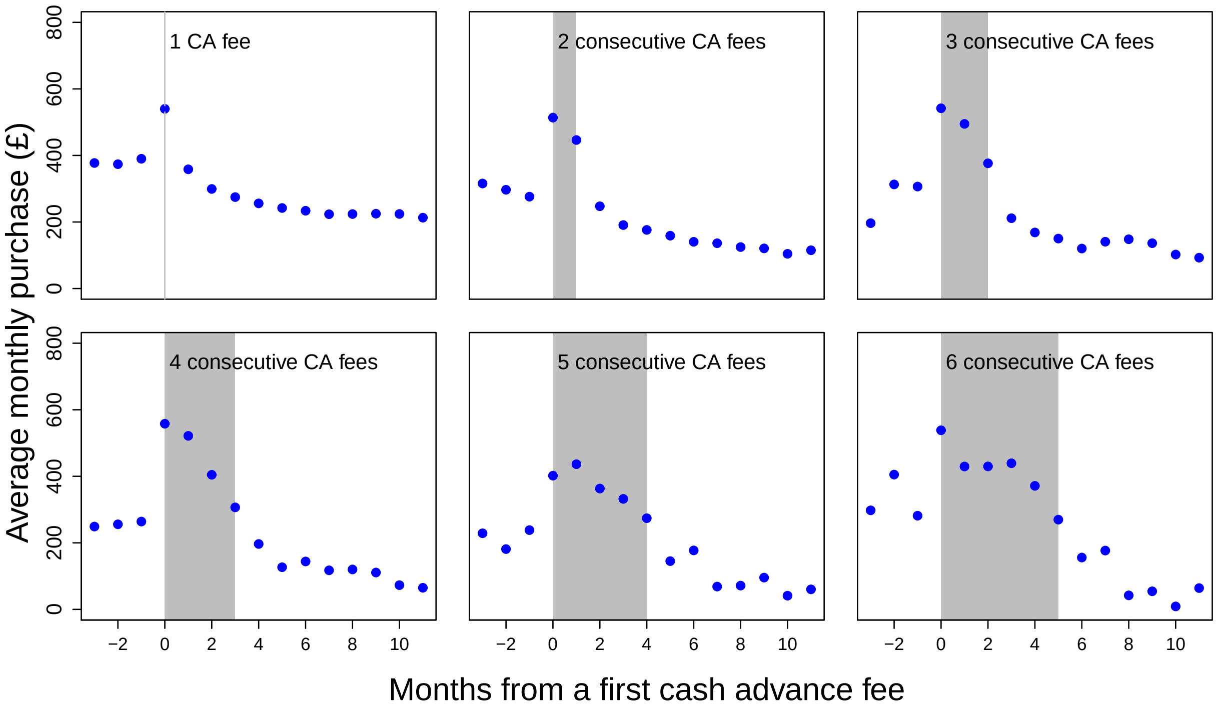
Note: Figure plots average credit card balances in each month by length of spell of consecutive months with at least one cash advance recorded on the account in each month. The x–axis ranges from three months before the first cash advance on the account through 11 months after.

Figure 8: Credit Card Utilization Through Spells of Cash Advance Fees



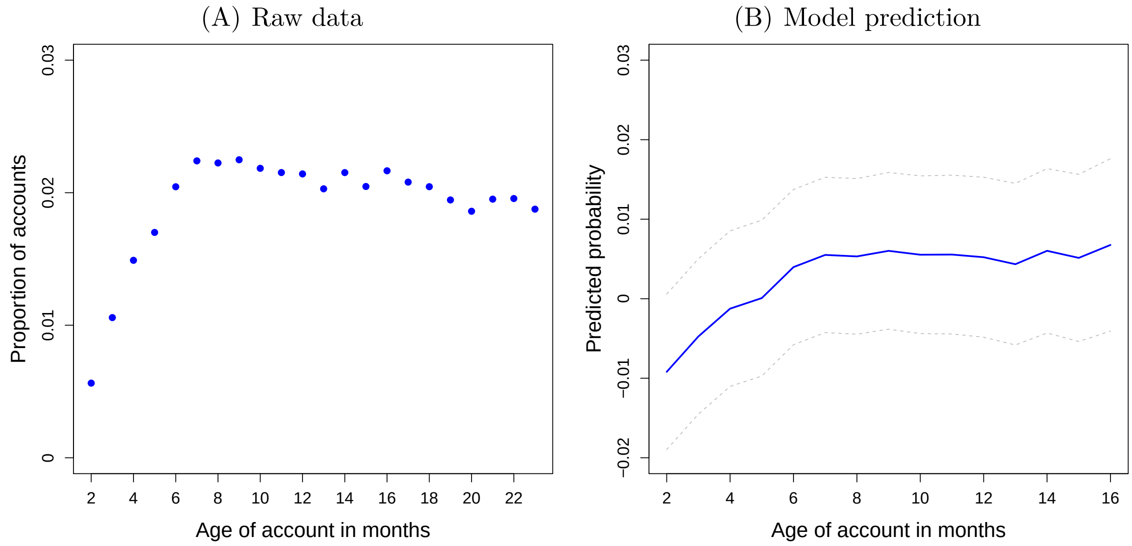
Note: Figure plots average utilization among accounts by length of spell of consecutive months with at least one cash advance recorded on the account in each month. The x–axis ranges from three months before the first cash advance on the account through 11 months after.

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



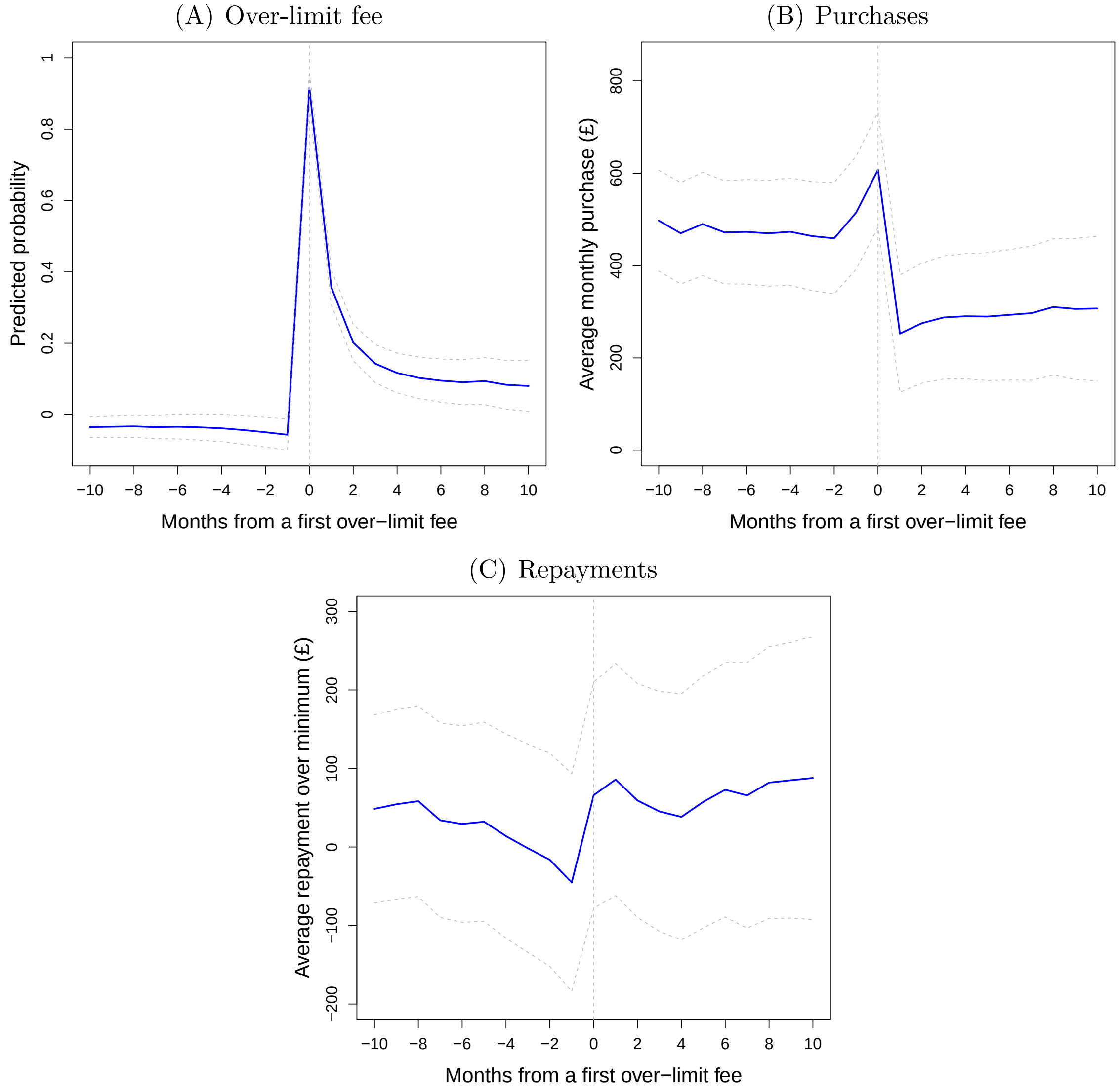
Note: Figure plots value of all credit card purchases within the month by length of spell of consecutive months with at least one cash advance recorded on the account in each month. The x–axis ranges from three months before the first cash advance on the account through 11 months after.

Figure 10: 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 A13. 95% confidence intervals are illustrated by dashed lines.

Figure 11: 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 covariates medians (Equation 2). 95% confidence intervals illustrated by dashed lines. The corresponding scatter plots are shown in Figure A9. Tables A14 to A16 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

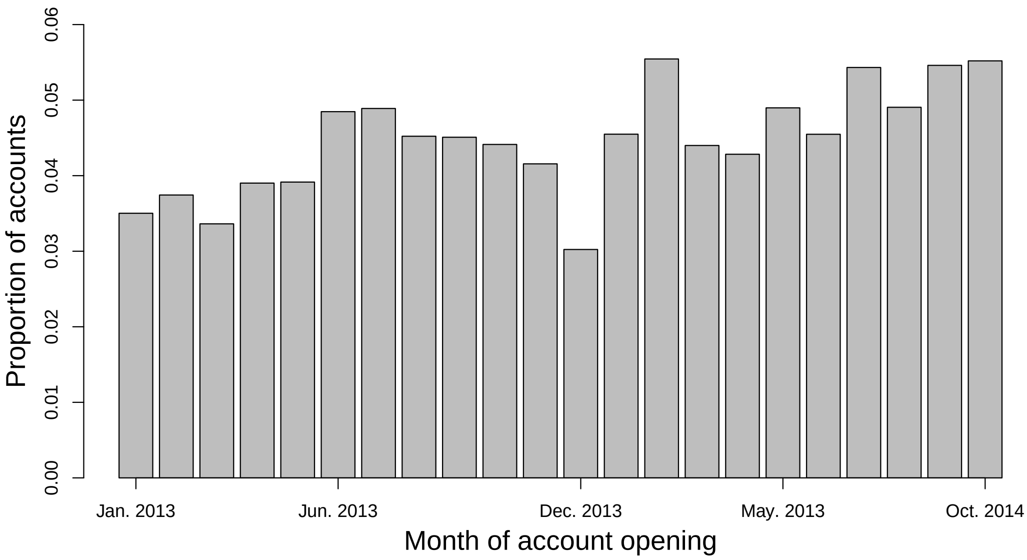
Variable name	All Mean	All S.D.	Non-Autopay Mean	Switch Mean	t score	p value
Socio-Economic Characteristics (Postcode)						
Mean house price (£)	206,490	112,899	204,718	211,194	-4.69	0.0000
Jobless claimants (%)	2.626	1.445	2.664	2.528	6.36	0.0000
Mean weekly income (£)	744.69	160.61	740.63	755.46	-7.53	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
Card Characteristics						
Mean balance (£)	1,948.08	1,878.21	1,737.40	2,460.98	-36.89	0.0000
Mean utilization (%)	55.71	35.13	53.43	61.25	-23.42	0.0000
Mean monthly purchase (£)	218.94	511.88	211.91	236.05	-4.38	0.0000
Mean repayment (£)	270.95	671.80	293.78	215.36	13.42	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

Note: Sample size for socio-economic characteristics as follows. For house price, weekly income and educational level: All 1.4m; Non-Autopay 1.1m; Switch 352,000. For jobless claimants: All 932,000; Non-Autopay 703,000; Switch 230,000. For Acorn category: All 1.5m; Non-Autopay 1.1m; Switch 376,000; For free school meals: All 1.4m; Non-Autopay 1m; Switch 334,000. Sample size for card characteristics: All 1.88m; Non-Autopay 1.53m; Switch 562,000.

Appendix

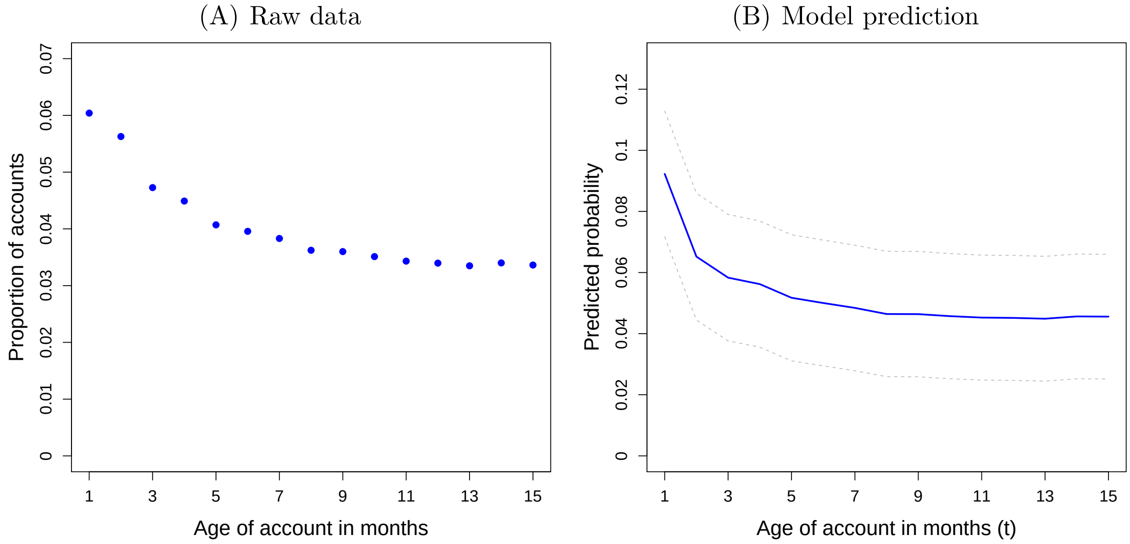
WEB APPENDIX – FOR ONLINE PUBLICATION ONLY

Figure A1: Account Openings by Calendar Month



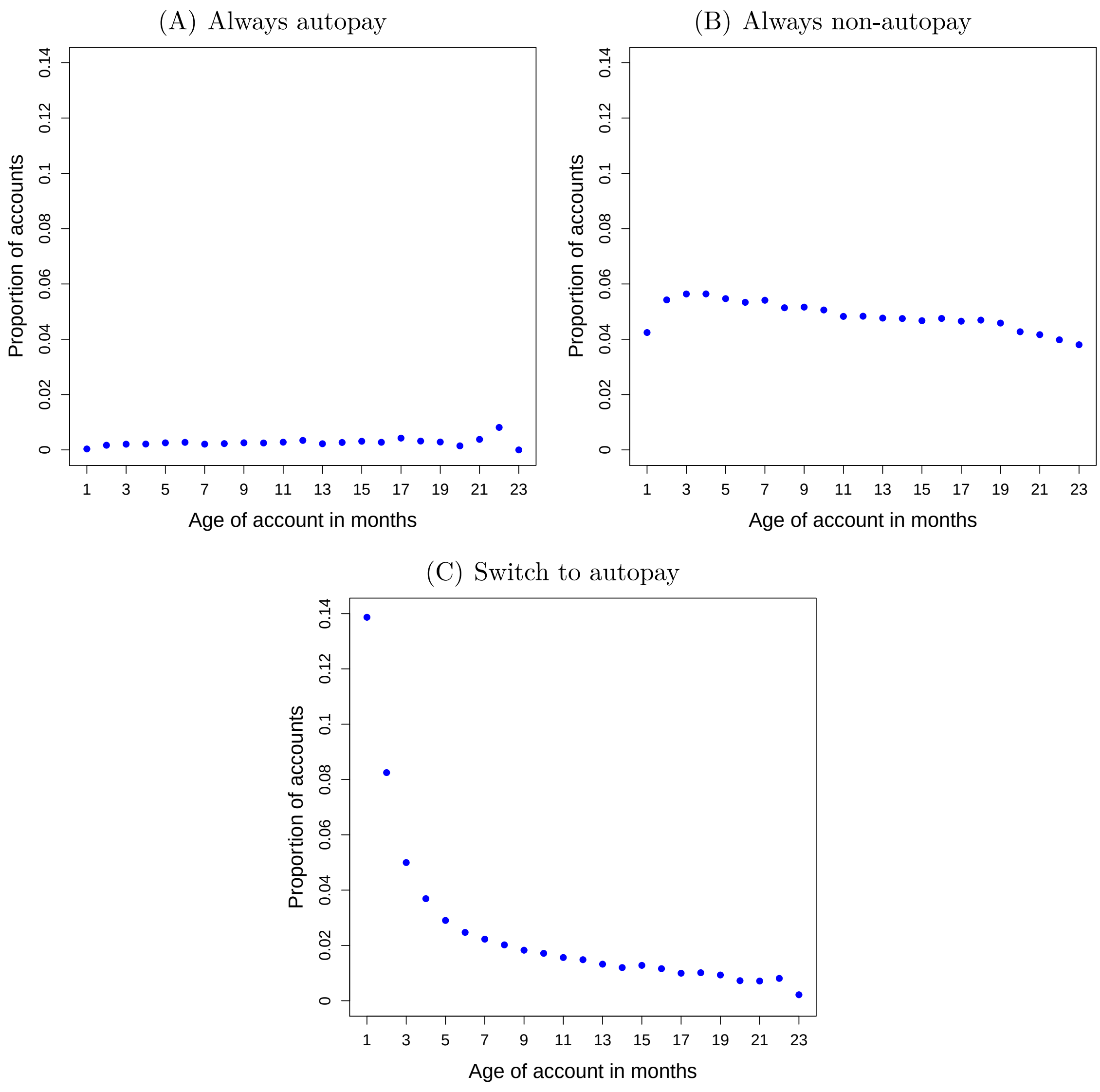
Note: Figure illustrates bar plot of proportion of total sample of new account openings that open in each calendar month.

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



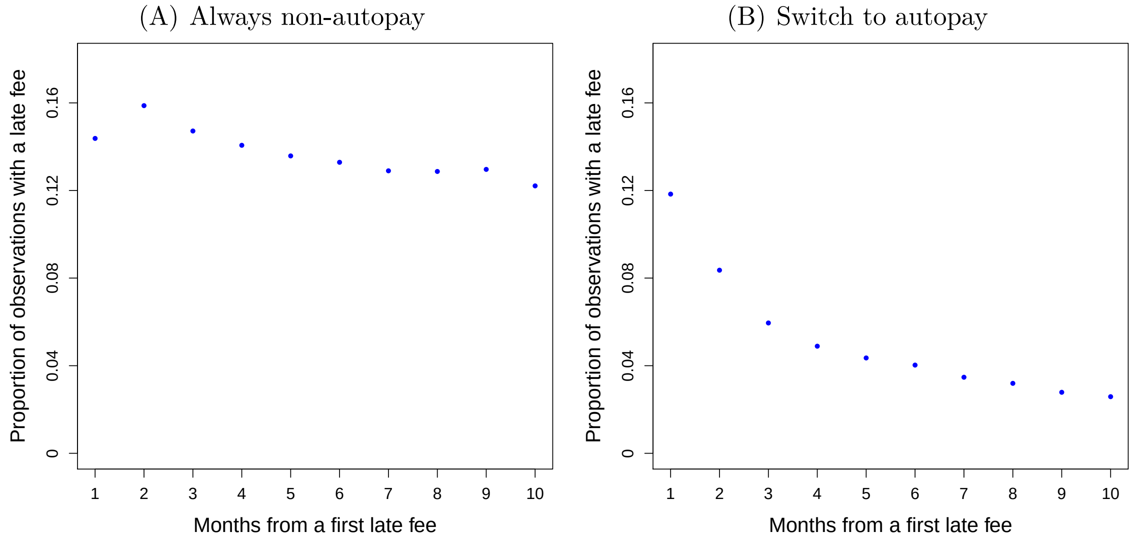
Note: Figure reproduces the plots in Figure 1 when the data is restricted to a balanced panel of accounts which open within the sample period and remain open for at least the following 15 months.

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

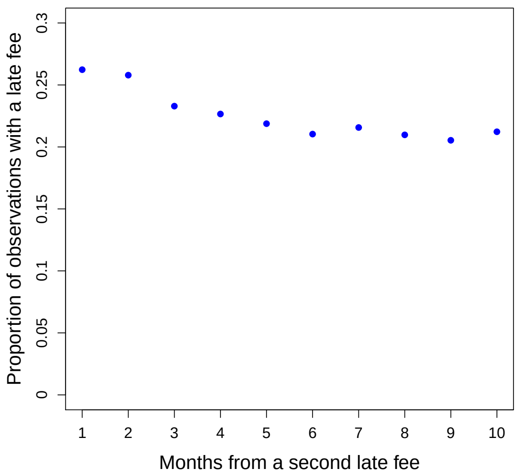


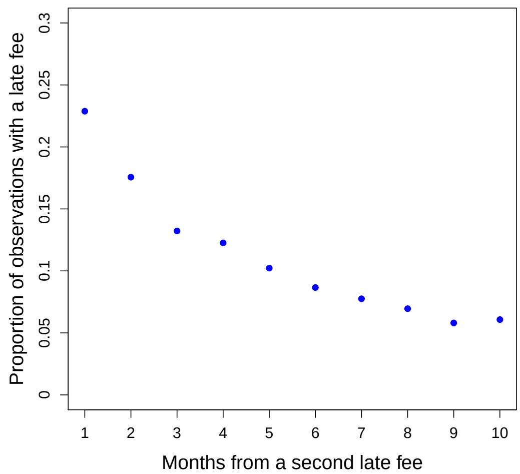
Note: Figures plot the proportion of accounts incurring a late payment fee in months after the first late payment fee incurred (month zero). The panels show two mutually exclusive groups: accounts which were never subject to an autopay instruction throughout the sample period; and accounts which switched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

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

(A) Always non-autopay

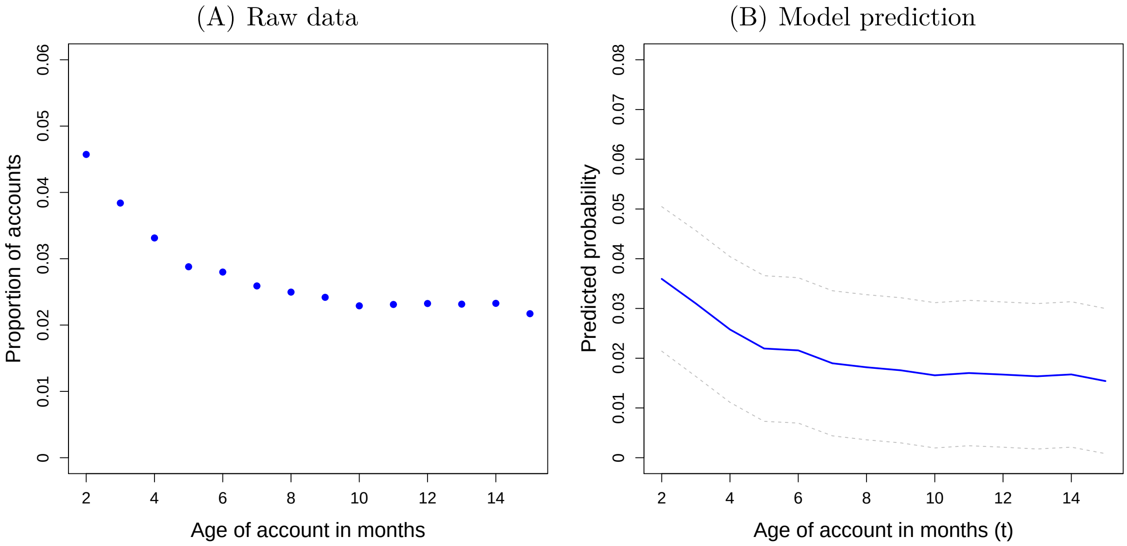
(B) Switch to autopay





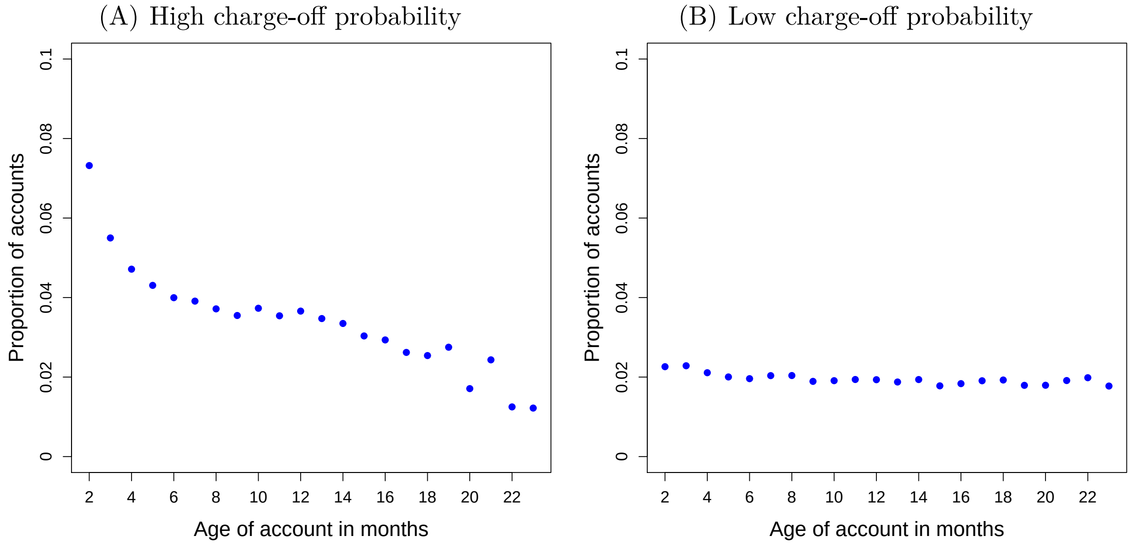
Note: Figures plot the proportion of accounts incurring a late payment fee in months after the second late payment fee incurred (month zero). Sample comprises accounts that incurred a first late payment fee and did not switch to autopay before incurring a second late payment fee (at least one month after 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 A6: Cash Advance Fees and Account Tenure, Balanced Panel



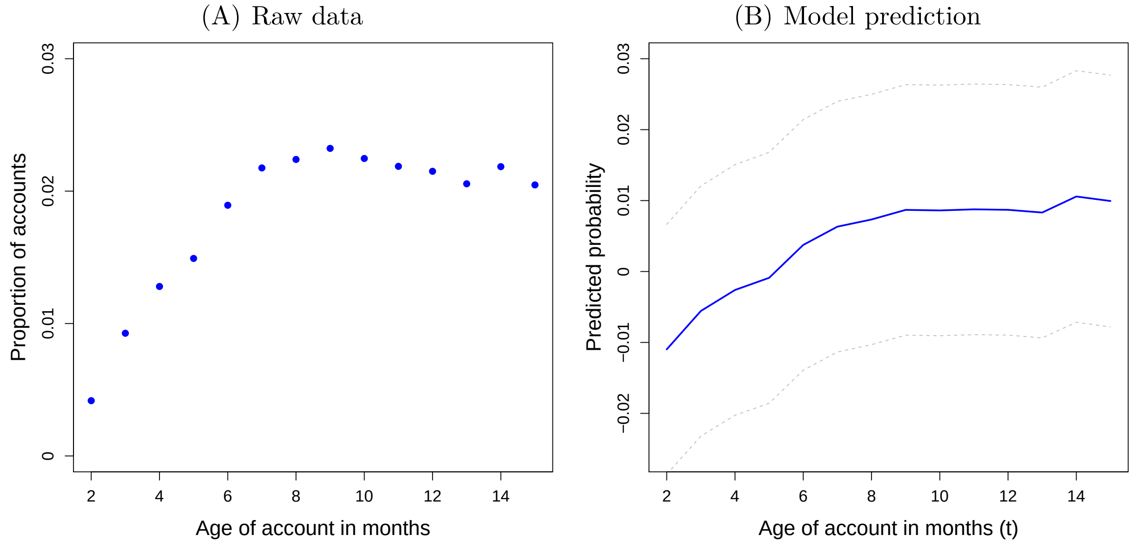
Note: Figure reproduces the plots in Figure 5 when the data is restricted to a balanced panel of accounts which open within the sample period and remain open for at least the following 15 months.

Figure A7: Cash Advance Fees by Tenure, High/Low Charge-Off Probability Accounts



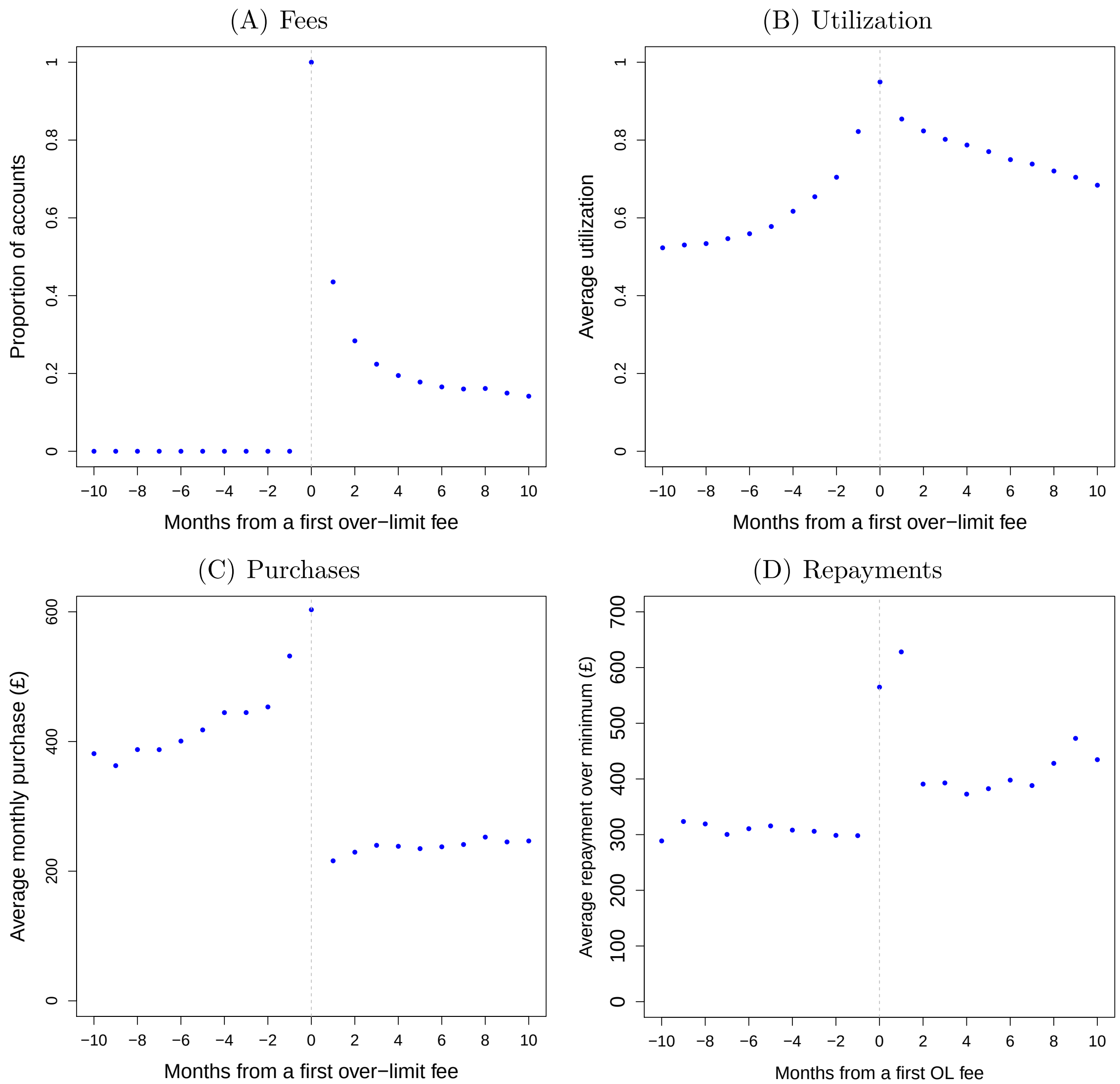
Note: Figure plots the proportion of accounts incurring a cash advance fee by age of account. The panels show plots from models estimated separately for accounts with high (Panel A) and low (Panel B) probability of charge-off at account opening (median split).

Figure A8: Over-Limit Fees and Account Tenure, Balanced Panel



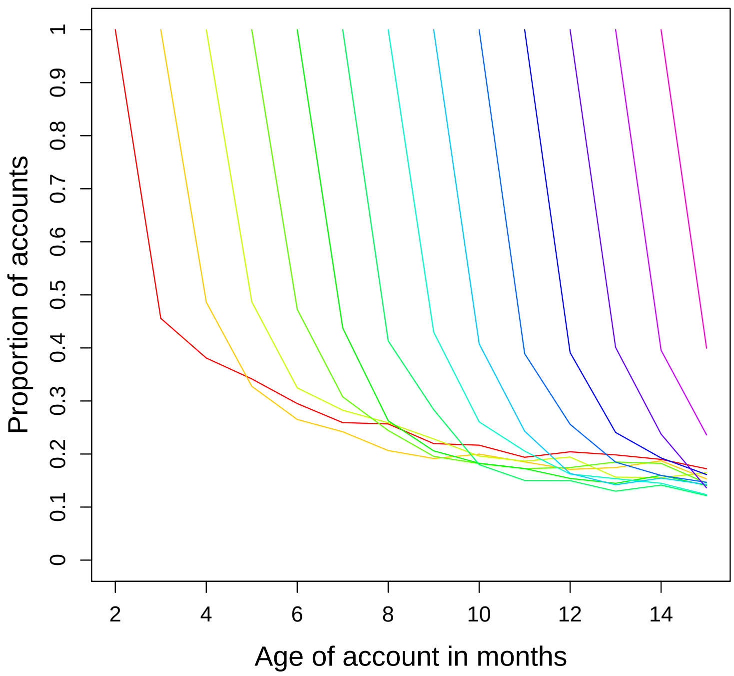
Note: Figure reproduces the plots in Figure 10 when the data is restricted to a balanced panel of accounts which open within the sample period and remain open for at least the following 15 months. 95% confidence intervals are illustrated by the dashed lines.

Figure A9: Purchases, Repayments and Utilization in Months Following First Over-Limit Fee



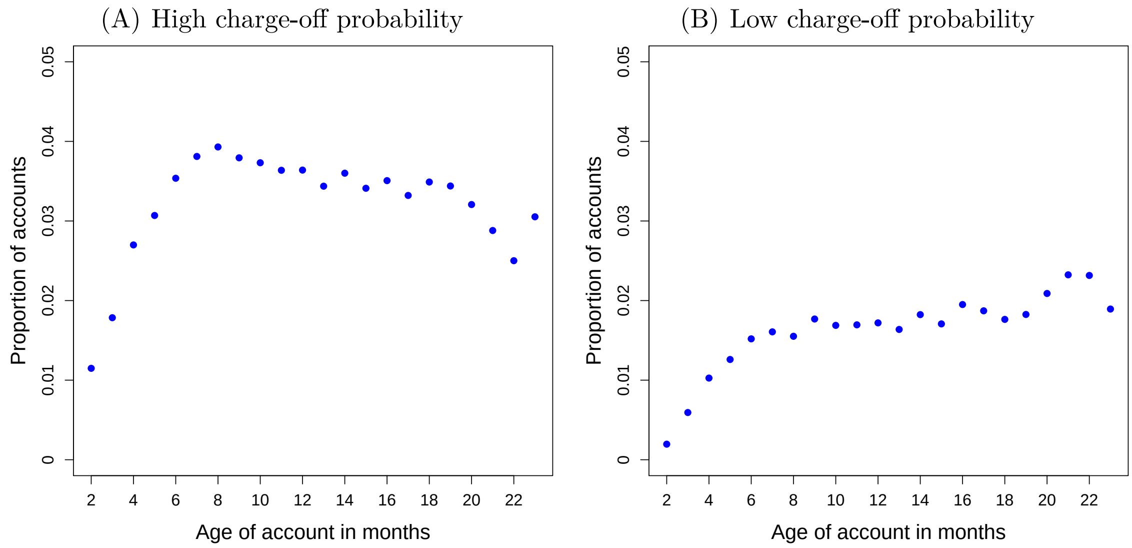
Note: Figures plot in Panel A average purchases (in £), in Panel B average repayment (in £) and in Panel C average utilization (balance expressed as a fraction of the credit limit) by number of months since the account first incurred an over-limit fee.

Figure A10: 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 A11: 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
Monthly Purchase^3	0.000	0.000	-3.479	0.001
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
$\text{Monthly Purchase}^3$	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 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
Monthly Purchase^3	0.000	0.000	0.193	0.847
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: 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
Socio-Economic Characteristics (Postcode)						
Ave. median house price (£; postcode)	207,521	115,875	206,082	214,376	-2.78	0.0055
Prop. jobless claimants (%; postcode)	2.635	1.451	2.662	2.506	3.76	0.0002
Ave. weekly income (£; postcode)	743.06	161.52	740.48	755.38	-3.82	0.0001
Prop. educational level 4+ (%; postcode)	28.302	8.790	28.156	28.997	-4.01	0.0001
Ave. Acorn category (postcode)	3.259	0.682	3.269	3.208	3.93	0.0001
Prop. free-school meal (%; postcode)	13.172	7.179	13.290	12.613	3.92	0.0001
Card Characteristics						
Ave. balance (£)	1,917.63	1,803.90	1,818.27	2,341.53	-14.21	0.0000
Ave. utilization (%)	63.99	36.19	62.70	69.49	-10.72	0.0000
Ave. monthly purchase (£)	140.56	381.59	143.92	126.19	2.59	0.0096
Ave. repayment (£)	252.14	651.82	263.08	205.50	5.11	0.0000
Ave. Merchant APR (%)	10.54	9.83	11.09	8.19	15.77	0.0000
Ave. Cash APR (%)	25.31	3.03	25.26	25.53	-5.29	0.0000

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 A10: 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
Monthly Purchase^3	0.000	0.000	4.447	0.000
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 5, Panel B

Table A11: 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 6.

Table A12: 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
Monthly Purchase^3	0.000	0.000	2.890	0.004
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 6.

Table A13: 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 10, Panel A

Table A14: 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 11.

Table A15: 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 11.

Table A16: 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
Monthly Purchase^3	0.000	0.000	-1.059	0.290
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 11.