Learning, Liquidity and Credit Card Fees

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Abstract

Declining penalty fees and charges on financial products are often interpreted as evidence of consumers learning from experience. Using data from a quarter of a million new credit card openings, we investigate whether the observed decline in fees is attributable to learning or other factors. We show the decline in late payment fees is entirely explained by some consumers switching to automatic payments after forgetting to repay once. More sophisticated consumers are more likely to make this switch, thereby insuring themselves against future forgetting. But less sophisticated consumers continue with manual repayments and incur higher future fees. However, the decline in some fee types is not due to learning. Cash advance and over-limit fees fall over time due to time-varying liquidity constraints, which are concentrated around the time of account opening.

Keywords: learning, liquidity constraints, credit cards, automatic payments

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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 fee, penalty 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].

In this paper, we investigate whether consumers learn to avoid contingent fees and charges in the credit card market. For credit cards, negative feedback takes the form of penalty fees, such as fees for late payments or exceeding a credit limit, which appear on credit card statements. Credit cards are the most common consumer unsecured borrowing product[2]. Whether consumers learn from these fees, and whether learning is common across consumers, are important issues (see, for example, 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 rich individual level account data on 250,000 new card openings across five card providers over a two-year period. Our data covers approximately 2.6 million account-cycles, and includes granular account level information. In addition, we observe information on how consumers manage their card repayments, such as whether they pay their account manually each month or instead use an automatic instruction for the bill to be paid. We show that this additional information on how consumers manage their repayments is crucial for understanding

[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.

whether and how consumers learn in response to fees.

Our analysis proceeds as follows. First, we show that late payment fees and cash advance fees are front-loaded, peaking in the first month of account life and then declining sharply over the next few 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 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 the response to late payment fees differs across consumers. The average decline across all accounts is wholly attributable to a group of consumers (the 'learners') who switch their 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 'non-learners') the probability of fee payment remains persistently high, at approximately 20% per month. These findings show that some consumers use the autopay facility to insure themselves against future forgetting, while others who choose not to remain exposed to future mistakes.

This raises the question why *some* consumers learn in response to late payment fees and decide to switch repayment mode while others do not. Using matched census geodata, we show that 'switchers' are disproportionately drawn from local populations with higher incomes, home values and education, lower unemployment and lower social insurance dependency. These results are in line with the notion that more sophisticated consumers learn in response to negative feedback, while less sophisticated consumers fail to respond[4]. 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.,

[4] Nevertheless, some sophisticated consumers may strategically default on their credit card repayments. The incentives for strategic default are weak in the UK consumer credit market as consumer bankruptcy fees are high (approximately £750) and the period of discharge can be lengthy, up to three years.

2016)[5].

In subsequent analysis we show that, in contrast with late payment fees, the decline in cash advance fees with tenure is unlikely to be explained by consumers learning in response to initial mistakes. Instead, the pattern of cash advance fees reflects time-varying liquidity needs focused around account openings. Consumers tend to use cash advances when liquidity constrained, and unsurprisingly this strongly correlates with taking a new credit card. We show that the decline in cash advance fees is concentrated among higher-risk accounts and the propensity to incur cash advance fees increases with higher levels of non-cash purchases, higher utilization and lower repayments.

We also analyze consumer responses to over-limit fees. We do not see a sharp decline in over-limit fees over account tenure (the median tenure at which accounts incur their first fee is seven months after opening). However, we do observe changes in behavior at the individual level following over-limit fees. The observed pattern of responses is that consumers on average avoid future over-limit fees by cutting purchase volumes sharply, while leaving repayments unchanged. This is also consistent with the existence of individual liquidity constraints, as the reduction in balances when faced with a binding credit limit is concentrated in the current period through lower consumption purchases.

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. 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

[5] 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).

(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[6]. 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.

Our paper builds on earlier work by Agarwal et al. (2013). In that paper, the authors use data from a US credit card issuer to show that the proportion of credit card accounts incurring penalty fees falls sharply over the first few months of account tenure. They argue that this reflects consumers learning from experience in response to negative feedback. We show a similar pattern for late payment fees and cash advance fees. One difference to our results is that the authors also find that over-limit fees peak at account opening and decline sharply with tenure. To our knowledge, we are the first to be able to reveal the economically important behaviors and mechanisms that drive these patterns, and the heterogeneity in behavior across consumer types.

We also contribute 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). 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., 2015; Liberman, 2016).

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

The structure of the remainder of our paper is as follows. In 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. These issuers serve a broad range of market segments from 'prime' cards which are designed to focus on revenue accrual through interchange fees to 'sub-prime' card issuers with high APRs. We source the data via Argus Information and Advisory Services, who collate and harmonize data from credit card issuers[7]. 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. Hence, 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 data (categorized spending and repayment) alongside account-cycle summary data (e.g., credit limits, purchases and repayments, average daily balances, revolving balances, interest and charges, etc.). 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[8].

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

[7] Argus specializes in providing 'wallet view' databases of 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 over time.

[8] 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.

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%.

2.1 Credit Card Fee Types

We focus on the three fee types: late payment fees, cash advance fees and over-limit fees[9]. 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 months in which a consumer can incur the fee. Late payments also lead to a deterioration in the consumer's credit score on their credit bureau file, and hence have an indirect cost in terms of future access to credit[10].

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%. And unlike purchases, interest is charged on

[9] These are the most common fees incurred on the majority of cards. 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 marks on credit files, which may reduce the supply of credit to consumers and potentially also worsen credit terms on existing products. Prior to the 2009 CARD Act, card issuers often adopted a policy of 'universal default', increasing interest rates on a card based on late payment on a different card issued by a different company. Agarwal et al. (2013) also focus on these three fee types.

[10] We do not consider these indirect penalties arising from fees in our analysis, in part because it is difficult to accurately evaluate the magnitude of the indirect penalty arising through 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 portfolio and the lenders to which they apply in future.

cash advances from the day of the advance, even if the consumer repays the cash advance by their next payment due date. In addition, cash advances are reported on credit files.

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

Table 2 summarizes the value and frequency of fees in our sample of the 243,000 new accounts, with summary data at the card level. Fees are quite common within our sample as 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. Consumers on average incur £9 in fees over the sample period (including those who incur no fees), approximately half of which are accounted for by late payment fees.

3 Credit Card Fees Decline With Tenure

We begin our results by corroborating in our data the main finding from Agarwal et al. (2013) that credit card fees decline with account tenure. First, in Figure 1 we illustrate this result with scatter plots of the proportion of account-months incurring each fee type by account tenure. Late payment and cash advance fees show a sharp decline in the proportion of accounts incurring a fee over the first few months of tenure. The proportion of accounts incurring late payment fees falls from 6% in the first month to 2.8% by month 23. Cash advance fees decline from 4.8% to 1.8% over the same period. The decline is fastest over the first few months of account tenure, then slows in subsequent months. For over-limit fees we observe a different pattern. The proportion of accounts incurring this fee increases steadily through the first few months of account tenure, then illustrates some slight decline over subsequent months.

This pattern in notably different from that in Agarwal et al. (2013), who find in their US data the same pattern in over-limit fees, late payment fees and cash advance fees. In our data, accounts take time after opening to accrue balances. Among accounts who incur an over-limit fee, the first fee is on average incurred at 7.58 months after opening. Very few accounts immediately accrue a balance after opening that is over the account limit (fewer than 0.5% of cards in our sample). 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.

The data shown in Figure 1 is an unbalanced panel. Therefore, the observed pattern of fee decline could potentially arise due to selective attrition, or 'survivorship bias', if accounts which incur a fee are more likely to close or fall dormant after the fee event. For this reason, we reproduce the plots of the fee data in Figure A1, with the sample restricted to accounts that open within our sample period and remain open and active for at least 15 months[11]. This balanced panel includes 46% of all observations. Figure A1 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.

Alternatively, the pattern of fee decline we observe could be caused by time-varying account characteristics or strong calendar time events which could 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

[11] 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. We see identical patterns of fee decline if we further shorten the panel length to 12 months.

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 is a dummy variable that is 1 if the consumer pays a fee for account i at tenure t. We estimate this equation separately for each of the three fee types we examine: late payment fees, cash advance fees and over-limit fees. 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 ($\beta(X)_{i,t}$)[12]. Standard errors are clustered by account and month. Predictions are shown at covariate medians. Tables A3 to A5 report the model estimates.

Figure 2 illustrates the prediction plot for each fee type, with 95% confidence intervals shown as dashed lines. The plots show very similar patterns to those in the raw data. The likelihood of late payment fees and cash advance fees falls steeply over the first few months of account tenure, whereas the likelihood of over-limit fees grows through the first six months of tenure. Figure A2 plots predictions for the balanced panel sample, in which the decline in late and cash advance 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, presenting another incentive for card issuers to acquire new customer accounts. 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, especially if initial fees are the result of mistakes by 'good' credit types and not due to high credit risk.

[12] 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.

4 Late Payment Fees and Learning

We first explore the dynamics of late payment fees we see in the data. The decline in late payment fees over tenure observed in the pooled sample of all new accounts in Figure 2 masks important heterogeneity across account types by their mode of repayment. In particular, the tenure-profile of late payment fees differs markedly across account types by their manual vs. autopay repayment mode. In our data, 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.

4.1 Late Payment Fees and Autopay

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 the manual repayment regime, a customer receives a bill each payment cycle, either electronically or in the mail, which must be repaid manually for example by bank transfer from a different account to settle the bill, 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[13]. Autopay is setup via a one-time instruction to the credit card company. Under UK law, an autopay instruction cannot be setup on behalf of a consumer without their consent and autopay is guaranteed by the government against failure of the payments system to clear the transaction[14].

In the UK, autopay instructions are commonly used for 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. Once an autopay instruction is set up on a credit card account, at each billing cycle, *at least* the minimum amount due will be

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

[14] 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.

automatically paid from the consumer's deposit account. Consumers can choose to set higher levels of autopay, including an instruction to repay a fixed amount, a percentage of the amount due, or the amount in full. Autopay therefore removes the need for the customer to be attentive to their bill and repayment, conditional upon having sufficient funds in their deposit account. The autopay facility is available on nearly all deposit accounts in the UK and by law must be offered by all credit card issuers[15].

Figure 3 illustrates the patterns in fee decline for three account types: accounts that open with an autopay regime and remain on that regime through the first 15 months of account life (Panel A); accounts that open with a manual repayment regime and keep this regime through the first 15 months of account life (Panel B); 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)[16]. These plots are obtained by estimating Equation 1 separately for each account type[17].

The late payment fee patterns differ markedly across the panels of Figure 3. Unsurprisingly, among accounts which have an autopay instruction throughout, shown in Panel A, the probability of a late payment fee is close to zero throughout the life of these accounts as at least a fraction of the bill 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 falls to effectively 0% after the first year.

[15] An autopay facility is not available on some so-called 'basic bank accounts', a type of deposit account designed for high-risk consumers which typically offers no overdraft facility. Less than 0.5% of UK deposit accounts do not offer an autopay facility as an option to a consumer (Source: British Bankers Association).

[16] 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.

[17] We show corresponding scatter plots of fees in Figure A3. Tables A6 to A8 report the model estimates.

4.2 Switching to Autopay Following a Late Payment Fee

To analyze the relationship between late payment fees and switching repayment mode to autopay, we use an event-study analysis around the month in which an account exhibits its first late payment fee. The event-study approach allows us to focus on changes in behavior which are close to the timing of the fee. The analysis incorporates a set of time-varying card characteristics to control for the possibility that changes in repayment mode reflect changes in purchase or repayment behavior, or changes in credit risk. For example, a switch to autopay could arise due to changes in the level of repayment. We estimate the following event-study equation:

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

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

In Figure 4 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) and those that switch to autopay (Panel B)[18]. By construction, the plots show months only 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. Among accounts that switch repayment regime, shown in Panel B, fee likelihood reduces immediately in the month after incurring the first fee to 5%, and falls to effectively 0% over the following 12 months (not all accounts that switch to autopay following a late payment fee do so in the month immediately following the

[18] We show corresponding scatter plots in Figure A4. Tables A9 and A10 report the model estimates.

first fee event). 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, we re-estimate the event study equation replacing the distance variable with distance in time from the first autopay payment. Figure 5 plots the predicted probability of incurring a late payment fee, where the x-axis is event time since the first autopay payment[19]. 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 5%, this spikes to 22% in the month before the switch. Following the setup of an autopay instruction, the likelihood of a late payment fee falls to effectively 0%.

The patterns shown so far illustrate that the decline in late payment fees over tenure is due to a subset of customers changing their repayment behavior, learning from a late payment fee that they should change their mode of repayment. The sharp decline in subsequent fees also strongly suggests that the late payment fees incurred by these customers were most 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 customers switching to autopay reflects a decision to insure themselves against future forgetting.

This raises the question of why some card holders switch to autopay after incurring a fee while others do not. The differences in subsequent fees between switches and non-switchers are substantial. Among non-switchers the fee probability persisting at 20% per month implies in expectation 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 with switching accounts. While these direct fee costs are moderate, this is an underestimate of the total difference in the economic costs of fees as these calculations reflect only the direct costs and do not measure indirect costs of credit markers on credit files.

[19] We show the corresponding scatter plots in Figure A5. Table A11 reports the model estimates.

4.3 Switchers and non-Switchers

Why do some consumers switch to autopay while others do not? In Table 3 we compare the average characteristics of switchers to autopay and non-switchers. We compare account characteristics using information from the Argus data and also match data on consumer characteristics using geocodes. This allows us to understand more about differences across the groups which might drive their different responses to a late payment fee. 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 records from the UK National Census for 2011[20].

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. 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.

Alternatively, consumers might not switch to autopay if they are financially constrained. A switch to autopay removes the opportunity for the customer to strategically not pay, or delay payment. 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 larger repayments each month compared to switchers.

When we compare the groups by their consumer characteristics, non-switchers appear less sophisticated compared to switchers. Consumers who switch to autopay are

[20] 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.

drawn from localities with higher median house prices, lower jobless claimants, higher weekly incomes, higher proportions of individuals in the locality with post-high school educational qualifications and a lower proportion of children in the locality entitled to free school meals. They also have lower ACORN scores, a postcode-level affluence score constructed by the UK statistics authority, indicating a higher degree of affluence. 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 strongly suggest that, in response to a late payment fee more sophisticated consumers 'learn', switching 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 this is much less effective in avoiding future fees.

5 Cash Advances, Over-Limit Fees and Liquidity Needs

Cash advance fees show a similar decline over account tenure as that seen for late payment fees. One explanation for this pattern is that cash advance fees might also decline due to learning dynamics – consumers might be initially unaware that using their credit card to finance cash withdrawal incurs an additional fee, and also incurs a higher interest rate, applicable to cash balances from the point of withdrawal with no within-cycle grace period. 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.

In this section, we show that the decline in cash advance fees over tenure is unlikely to be explained by consumers learning from unintended mistakes. Instead, our analysis indicates the decline is due to the time-varying liquidity needs of consumers, which focus around the point of card opening. We also show patterns in account behavior around the timing of over-limit fees which suggest that this fee type is also incurred on average during periods in which consumers are liquidity constrained.

5.1 Cash Advances, Risk and Utilization

We first show that the decline in cash advance fees with tenure is not uniform across all accounts. The pattern of initially high fee rates followed by a sharp decline is seen only among accounts which open with high initial rates of charge-off probability. This is the probability that the account charges-off within the next six months. The probability 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 the dependent variable is a dummy variable indicating whether the account-month incurred a cash advance fee for accounts with high and low probability of charge-off (split at the median)[21]. 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 like.

These patterns reflect the concentration of cash advance fees among higher risk accounts, with the riskiest 10% of accounts incurring 38% of all cash advance fees in our sample. The concentration of cash advance fees at account opening among higher risk accounts does not rule out the possibility that learning from unintended mistakes might explain the pattern of decline in cash advance fees over tenure. Higher risk accounts might reflect a greater propensity to committing mistakes among a subset of customers (whose worse risk profile might be attributable to past mistakes).

However, we also find that the propensity of accounts to incur cash advance fees increases with their non-cash utilization and occurs during periods of upswings in the level of purchases, consistent with consumers facing liquidity constraints. We show patterns in card usage for non-cash purchases and repayments during spells of accounts incurring cash advance fees. Figure 7 shows the average balance among accounts in the months before,

[21] The corresponding scatter plots of fees over tenure for each group are shown in Figure A6. Tables A12 and A13 report the model estimates.

during and after the account first incurs a cash advance fee. Each account contributes to one of the panels in the figure, depending on the number of consecutive cash advance fees in the first spell of the account's history in which a cash advance is incurred[22]. 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 spells of cash advances. The panels illustrate that most spells of cash advances show large average increases in purchases in the month in which the spell of cash advances begins. Purchases tend downwards through the spell of cash advances due to binding credit limits.

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 consumer is more likely to be liquidity constrained. This pattern is 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. This behavior among accounts in our sample 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. In contrast, we show that cash advance fees are incurred during periods in which consumers appear liquidity constrained.

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

5.2 Over-Limit Fees, Purchases and Repayments

Our earlier analysis showed that over-limit fees initially increase with tenure during the first few months of card life, again in contrast with Agarwal et al. (2013), who find that over-limit fees peak at the first month of card opening. These differences potentially reflect differences in credit card samples. It is possible that particularly high-risk customers might be offered accounts with initially low credit limits as credit card companies seek to limit their exposure to the riskiest customers, or such customers may be more likely to initially misunderstand credit card terms. This is not a pattern we observe, however, in our data as 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 A9). The pattern in fees over tenure in our data suggest 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.

However, we do observe sharp responses to fees incurred among accounts, which we investigate in this section. We examine how consumers respond to the first over-limit fee they incur. To do so, we estimate Equation 2 for over-limit fees and illustrate the predicted probability plots in Panel A of Figure 10[23]. 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[24].

In subsequent panels of Figure 10 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

[23] The corresponding scatter plots of fees over tenure for each group are shown in Figure A7. Tables A14 to A16 report the model estimates.

[24] Figure A8 shows that, by tenure, among accounts which incur an over-limit fee the likelihood of subsequent fees in the following months declines sharply.

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. This suggests that over-limit fees are incurred during periods in which the consumer is liquidity constrained.

Finally, in Figure 11 we illustrate patterns in purchases and also cash advances around the last over-limit fee incurred in our sample period for each account[25]. Here we see that the last fee incurred is associated with a similar pattern in purchases: a spike in the month of the over-limit fee followed by a permanent step down in purchase volume over subsequent months. This pattern closely resembles that seen around the first over-limit fee, suggesting that the same dynamics of purchase behavior are at work, which would be very unlikely if the consumer learned to change their behavior after the first fee. In Panel B of the figure we also see that cash advances peak at the month of last over-limit fee and decline afterwards, again consistent with liquidity constraints driving fee behavior.

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 rate of late payment and cash advance fees peaks in the first month of account life, then declines sharply. We investigate whether this decline is due to consumers learning to avoid fees, or due to time-varying liquidity needs which focus around the point of account opening.

We find a pattern of uneven learning across consumers in response to late payment fees. All of the decline in late payment fees over account tenure is due to some consumers who switch from manual repayment to automatic repayment following the incursion of a late payment fee. Among non-switchers, the rate of late payment fees remains persistently high. That is, without using automatic repayment, late payment fees do not help card holders learn to repay their bill on time. Our results indicate that switchers who 'learn' in response to late payment fees are more sophisticated (with higher income and education)

[25] Tables A17 and A18 report the model estimates.

compared to the non-switchers who do not ‘learn’.

By contrast, our analysis of cash advance and over-limit fees shows that these fees are associated with time-varying liquidity needs on the part of consumers, which are concentrated at the point of account opening. Fees are more common among accounts that have higher risk profiles at the point of opening. Cash advance fees correlate with non-cash purchases and high utilization; over-limit fees correlate with purchase spikes and spells of cash advance fees. These patterns indicate that consumers incur these fees when they are liquidity constrained.

Our findings have two important implications for understanding how consumer learn in financial markets. First, the uneven pattern of learning across individuals implies that learning involves redistribution from more sophisticated to less sophisticated consumers through the pricing of credit agreements. It also suggests that sophisticated consumers may benefit more from technological innovation in payments technology, such as automatic repayment, while less sophisticated consumers may fail to realize the benefits of these new technologies.

Second, our results emphasize that not all patterns which resemble ‘learning’ in fee payments are necessarily the result of mistakes and corrective responses on the part of consumers. Traditional economic mechanisms associated with payments of contingent fees and charges, such as time-varying liquidity needs, can generate similar overall patterns from very different underlying mechanisms.

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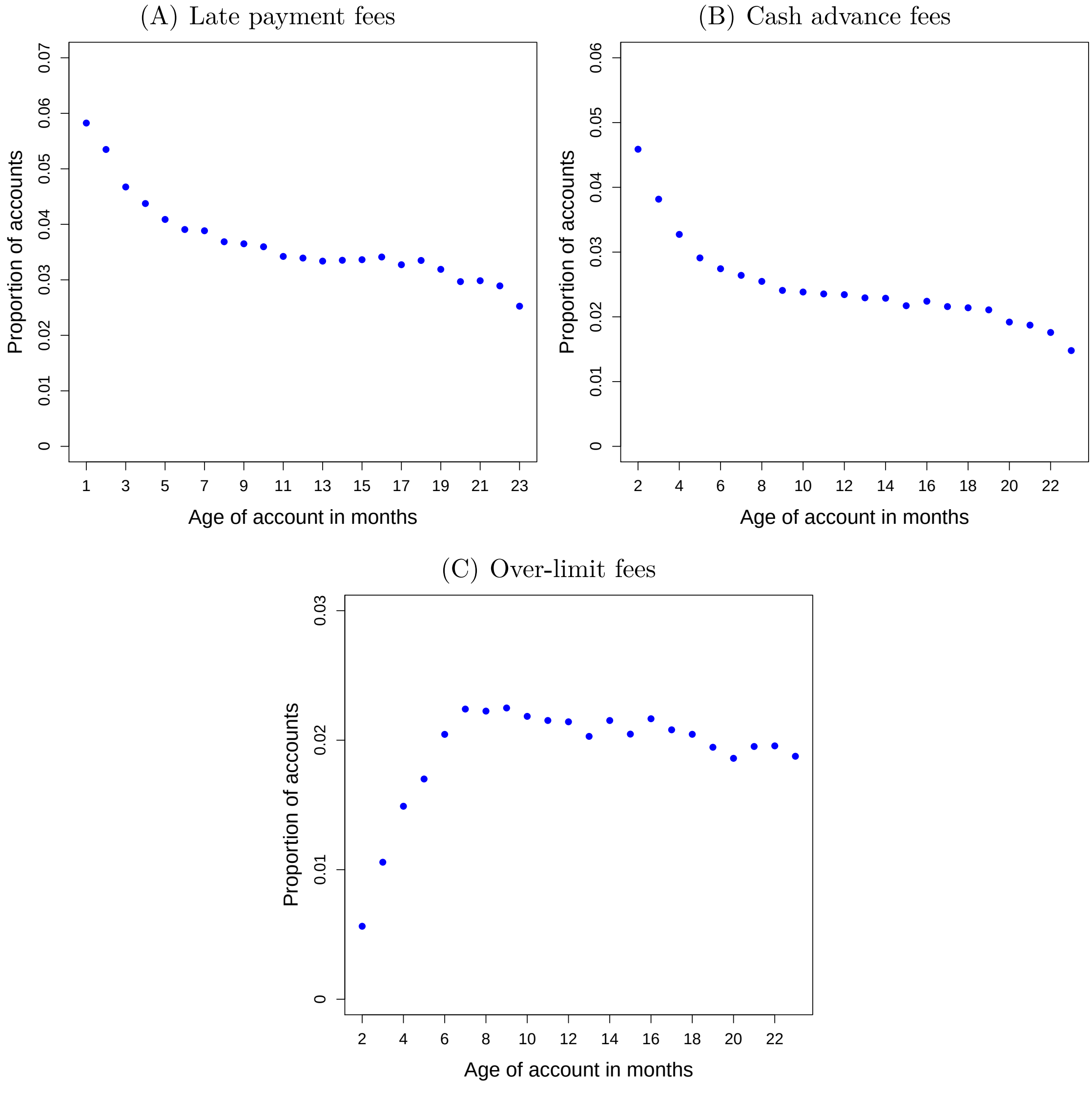
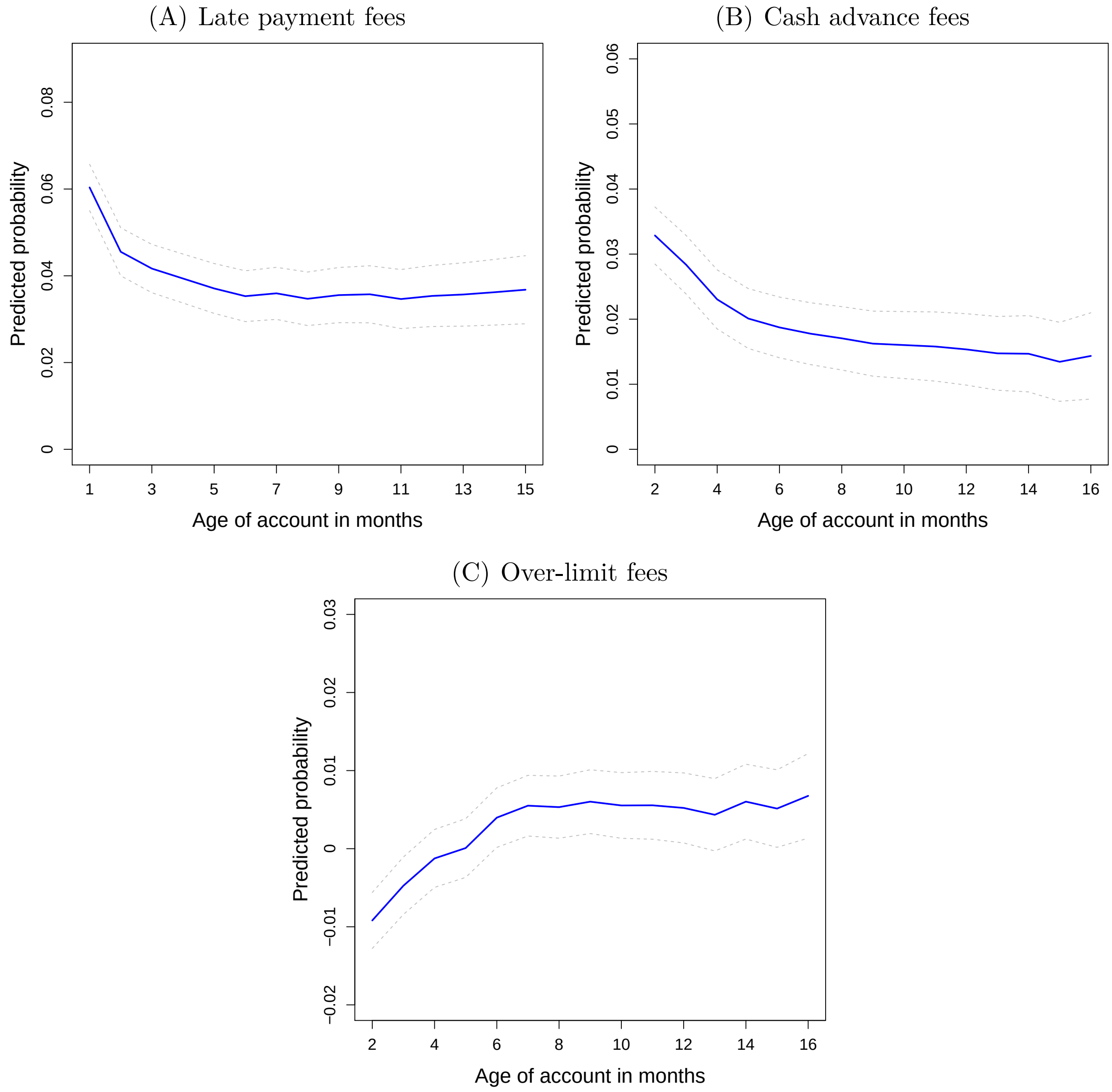
Figure 1: Proportion of credit cards incurring fees by account tenure



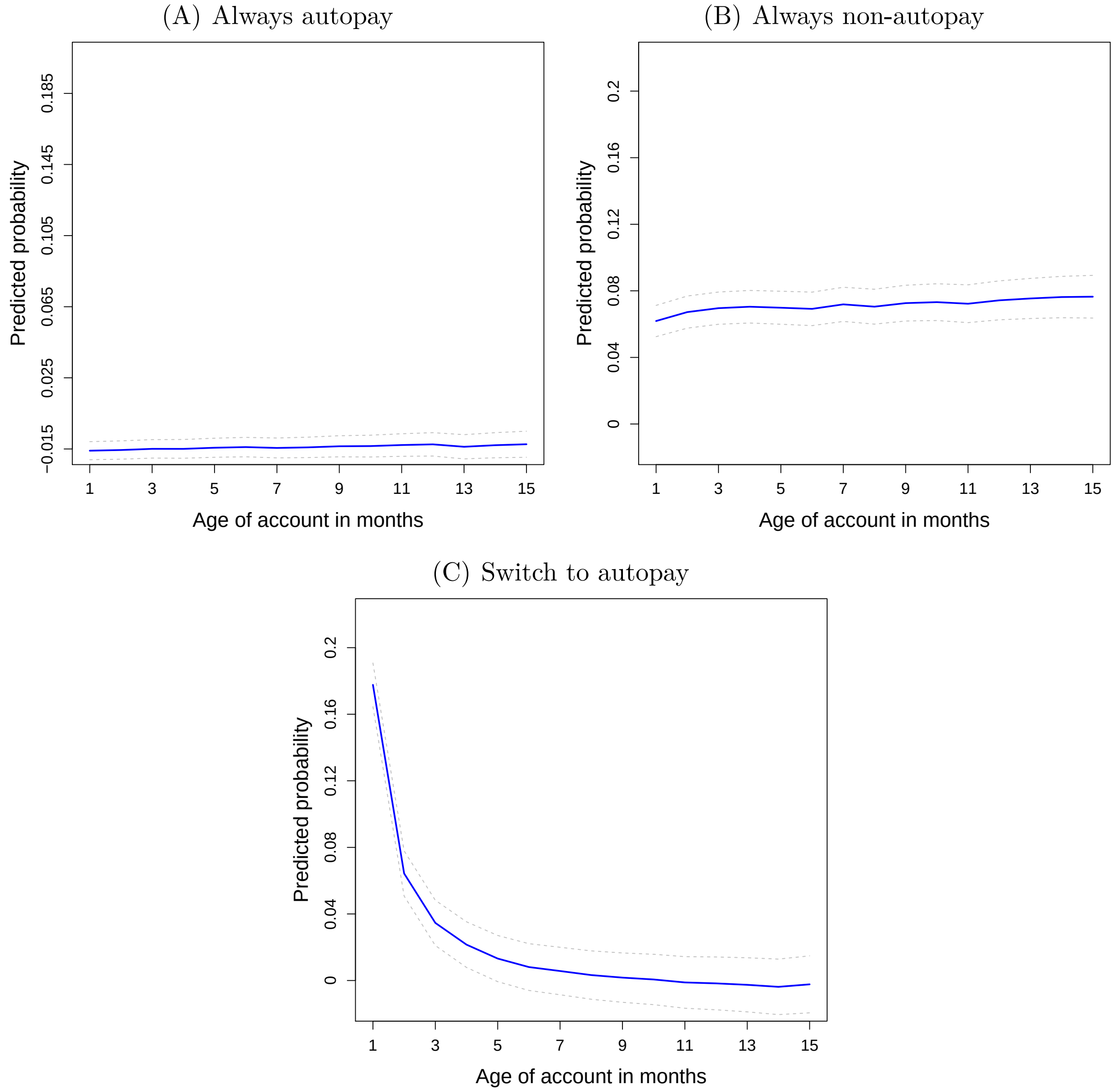
Note: Panels plot the mean of the y-axis variable (dummy variable indicating whether the account incurred a fee) by units of the x-axis variable (age of the account in months). In Panel A the x-axis variable is adjusted one month forward as late payment fees are incurred in the next account cycle, the cycle in which payment is due. The sample comprises all accounts opened at or after January 2013.

Figure 2: Predicted probability of credit cards incurring fees by account tenure



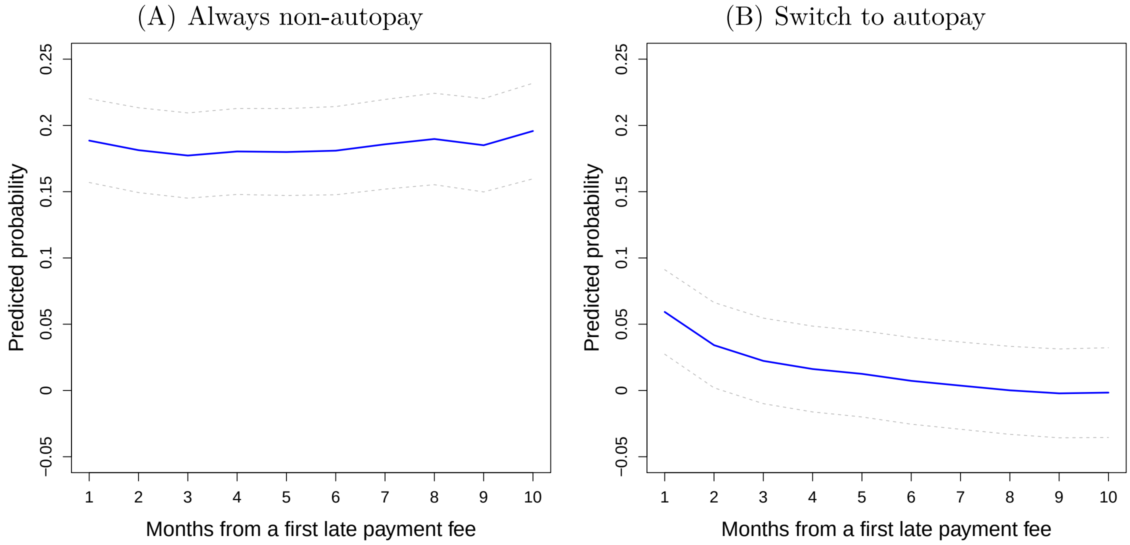
Note: Panels plot the predicted probability of an account incurring a fee within the month based on estimates of (Equation 1). Predictions are from a linear probability model with at covariate medians with clustered standard errors at account and month. Full model estimates are reported in Tables A3 to A5. 95% confidence intervals are illustrated by dashed lines.

Figure 3: Predicted probability of late payment fees by repayment mode



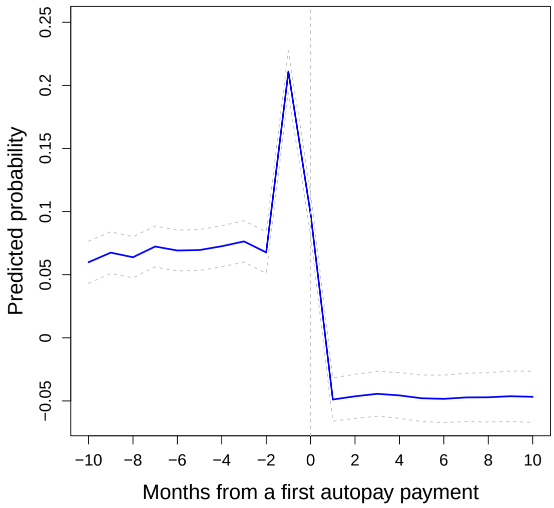
Note: Figure plots the predicted probability of accounts incurring a late payment fee in the next period by the age of the account. Predictions are from a linear probability model at covariates medians (Equation 1). The panels show three mutually exclusive groups: accounts which were always subject to an autopay instruction throughout the sample period; 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. 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 A6 to A8 report the model estimates.

Figure 4: Predicted probability of late payment fee after first fee by autopay status



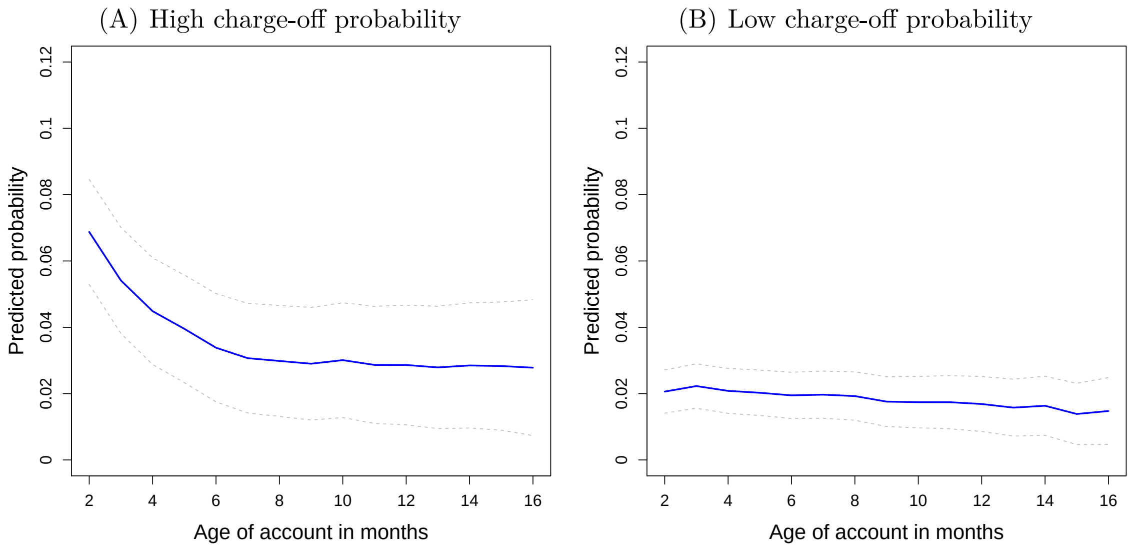
Note: Figure plots the predicted probability of accounts incurring a late payment fee in months after the first late payment fee is incurred. Predictions are from a linear probability model at covariates medians (Equation 2). The panels show two mutually exclusive groups: accounts which were never subject to an autopay instruction throughout the sample period; and accounts which switched from manual to autopay within the sample period. By construction, 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 A9 and A10 report the model estimates.

Figure 5: Predicted probability of late payment fee before and after switch to autopay



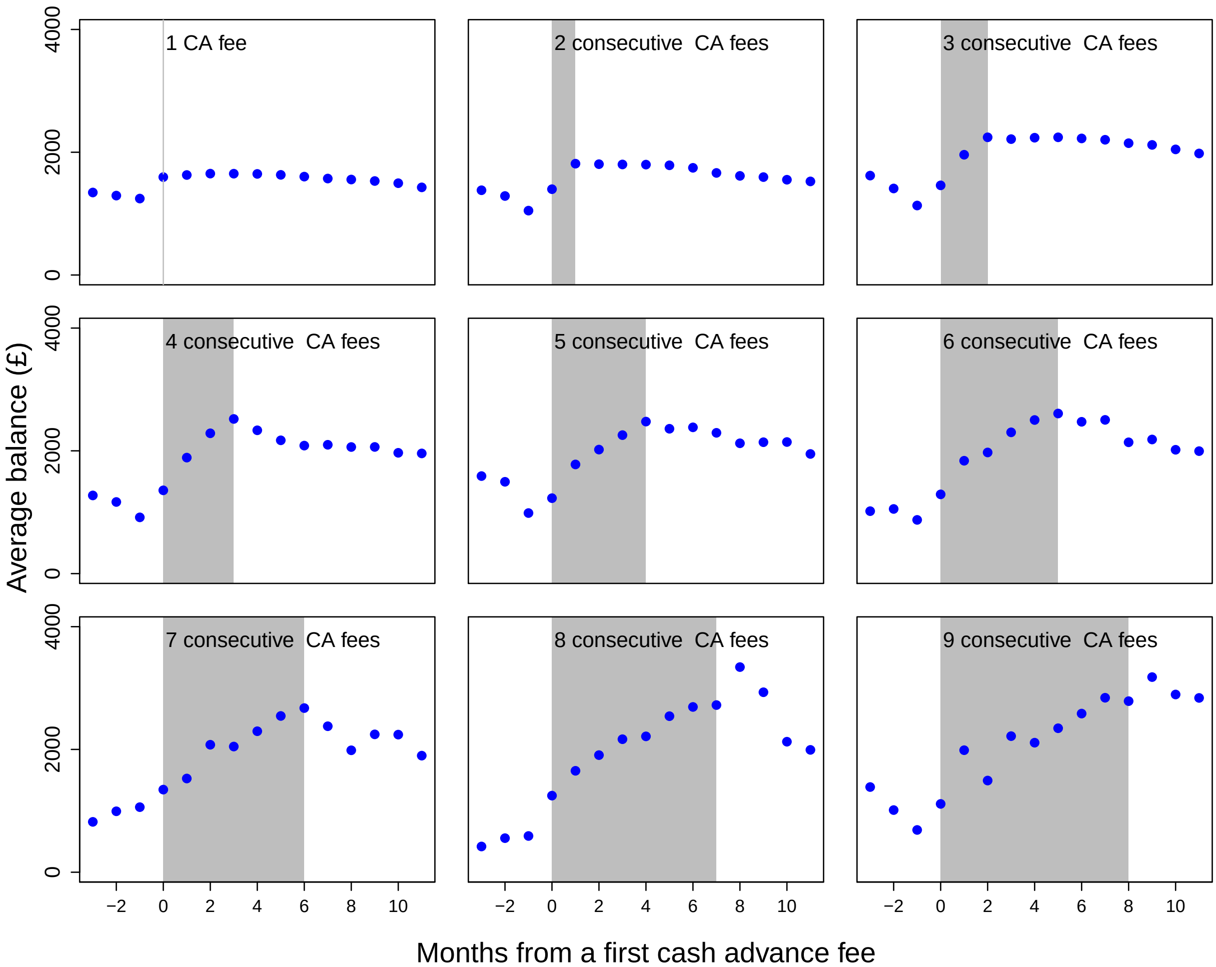
Note: Figure plots the predicted probability of accounts incurring a late payment fee in months after the first late payment fee is incurred. Predictions are from a linear probability model at covariates medians. 95% confidence intervals are illustrated by the dashed lines. The corresponding scatter plot of fees shown in Figure A5. Table A11 reports the model estimates.

Figure 6: Predicted probability of cash advance fees by tenure, high/low risk accounts



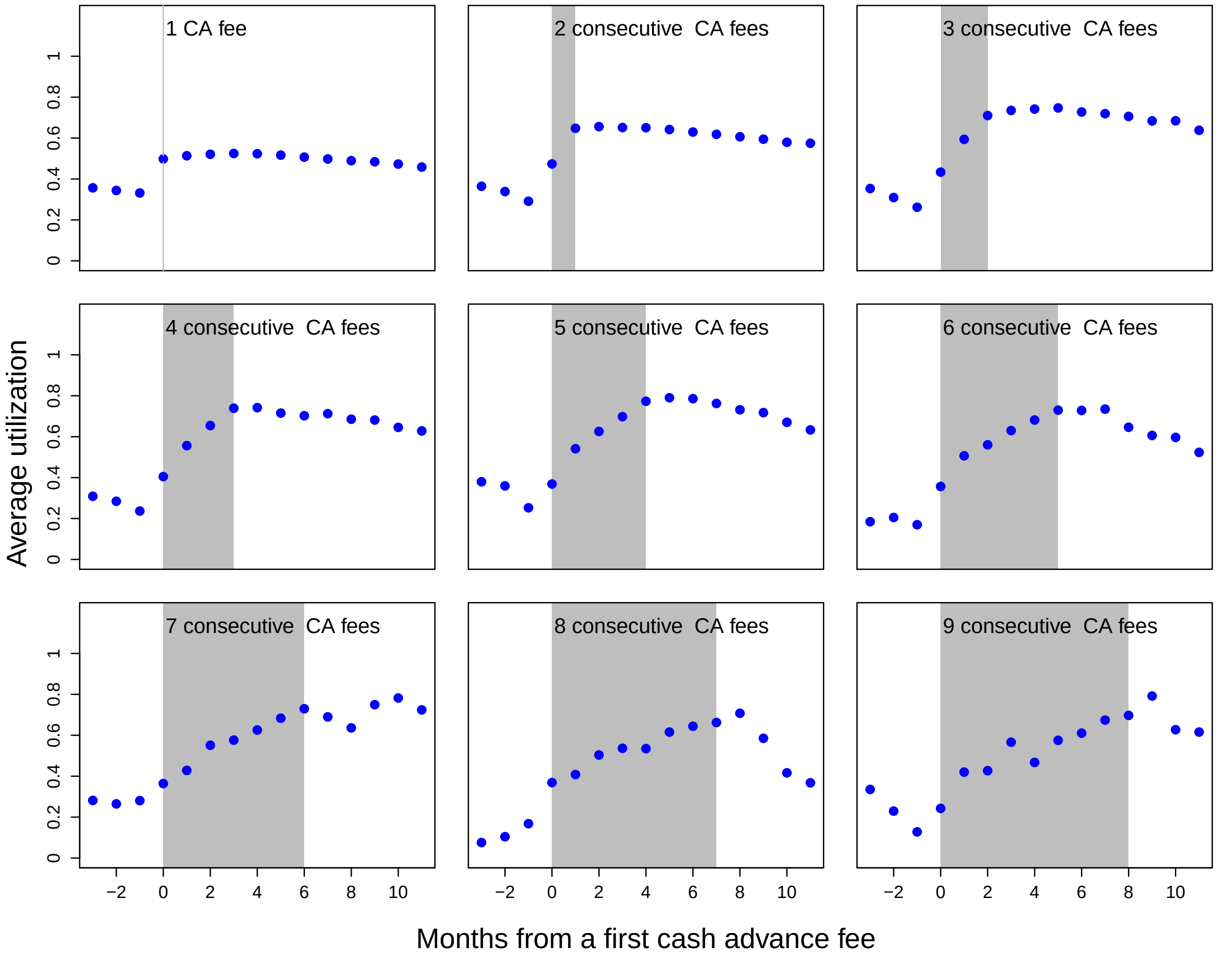
Note: Figure plots the predicted probability of accounts incurring a cash advance fee by age of account. Predictions are from a linear probability model at covariates medians (Equation 1). The panels show plots from models estimated separately for accounts with high and low probability of charge-off 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 A6. Tables A12 to A13 report the model estimates.

Figure 7: Average card balances through spells of cash advance (CA) fees



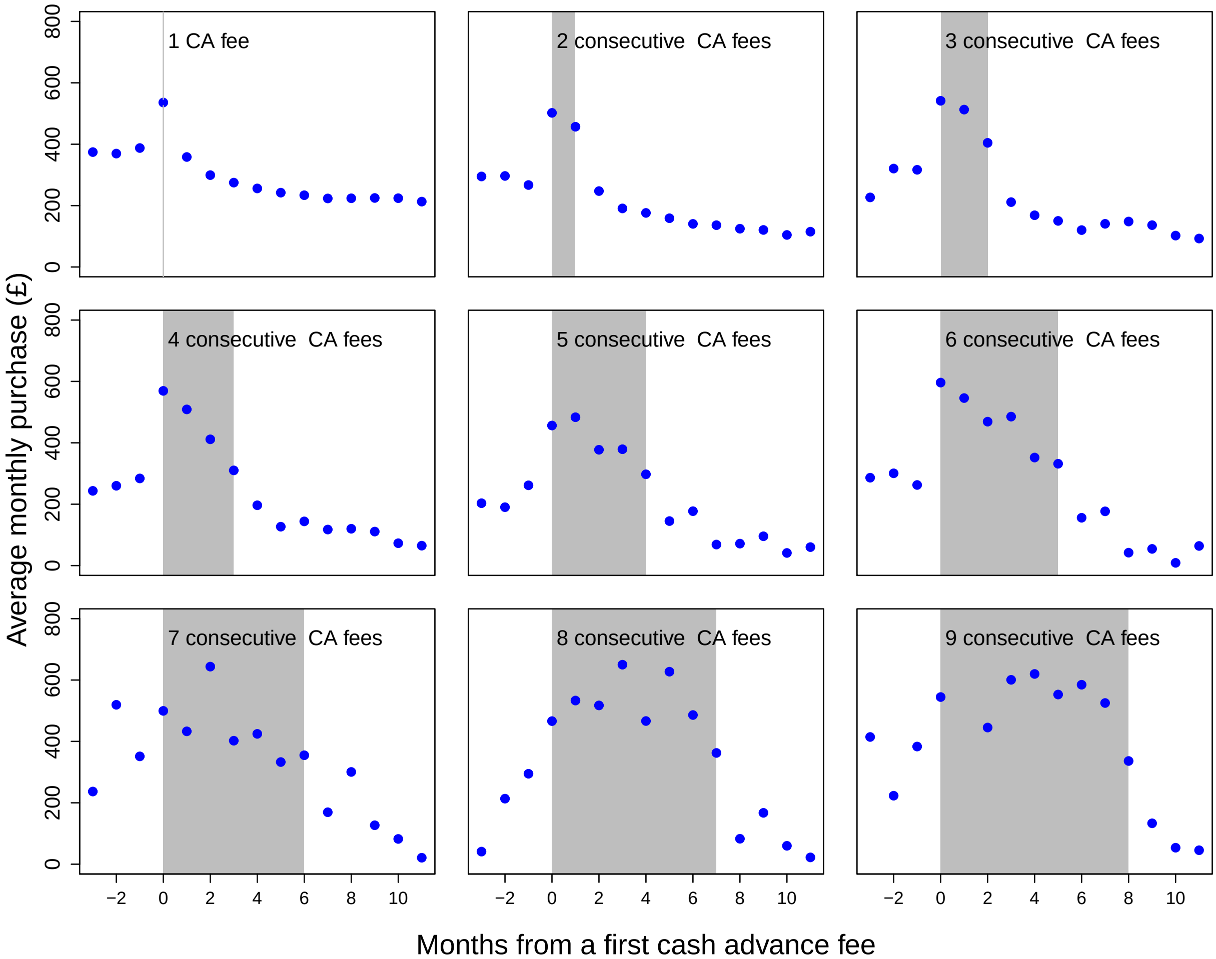
Note: Figure plots average credit balances for accounts by length of spell of consecutive months with at least one cash advance recorded on the account, from two months before the first cash advance on the account through 10 months after.

Figure 8: Average card utilization through spells of cash advances (CA) fees



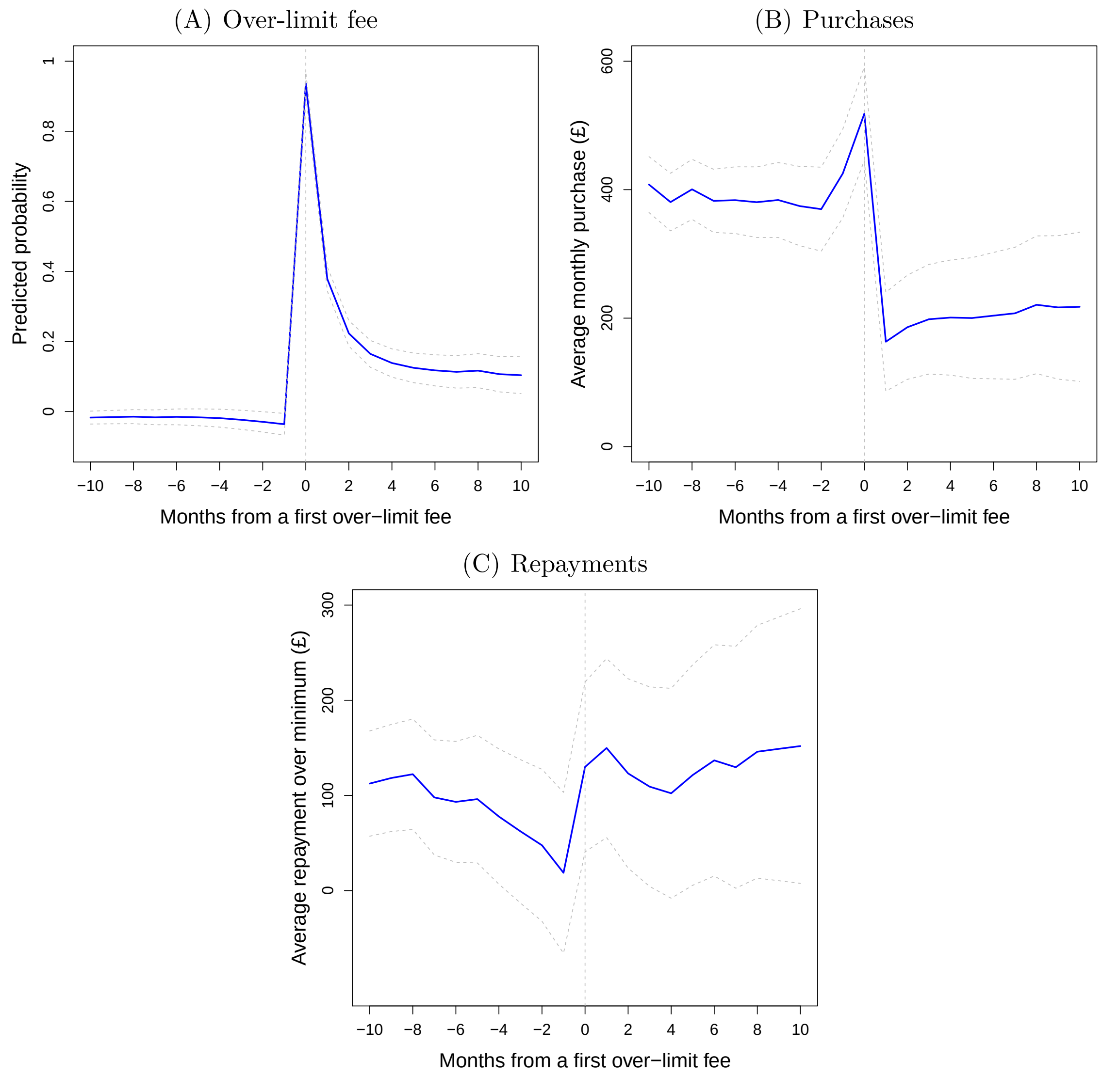
Note: Figure plots average utilization for accounts by length of spell of consecutive months with at least one cash advance recorded on the account, from two months before the first cash advance on the account through 10 months after.

Figure 9: Average card purchases through spells of cash advances (CA) fees



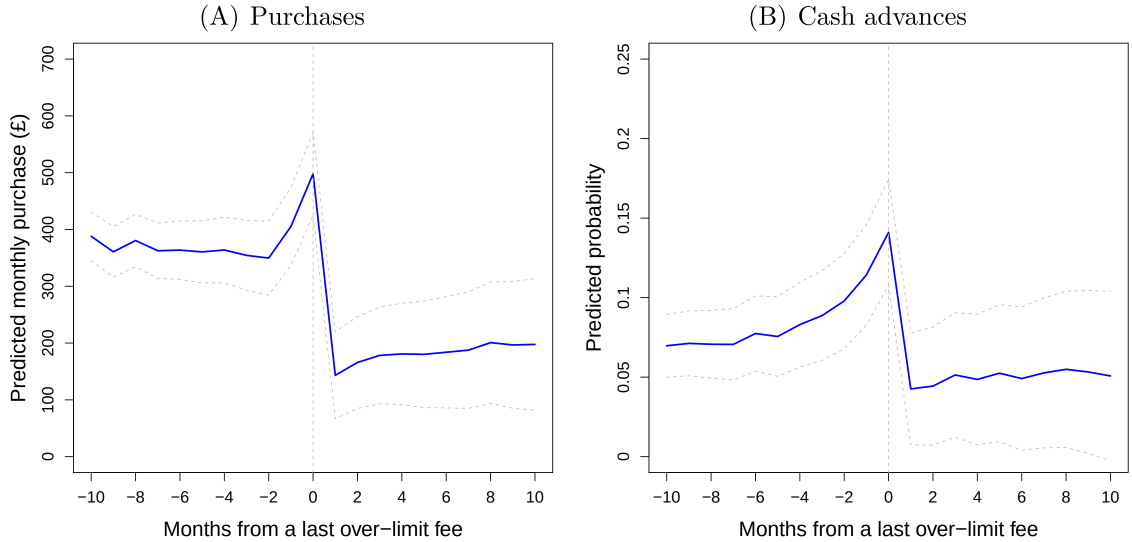
Note: Figure plots average purchase value for accounts by length of spell of consecutive months with at least one cash advance recorded on the account, from two months before the first cash advance on the account through 10 months after.

Figure 10: Predicted fees, purchases and repayments around first over-limit (OL) fee



Note: Figure plots the predicted probability of accounts incurring an over-limit in months after the over-limit fee is incurred (Panel A) and predicted average values of purchases and repayments in months before and after (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 of fees over tenure for each group are shown in Figure A7. Tables A14 to A16 report the model estimates.

Figure 11: Predicted purchases and cash advance fees around last over-limit (OL) fee



Note: Figure plots the predicted average values of purchases and cash advances in months before and after the final over-limit fee incurred on the account during the sample period. 95% confidence intervals are illustrated by the dashed lines. Tables A17 to A18 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 (%)	Average fee (£)
Any fee	33.63	8.99
Late payment fee	24.17	4.33
Cash advance fee	13.05	2.59
Over-limit fee	7.26	2.06

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

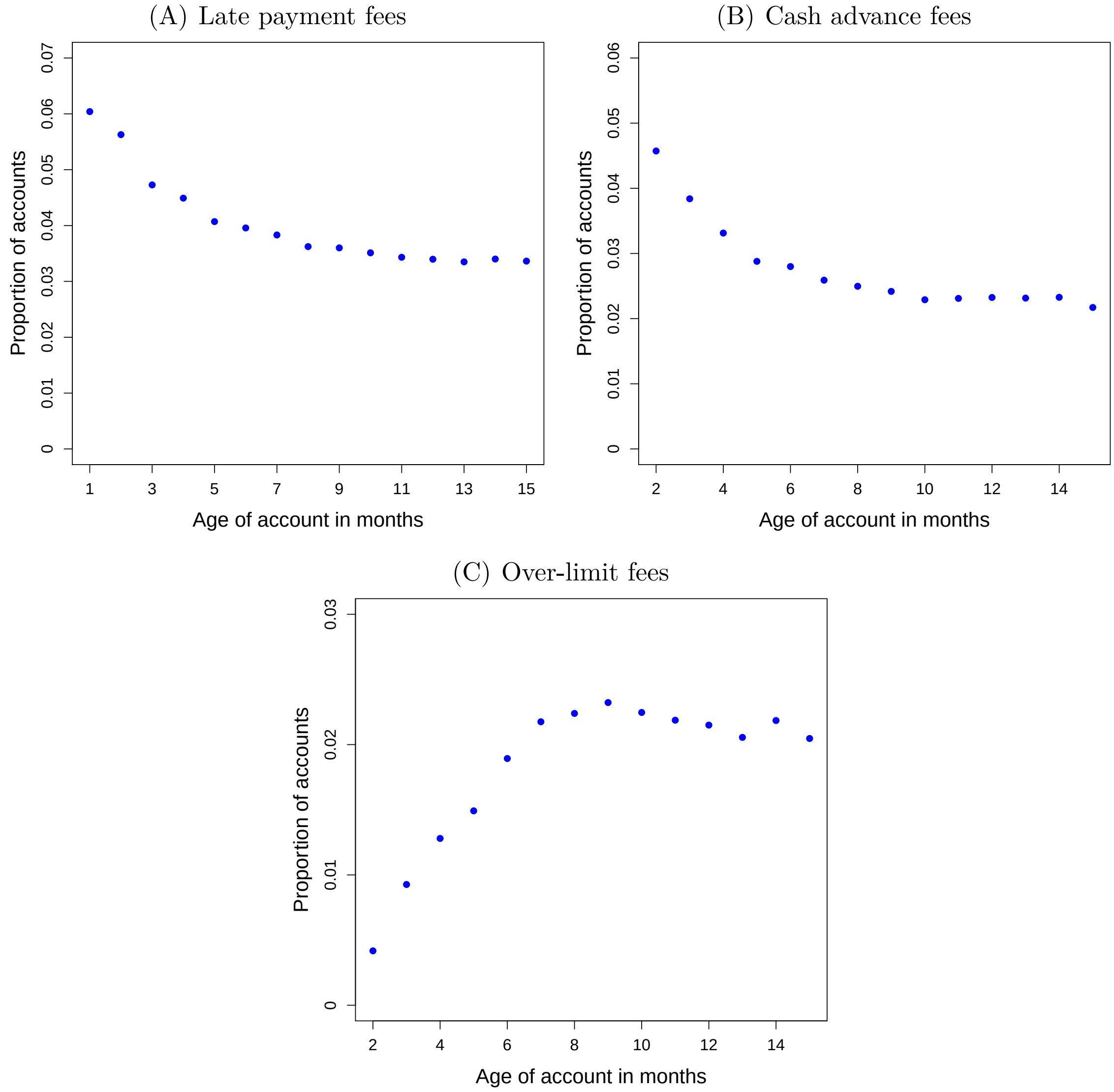
Table 3: Matched card and socio-economic characteristics: autopay switchers and non-switchers

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.

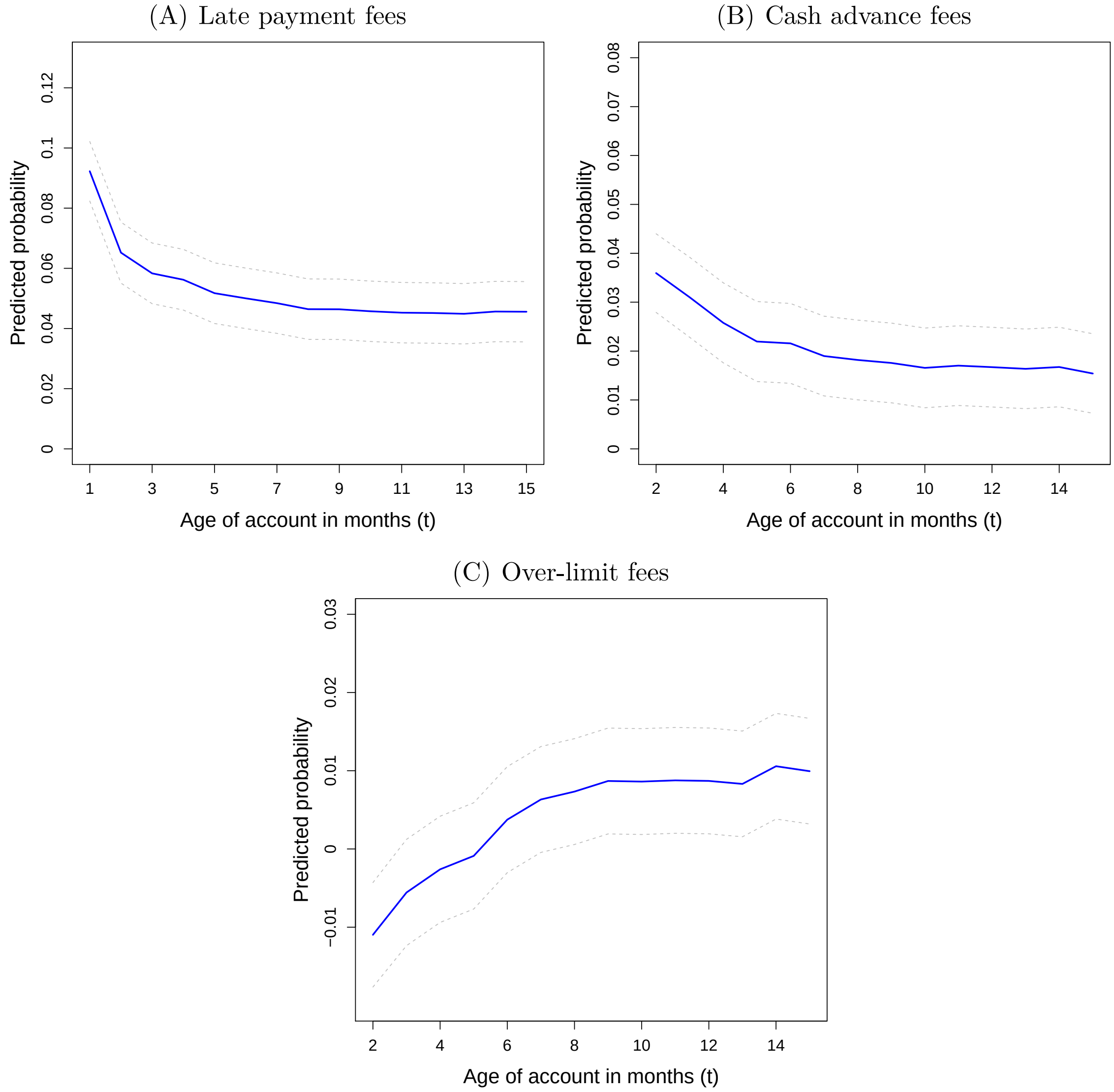
Appendix

Figure A1: Proportion of credit cards incurring fees by account tenure, balanced panel



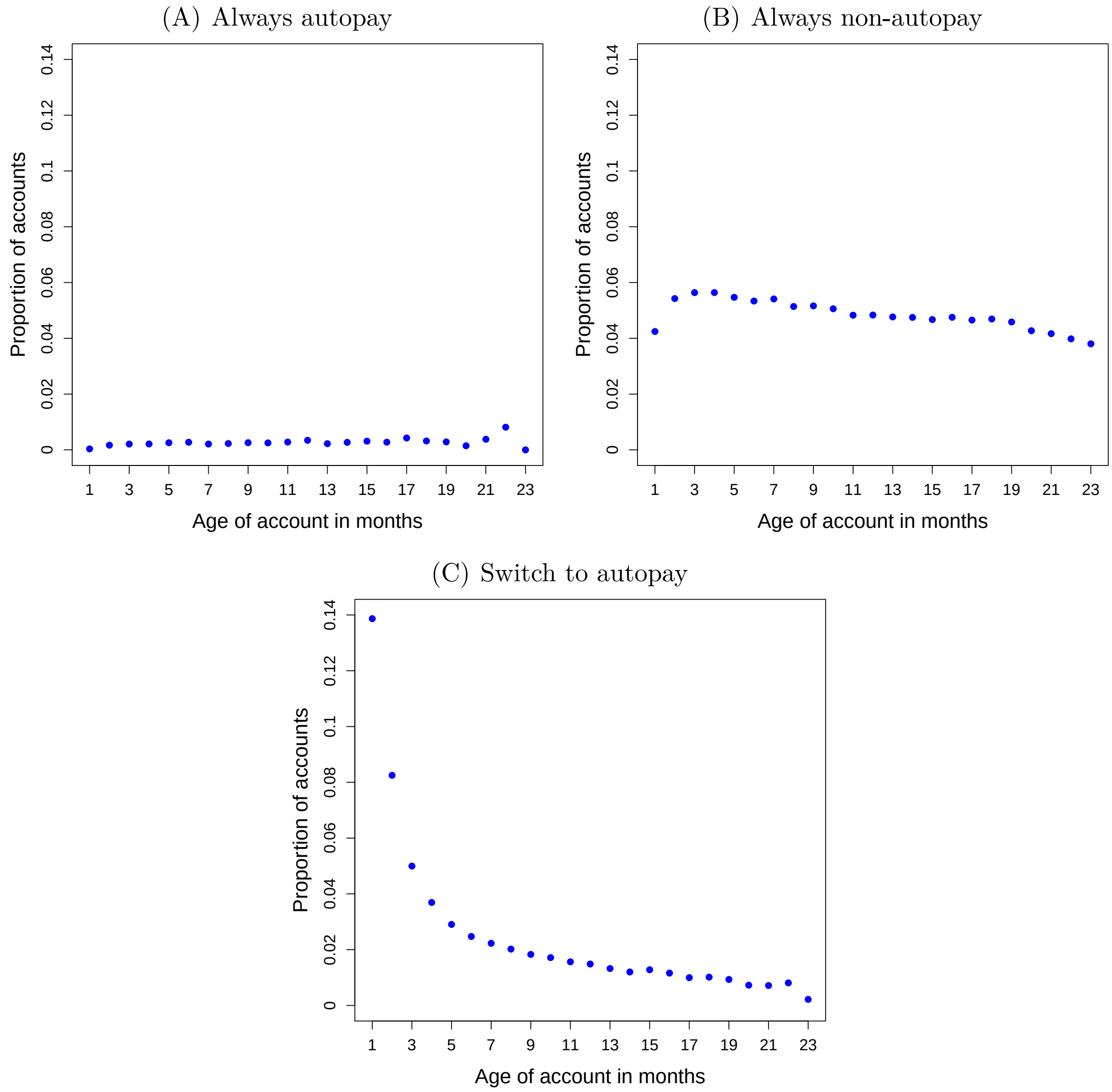
Note: Figure reproduces the plots in Figure 1 when the data is restricted to a balanced panel of accounts which open within the sample period and remain open for 15 months. Panels plot the mean of the y-axis variable (dummy variable indicating whether the account incurred a fee) by units of the x-axis variable (age of the account in months). In Panel A 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.

Figure A2: Predicted probability of credit cards incurring fees by account tenure, balanced panel



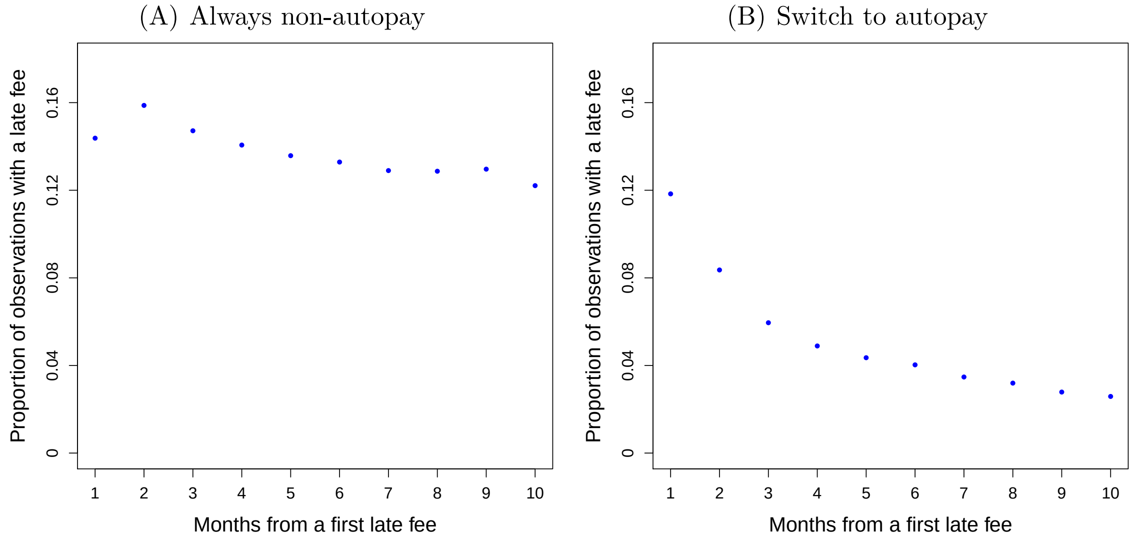
Note: Figure reproduces the plots in Figure 2 when the data is restricted to a balanced panel of accounts which open within the sample period and remain open for 15 months. 95% confidence intervals are illustrated by the dashed lines.

Figure A3: Incidence of late payment fees among accounts, by autopay status



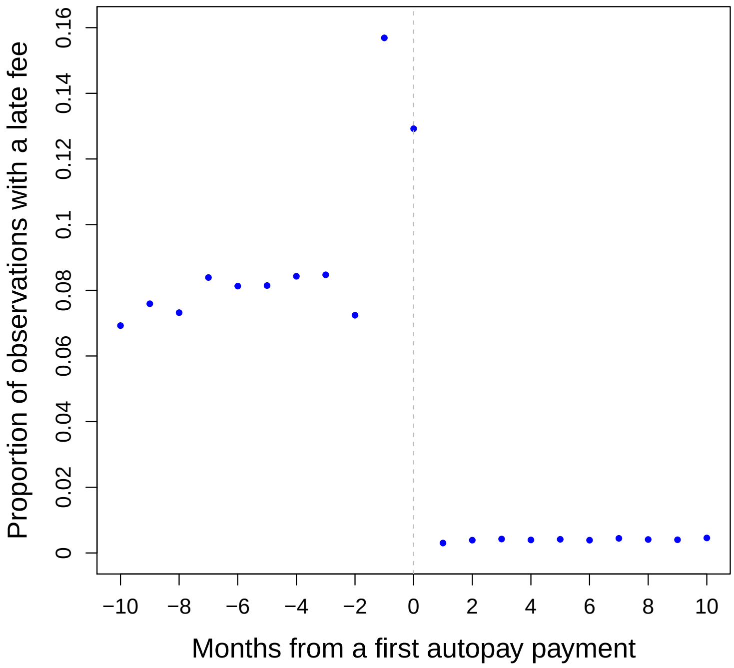
Note: Figure plots the proportion of accounts incurring a late payment fee in the next period by age of account. The panels show three mutually exclusive groups: accounts which were always subject to an autopay instruction throughout the sample period; accounts which were never subject to an autopay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

Figure A4: Incidence of late payment fees in months following a first fee, by autopay status



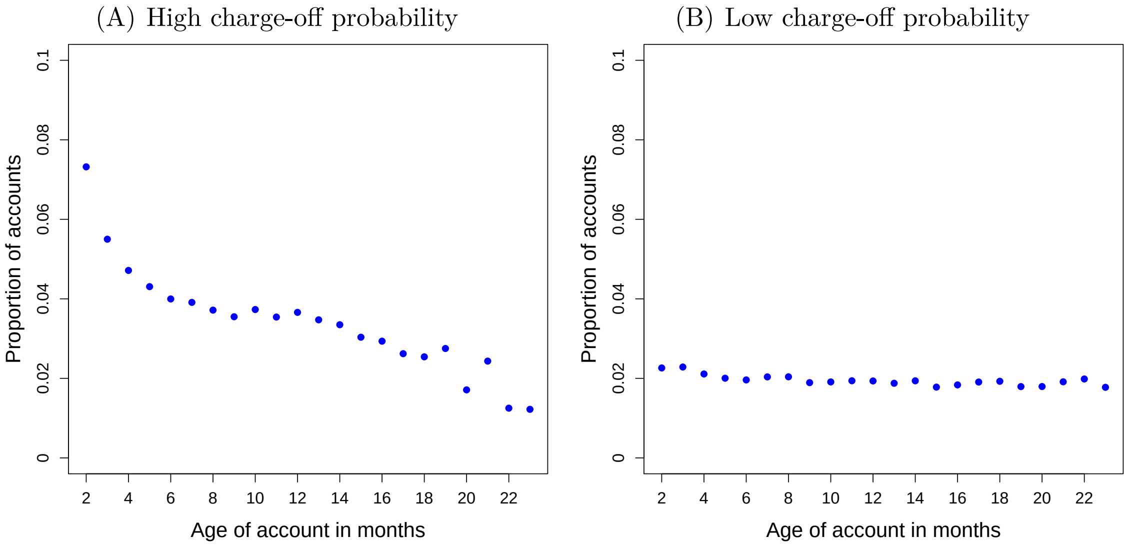
Note: Figures plot the proportion of accounts incurring a late payment fee in months after the first late payment fee incurred. The panels show two mutually exclusive groups: accounts which were never subject to an autopay instruction throughout the sample period; and accounts which switched from manual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

Figure A5: Incidence of late payment fees in months before and after switch to autopay



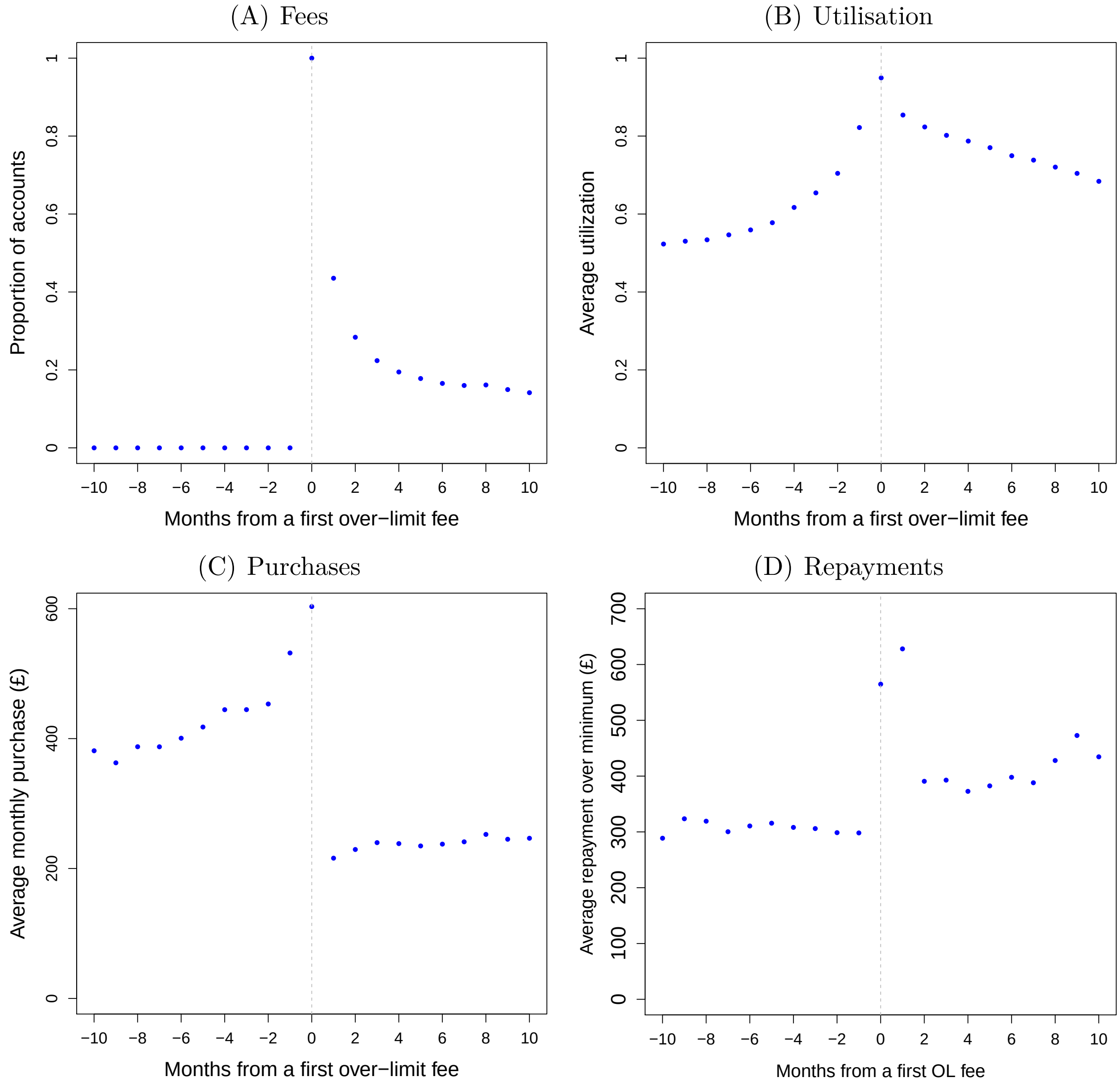
Note: Figure plots the proportion of accounts incurring a late payment fee in months before and safer the account switches to autopay.

Figure A6: Proportion of accounts with cash advance fees by tenure, high/low charge-off probability accounts



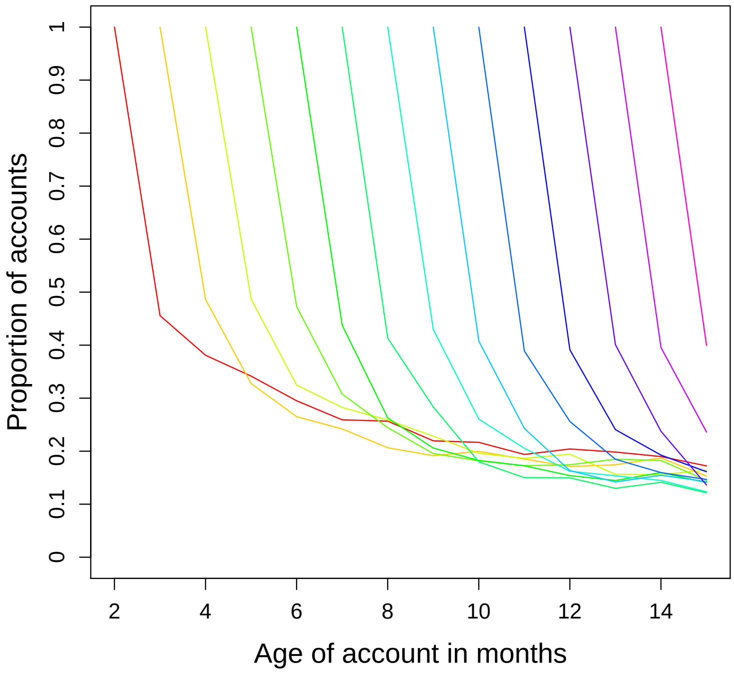
Note: Figure plots the proportion of accounts incurring a cash advance fee by age of account. The panels show plots from models estimated separately for accounts with high and low probability of charge-off at account opening (median split).

Figure A7: Purchases, repayments and utilization in months following first over-limit fee



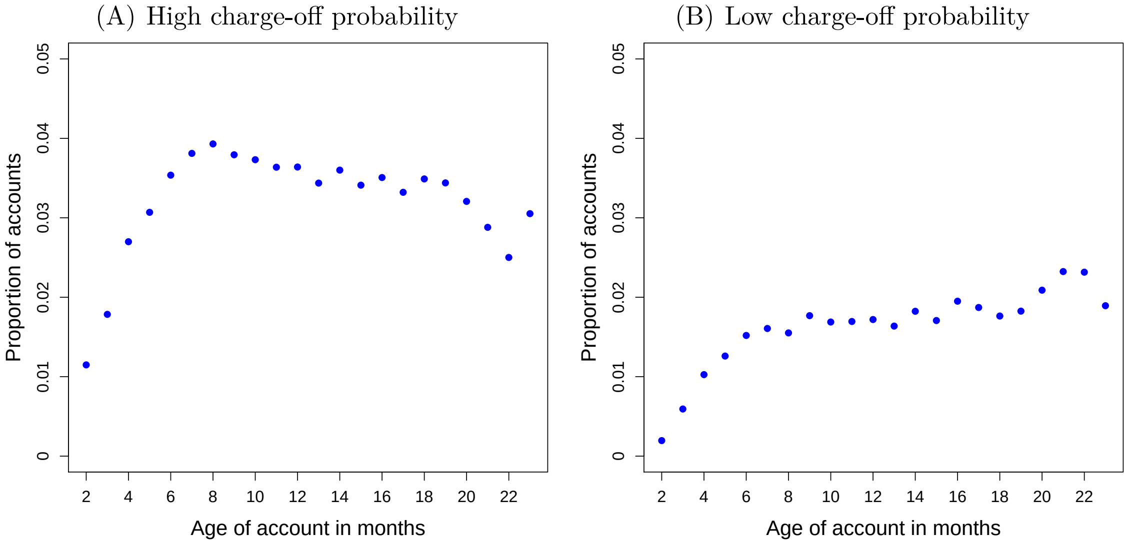
Note: Figures plot in Panel A average purchases (in £), in Panel B average repayment (in £) and in Panel C average utilization (balance expressed as a fraction of the credit limit) by number of months since the account first incurred an over-limit fee.

Figure A8: 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 months from first over-limit fee, for accounts incurring first overlimit fee at different tenures.

Figure A9: 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 (%)	Average fee (£)
Any fee	41.76	12.13
Late payment fee	30.65	6.02
Cash advance fee	15.73	3.19
Over-limit fee	10.01	2.92

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	0.004	-4.230	0.000
Tenure 3	-0.019	0.004	-5.213	0.000
Tenure 4	-0.021	0.004	-5.908	0.000
Tenure 5	-0.023	0.004	-6.463	0.000
Tenure 6	-0.025	0.003	-7.168	0.000
Tenure 7	-0.024	0.003	-7.353	0.000
Tenure 8	-0.026	0.004	-7.074	0.000
Tenure 9	-0.025	0.004	-6.840	0.000
Tenure 10	-0.025	0.004	-6.558	0.000
Tenure 11	-0.026	0.004	-6.826	0.000
Tenure 12	-0.025	0.004	-6.635	0.000
Tenure 13	-0.025	0.004	-6.109	0.000
Tenure 14	-0.024	0.004	-5.746	0.000
Tenure 15	-0.024	0.004	-5.778	0.000
Tenure 16+	-0.022	0.005	-4.901	0.000
Balance^3	0.000	0.000	-0.454	0.650
Balance^2	0.000	0.000	0.969	0.333
Balance	0.000	0.000	-7.533	0.000
Credit Limit^3	0.000	0.000	5.667	0.000
Credit Limit^2	0.000	0.000	-7.486	0.000
Credit Limit	0.000	0.000	8.613	0.000
Utilization^3	0.000	0.000	-5.361	0.000
Utilization^2	-0.007	0.002	-3.843	0.000
Utilization	0.047	0.005	9.865	0.000
Charge-off Rate^3	-1.304	0.460	-2.836	0.005
Charge-off Rate^2	1.202	0.540	2.226	0.026
Charge-off Rate	-0.119	0.196	-0.606	0.544
Monthly Purchase^3	0.000	0.000	-2.487	0.013
Monthly Purchase^2	0.000	0.000	2.188	0.029
Monthly Purchase	0.000	0.000	-1.341	0.180
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 and month. The baseline for the tenure dummies is Tenure 1. Prediction plot from the model is illustrated in Figure 2, Panel A.

Table A4: Fixed effects OLS estimates of Equation 1, cash fees

	β	S.E.	t-value	p-value
Tenure 3	-0.004	0.001	-4.936	0.000
Tenure 4	-0.010	0.001	-11.761	0.000
Tenure 5	-0.013	0.001	-13.761	0.000
Tenure 6	-0.014	0.001	-12.529	0.000
Tenure 7	-0.015	0.001	-12.629	0.000
Tenure 8	-0.016	0.001	-12.409	0.000
Tenure 9	-0.017	0.001	-12.255	0.000
Tenure 10	-0.017	0.001	-12.091	0.000
Tenure 11	-0.017	0.002	-10.545	0.000
Tenure 12	-0.018	0.002	-10.494	0.000
Tenure 13	-0.018	0.002	-10.209	0.000
Tenure 14	-0.018	0.002	-8.432	0.000
Tenure 15	-0.019	0.002	-9.768	0.000
Tenure 16+	-0.019	0.003	-7.216	0.000
Balance^3	0.000	0.000	4.040	0.000
Balance^2	0.000	0.000	0.297	0.767
Balance	0.000	0.000	-4.395	0.000
Credit Limit^3	0.000	0.000	7.268	0.000
Credit Limit^2	0.000	0.000	-10.050	0.000
Credit Limit	0.000	0.000	12.925	0.000
Utilization^3	0.000	0.000	-2.931	0.003
Utilization^2	-0.008	0.003	-2.692	0.007
Utilization	0.017	0.004	3.938	0.000
Charge-off Rate^3	4.380	0.303	14.448	0.000
Charge-off Rate^2	-5.203	0.296	-17.555	0.000
Charge-off Rate	1.178	0.061	19.429	0.000
Monthly Purchase^3	0.000	0.000	4.561	0.000
Monthly Purchase^2	0.000	0.000	-5.359	0.000
Monthly Purchase	0.000	0.000	14.626	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 and month. The baseline for the tenure dummies is Tenure 2. Prediction plot from the model is illustrated in Figure 2, Panel A

Table A5: Fixed effects OLS estimates of Equation 1, over-limit fees

	β	S.E.	t-value	p-value
Tenure 3	0.004	0.000	12.493	0.000
Tenure 4	0.008	0.001	12.896	0.000
Tenure 5	0.009	0.001	12.350	0.000
Tenure 6	0.013	0.001	14.653	0.000
Tenure 7	0.015	0.001	13.644	0.000
Tenure 8	0.015	0.001	11.208	0.000
Tenure 9	0.015	0.001	11.186	0.000
Tenure 10	0.015	0.001	10.069	0.000
Tenure 11	0.015	0.002	8.220	0.000
Tenure 12	0.014	0.002	7.141	0.000
Tenure 13	0.014	0.002	6.253	0.000
Tenure 14	0.015	0.002	6.372	0.000
Tenure 15	0.014	0.003	5.388	0.000
Tenure 16+	0.016	0.003	5.245	0.000
Balance^3	0.000	0.000	-5.120	0.000
Balance^2	0.000	0.000	7.492	0.000
Balance	0.000	0.000	-11.552	0.000
Credit Limit^3	0.000	0.000	4.631	0.000
Credit Limit^2	0.000	0.000	-9.014	0.000
Credit Limit	0.000	0.000	12.621	0.000
Utilization^3	0.002	0.001	1.642	0.101
Utilization^2	0.048	0.024	1.957	0.050
Utilization	0.102	0.025	4.106	0.000
Charge-off Rate^3	-0.165	0.208	-0.794	0.427
Charge-off Rate^2	-0.537	0.196	-2.735	0.006
Charge-off Rate	0.917	0.053	17.191	0.000
$\text{Monthly Purchase}^3$	0.000	0.000	-1.198	0.231
$\text{Monthly Purchase}^2$	0.000	0.000	0.905	0.365
Monthly Purchase	0.000	0.000	6.827	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 and month. The baseline for the tenure dummies is Tenure 2. Prediction plot from the model is illustrated in Figure 2, Panel A

Table A6: 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	0.894	0.371
Tenure 3	0.001	0.001	1.932	0.053
Tenure 4	0.001	0.001	1.430	0.153
Tenure 5	0.002	0.001	1.758	0.079
Tenure 6	0.002	0.001	1.822	0.068
Tenure 7	0.002	0.001	1.210	0.226
Tenure 8	0.002	0.002	1.198	0.231
Tenure 9	0.002	0.002	1.408	0.159
Tenure 10	0.003	0.002	1.358	0.175
Tenure 11	0.003	0.002	1.450	0.147
Tenure 12	0.004	0.002	1.572	0.116
Tenure 13	0.002	0.002	0.902	0.367
Tenure 14	0.003	0.003	1.098	0.272
Tenure 15	0.004	0.003	1.165	0.244
Tenure 16+	0.004	0.004	1.122	0.262
Balance^3	0.000	0.000	-0.402	0.687
Balance^2	0.000	0.000	0.444	0.657
Balance	0.000	0.000	-0.881	0.378
Credit Limit^3	0.000	0.000	1.589	0.112
Credit Limit^2	0.000	0.000	-1.648	0.099
Credit Limit	0.000	0.000	1.660	0.097
Utilization^3	0.004	0.003	1.438	0.150
Utilization^2	0.000	0.003	-0.034	0.973
Utilization	0.003	0.004	0.636	0.525
Charge-off Rate^3	-1.432	0.770	-1.860	0.063
Charge-off Rate^2	1.259	0.644	1.954	0.051
Charge-off Rate	0.098	0.057	1.740	0.082
$\text{Monthly Purchase}^3$	0.000	0.000	0.447	0.655
$\text{Monthly Purchase}^2$	0.000	0.000	-0.573	0.567
Monthly Purchase	0.000	0.000	0.968	0.333
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 and month. The baseline for the tenure dummies is Tenure 1. Prediction plot from the model is illustrated in Figure 3, Panel A

Table A7: Fixed effects OLS estimates late payment fees and tenure, non-autopay accounts

	β	S.E.	t-value	p-value
Tenure 2	0.005	0.002	3.116	0.002
Tenure 3	0.008	0.002	4.019	0.000
Tenure 4	0.009	0.002	4.611	0.000
Tenure 5	0.008	0.002	4.159	0.000
Tenure 6	0.007	0.002	4.123	0.000
Tenure 7	0.010	0.002	4.447	0.000
Tenure 8	0.009	0.002	3.645	0.000
Tenure 9	0.011	0.002	4.360	0.000
Tenure 10	0.011	0.003	3.965	0.000
Tenure 11	0.010	0.003	3.458	0.001
Tenure 12	0.012	0.003	3.930	0.000
Tenure 13	0.014	0.003	3.879	0.000
Tenure 14	0.014	0.004	3.355	0.001
Tenure 15	0.015	0.004	3.736	0.000
Tenure 16+	0.018	0.004	3.964	0.000
Balance^3	0.000	0.000	3.819	0.000
Balance^2	0.000	0.000	-2.966	0.003
Balance	0.000	0.000	-0.442	0.659
Credit Limit^3	0.000	0.000	8.132	0.000
Credit Limit^2	0.000	0.000	-9.240	0.000
Credit Limit	0.000	0.000	9.824	0.000
Utilization^3	-0.001	0.000	-2.579	0.010
Utilization^2	-0.010	0.005	-2.089	0.037
Utilization	0.059	0.007	8.427	0.000
Charge-off Rate^3	-1.602	0.449	-3.564	0.000
Charge-off Rate^2	1.601	0.501	3.198	0.001
Charge-off Rate	-0.339	0.189	-1.792	0.073
$\text{Monthly Purchase}^3$	0.000	0.000	-3.259	0.001
$\text{Monthly Purchase}^2$	0.000	0.000	3.795	0.000
Monthly Purchase	0.000	0.000	-7.903	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 and month. The baseline for the tenure dummies is Tenure 1. Prediction plot from the model is illustrated in Figure 3, Panel B

Table A8: Fixed effects OLS estimates late payment fees and tenure, switch to autopay

	β	S.E.	t-value	p-value
Tenure 2	-0.113	0.010	-11.076	0.000
Tenure 3	-0.143	0.009	-16.390	0.000
Tenure 4	-0.156	0.009	-17.669	0.000
Tenure 5	-0.164	0.009	-18.730	0.000
Tenure 6	-0.170	0.009	-19.690	0.000
Tenure 7	-0.172	0.009	-19.946	0.000
Tenure 8	-0.174	0.009	-19.438	0.000
Tenure 9	-0.176	0.009	-19.888	0.000
Tenure 10	-0.177	0.009	-19.989	0.000
Tenure 11	-0.179	0.009	-19.650	0.000
Tenure 12	-0.179	0.009	-19.666	0.000
Tenure 13	-0.180	0.009	-19.102	0.000
Tenure 14	-0.181	0.009	-19.681	0.000
Tenure 15	-0.180	0.009	-19.171	0.000
Tenure 16+	-0.180	0.010	-18.264	0.000
Balance^3	0.000	0.000	1.211	0.226
Balance^2	0.000	0.000	-1.148	0.251
Balance	0.000	0.000	-0.080	0.936
Credit Limit^3	0.000	0.000	5.239	0.000
Credit Limit^2	0.000	0.000	-5.709	0.000
Credit Limit	0.000	0.000	6.509	0.000
Utilization^3	-0.001	0.000	-4.884	0.000
Utilization^2	-0.006	0.001	-4.099	0.000
Utilization	0.041	0.010	3.989	0.000
Charge-off Rate^3	-3.704	1.241	-2.985	0.003
Charge-off Rate^2	3.482	1.128	3.088	0.002
Charge-off Rate	-0.520	0.327	-1.589	0.112
$\text{Monthly Purchase}^3$	0.000	0.000	2.020	0.043
$\text{Monthly Purchase}^2$	0.000	0.000	-2.845	0.004
Monthly Purchase	0.000	0.000	3.569	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 and month. The baseline for the tenure dummies is Tenure 1. Prediction plot from the model is illustrated in Figure 3, Panel C

Table A9: 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	-0.007	0.003	-2.353	0.019
Months fr 1st Late Fee 3	-0.011	0.004	-2.981	0.003
Months fr 1st Late Fee 4	-0.008	0.004	-1.855	0.064
Months fr 1st Late Fee 5	-0.009	0.005	-1.751	0.080
Months fr 1st Late Fee 6	-0.008	0.006	-1.356	0.175
Months fr 1st Late Fee 7	-0.003	0.006	-0.436	0.663
Months fr 1st Late Fee 8	0.001	0.007	0.162	0.871
Months fr 1st Late Fee 9	-0.004	0.008	-0.455	0.649
Months fr 1st Late Fee 10	0.007	0.008	0.958	0.338
Months fr 1st Late Fee 11	0.006	0.010	0.656	0.512
Months fr 1st Late Fee 12+	0.011	0.010	1.037	0.300
Balance^3	0.000	0.000	-0.214	0.831
Balance^2	0.000	0.000	0.690	0.490
Balance	0.000	0.000	-1.725	0.085
Credit Limit^3	0.000	0.000	1.878	0.060
Credit Limit^2	0.000	0.000	-3.218	0.001
Credit Limit	0.000	0.000	7.374	0.000
Utilization^3	-0.023	0.006	-3.823	0.000
Utilization^2	-0.085	0.025	-3.456	0.001
Utilization	0.187	0.037	5.039	0.000
Charge-off Rate^3	-1.556	0.443	-3.513	0.000
Charge-off Rate^2	1.856	0.558	3.328	0.001
Charge-off Rate	-0.744	0.236	-3.150	0.002
Monthly Purchase^3	0.000	0.000	-1.203	0.229
Monthly Purchase^2	0.000	0.000	1.768	0.077
Monthly Purchase	0.000	0.000	-4.528	0.000
R^2	0.337			
Number of observations	249,962			
Number of accounts	31,748			

Note: OLS regression with clustered standard errors clustered by account and month. Prediction plot from the model is illustrated in Figure 4, Panel A.

Table A10: 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	-0.025	0.004	-7.149	0.000
Months fr 1st Late Fee 3	-0.037	0.003	-12.099	0.000
Months fr 1st Late Fee 4	-0.043	0.004	-11.906	0.000
Months fr 1st Late Fee 5	-0.047	0.004	-11.131	0.000
Months fr 1st Late Fee 6	-0.052	0.004	-14.151	0.000
Months fr 1st Late Fee 7	-0.056	0.005	-11.313	0.000
Months fr 1st Late Fee 8	-0.059	0.004	-14.499	0.000
Months fr 1st Late Fee 9	-0.061	0.005	-11.619	0.000
Months fr 1st Late Fee 10	-0.061	0.005	-11.984	0.000
Months fr 1st Late Fee 11	-0.064	0.006	-9.989	0.000
Months fr 1st Late Fee 12+	-0.068	0.007	-9.678	0.000
Balance^3	0.000	0.000	-1.401	0.161
Balance^2	0.000	0.000	1.652	0.098
Balance	0.000	0.000	-2.368	0.018
Credit Limit^3	0.000	0.000	2.825	0.005
Credit Limit^2	0.000	0.000	-3.667	0.000
Credit Limit	0.000	0.000	4.855	0.000
Utilization^3	-0.001	0.002	-0.424	0.671
Utilization^2	-0.004	0.021	-0.201	0.840
Utilization	0.025	0.025	0.994	0.320
Charge-off Rate^3	-4.868	1.105	-4.407	0.000
Charge-off Rate^2	4.849	0.906	5.352	0.000
Charge-off Rate	-0.986	0.248	-3.972	0.000
Monthly Purchase^3	0.000	0.000	-0.698	0.485
Monthly Purchase^2	0.000	0.000	0.480	0.631
Monthly Purchase	0.000	0.000	0.096	0.924
R^2	0.292			
Number of observations	133,450			
Number of accounts	14,048			

Note: OLS regression with clustered standard errors clustered by account and month. Prediction plot from the model is illustrated in Figure 4, Panel B.

Table A11: Fixed effects OLS estimates late payment fees in months following before and after switch to autopay

	β	S.E.	t-value	p-value
Months fr 1st Late Fee -11	-0.007	0.008	-0.911	0.362
Months fr 1st Late Fee -10	-0.030	0.008	-3.644	0.000
Months fr 1st Late Fee -9	-0.022	0.011	-2.069	0.039
Months fr 1st Late Fee -8	-0.026	0.009	-2.735	0.006
Months fr 1st Late Fee -7	-0.017	0.012	-1.451	0.147
Months fr 1st Late Fee -6	-0.020	0.011	-1.831	0.067
Months fr 1st Late Fee -5	-0.020	0.010	-1.975	0.048
Months fr 1st Late Fee -4	-0.017	0.010	-1.658	0.097
Months fr 1st Late Fee -3	-0.013	0.010	-1.283	0.199
Months fr 1st Late Fee -2	-0.022	0.011	-2.067	0.039
Months fr 1st Late Fee -1	0.121	0.011	11.198	0.000
Months fr 1st Late Fee 0	0.009	0.016	0.548	0.584
Months fr 1st Late Fee 1	-0.138	0.016	-8.674	0.000
Months fr 1st Late Fee 2	-0.136	0.016	-8.411	0.000
Months fr 1st Late Fee 3	-0.134	0.017	-8.078	0.000
Months fr 1st Late Fee 4	-0.135	0.017	-7.986	0.000
Months fr 1st Late Fee 5	-0.137	0.017	-8.047	0.000
Months fr 1st Late Fee 6	-0.138	0.017	-8.037	0.000
Months fr 1st Late Fee 7	-0.137	0.017	-7.892	0.000
Months fr 1st Late Fee 8	-0.137	0.018	-7.592	0.000
Months fr 1st Late Fee 9	-0.136	0.019	-7.220	0.000
Months fr 1st Late Fee 10	-0.136	0.020	-6.902	0.000
Months fr 1st Late Fee 11	-0.136	0.021	-6.595	0.000
Months fr 1st Late Fee 12+	-0.134	0.022	-6.182	0.000
Balance^3	0.000	0.000	3.468	0.001
Balance^2	0.000	0.000	-4.306	0.000
Balance	0.000	0.000	3.368	0.001
Credit Limit^3	0.000	0.000	2.870	0.004
Credit Limit^2	0.000	0.000	-3.275	0.001
Credit Limit	0.000	0.000	3.654	0.000
Utilization^3	0.000	0.000	-0.040	0.968
Utilization^2	-0.004	0.004	-0.943	0.346
Utilization	-0.044	0.011	-4.106	0.000
Charge-off Rate^3	9.063	1.188	7.631	0.000
Charge-off Rate^2	-14.324	1.334	-10.741	0.000
Charge-off Rate	6.752	0.382	17.677	0.000
Monthly Purchase^3	0.000	0.000	3.196	0.001
Monthly Purchase^2	0.000	0.000	-4.049	0.000
Monthly Purchase	0.000	0.000	6.305	0.000
R^2	0.411			
Number of observations	501,489			
Number of accounts	47,188			

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

Table A12: Fixed effects OLS estimates cash advance fees and tenure, high probability of charge-off accounts

	β	S.E.	t-value	p-value
Tenure 3	-0.015	0.004	-3.830	0.000
Tenure 4	-0.024	0.004	-5.539	0.000
Tenure 5	-0.029	0.005	-5.514	0.000
Tenure 6	-0.035	0.005	-7.121	0.000
Tenure 7	-0.038	0.005	-7.460	0.000
Tenure 8	-0.039	0.005	-7.317	0.000
Tenure 9	-0.040	0.006	-6.773	0.000
Tenure 10	-0.039	0.006	-6.372	0.000
Tenure 11	-0.040	0.007	-5.994	0.000
Tenure 12	-0.040	0.007	-5.830	0.000
Tenure 13	-0.041	0.007	-6.053	0.000
Tenure 14	-0.040	0.007	-5.698	0.000
Tenure 15	-0.040	0.008	-5.145	0.000
Tenure 16+	-0.041	0.009	-4.459	0.000
Balance^3	0.000	0.000	0.962	0.336
Balance^2	0.000	0.000	0.181	0.856
Balance	0.000	0.000	-2.094	0.036
Credit Limit^3	0.000	0.000	2.082	0.037
Credit Limit^2	0.000	0.000	-3.136	0.002
Credit Limit	0.000	0.000	4.987	0.000
Utilization^3	-0.001	0.001	-1.554	0.120
Utilization^2	-0.029	0.019	-1.549	0.121
Utilization	0.035	0.023	1.510	0.131
Charge-off Rate^3	4.758	0.531	8.964	0.000
Charge-off Rate^2	-5.234	0.486	-10.765	0.000
Charge-off Rate	1.057	0.101	10.482	0.000
Monthly Purchase^3	0.000	0.000	1.859	0.063
Monthly Purchase^2	0.000	0.000	-2.181	0.029
Monthly Purchase	0.000	0.000	4.907	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 and month. 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 cash advance fees and tenure, low probability of charge-Off accounts

	β	S.E.	t-value	p-value
Tenure 3	0.002	0.001	1.529	0.126
Tenure 4	0.000	0.001	0.168	0.867
Tenure 5	0.000	0.002	-0.219	0.827
Tenure 6	-0.001	0.002	-0.661	0.509
Tenure 7	-0.001	0.002	-0.587	0.557
Tenure 8	-0.001	0.002	-0.777	0.437
Tenure 9	-0.003	0.002	-1.579	0.114
Tenure 10	-0.003	0.002	-1.458	0.145
Tenure 11	-0.003	0.002	-1.459	0.145
Tenure 12	-0.004	0.002	-1.673	0.094
Tenure 13	-0.005	0.002	-2.015	0.044
Tenure 14	-0.004	0.003	-1.517	0.129
Tenure 15	-0.007	0.003	-2.201	0.028
Tenure 16+	-0.006	0.004	-1.605	0.108
Balance^3	0.000	0.000	0.824	0.410
Balance^2	0.000	0.000	-1.203	0.229
Balance	0.000	0.000	-0.736	0.462
Credit Limit^3	0.000	0.000	2.350	0.019
Credit Limit^2	0.000	0.000	-4.200	0.000
Credit Limit	0.000	0.000	8.185	0.000
Utilization^3	0.000	0.000	-2.639	0.008
Utilization^2	-0.002	0.002	-1.442	0.149
Utilization	0.016	0.004	3.695	0.000
Charge-off Rate^3	4.433	0.568	7.800	0.000
Charge-off Rate^2	-4.906	0.554	-8.850	0.000
Charge-off Rate	1.065	0.122	8.740	0.000
$\text{Monthly Purchase}^3$	0.000	0.000	2.935	0.003
$\text{Monthly Purchase}^2$	0.000	0.000	-3.307	0.001
Monthly Purchase	0.000	0.000	10.380	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 and month. The baseline for the tenure dummies is Tenure 2. Prediction plot from the model is illustrated in Figure 6.

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	0.000	0.003	0.073	0.942
Months fr 1st OL Fee -10	-0.001	0.004	-0.146	0.884
Months fr 1st OL Fee -9	0.001	0.005	0.122	0.903
Months fr 1st OL Fee -8	0.002	0.007	0.291	0.771
Months fr 1st OL Fee -7	0.000	0.008	-0.001	0.999
Months fr 1st OL Fee -6	0.001	0.009	0.158	0.874
Months fr 1st OL Fee -5	0.000	0.010	0.007	0.994
Months fr 1st OL Fee -4	-0.002	0.011	-0.204	0.839
Months fr 1st OL Fee -3	-0.007	0.012	-0.572	0.567
Months fr 1st OL Fee -2	-0.013	0.014	-0.942	0.346
Months fr 1st OL Fee -1	-0.020	0.014	-1.352	0.176
Months fr 1st OL Fee 0	0.953	0.016	60.999	0.000
Months fr 1st OL Fee 1	0.395	0.020	20.212	0.000
Months fr 1st OL Fee 2	0.240	0.020	12.270	0.000
Months fr 1st OL Fee 3	0.181	0.020	9.205	0.000
Months fr 1st OL Fee 4	0.155	0.021	7.247	0.000
Months fr 1st OL Fee 5	0.141	0.021	6.656	0.000
Months fr 1st OL Fee 6	0.134	0.023	5.833	0.000
Months fr 1st OL Fee 7	0.130	0.025	5.288	0.000
Months fr 1st OL Fee 8	0.133	0.025	5.254	0.000
Months fr 1st OL Fee 9	0.123	0.027	4.516	0.000
Months fr 1st OL Fee 10	0.120	0.029	4.205	0.000
Months fr 1st OL Fee 11	0.136	0.030	4.597	0.000
Months fr 1st OL Fee 12+	0.130	0.032	3.996	0.000
Credit Limit^3	0.000	0.000	3.349	0.001
Credit Limit^2	0.000	0.000	-3.971	0.000
Credit Limit	0.000	0.000	2.350	0.019
Charge-off Rate^3	2.845	0.393	7.236	0.000
Charge-off Rate^2	-4.287	0.466	-9.205	0.000
Charge-off Rate	2.289	0.155	14.731	0.000
Monthly Purchase^3	0.000	0.000	0.581	0.562
Monthly Purchase^2	0.000	0.000	-0.859	0.390
Monthly Purchase	0.000	0.000	6.984	0.000
R^2	0.611			
Number of observations	234,221			
Number of accounts	17,606			

Note: OLS regression with cluster standard errors clustered by account and month. Prediction plot from the model is illustrated in Figure 10.

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	14.744	-1.036	0.300
Months fr 1st OL Fee -10	-17.791	20.098	-0.885	0.376
Months fr 1st OL Fee -9	-45.072	20.841	-2.163	0.031
Months fr 1st OL Fee -8	-25.193	26.058	-0.967	0.334
Months fr 1st OL Fee -7	-43.142	29.312	-1.472	0.141
Months fr 1st OL Fee -6	-42.070	34.087	-1.234	0.217
Months fr 1st OL Fee -5	-45.233	38.390	-1.178	0.239
Months fr 1st OL Fee -4	-41.833	41.597	-1.006	0.315
Months fr 1st OL Fee -3	-51.284	47.101	-1.089	0.276
Months fr 1st OL Fee -2	-56.075	51.121	-1.097	0.273
Months fr 1st OL Fee -1	-0.589	53.794	-0.011	0.991
Months fr 1st OL Fee 0	92.407	59.620	1.550	0.121
Months fr 1st OL Fee 1	-262.439	61.088	-4.296	0.000
Months fr 1st OL Fee 2	-239.912	62.500	-3.839	0.000
Months fr 1st OL Fee 3	-227.456	66.372	-3.427	0.001
Months fr 1st OL Fee 4	-224.859	69.521	-3.234	0.001
Months fr 1st OL Fee 5	-225.571	70.426	-3.203	0.001
Months fr 1st OL Fee 6	-221.846	75.502	-2.938	0.003
Months fr 1st OL Fee 7	-218.180	77.199	-2.826	0.005
Months fr 1st OL Fee 8	-204.942	81.131	-2.526	0.012
Months fr 1st OL Fee 9	-209.027	81.713	-2.558	0.011
Months fr 1st OL Fee 10	-208.088	86.063	-2.418	0.016
Months fr 1st OL Fee 11	-186.031	92.339	-2.015	0.044
Months fr 1st OL Fee 12+	-203.980	99.428	-2.052	0.040
Balance^3	0.000	0.000	5.220	0.000
Balance^2	0.000	0.000	-7.668	0.000
Balance	0.324	0.021	15.730	0.000
Credit Limit^3	0.000	0.000	1.810	0.070
Credit Limit^2	0.000	0.000	-0.409	0.682
Credit Limit	0.024	0.024	1.015	0.310
Utilization^3	-3.450	4.327	-0.797	0.425
Utilization^2	56.488	37.082	1.523	0.128
Utilization	-247.259	43.418	-5.695	0.000
Charge-off Rate^3	-8,881.306	628.072	-14.141	0.000
Charge-off Rate^2	11,430.993	604.921	18.897	0.000
Charge-off Rate	-3,909.626	156.447	-24.990	0.000
R^2	0.547			
Number of observations	234,232			
Number of accounts	17,606			

Note: OLS regression with cluster standard errors clustered by account and month. Prediction plot from the model is illustrated in Figure 10.

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	15.238	-0.627	0.531
Months fr 1st OL Fee -10	-3.713	16.470	-0.225	0.822
Months fr 1st OL Fee -9	0.276	20.096	0.014	0.989
Months fr 1st OL Fee -8	-24.107	24.383	-0.989	0.323
Months fr 1st OL Fee -7	-28.799	28.244	-1.020	0.308
Months fr 1st OL Fee -6	-25.901	32.640	-0.794	0.427
Months fr 1st OL Fee -5	-44.229	35.278	-1.254	0.210
Months fr 1st OL Fee -4	-59.750	39.502	-1.513	0.130
Months fr 1st OL Fee -3	-74.421	44.733	-1.664	0.096
Months fr 1st OL Fee -2	-103.317	49.309	-2.095	0.036
Months fr 1st OL Fee -1	7.923	55.092	0.144	0.886
Months fr 1st OL Fee 0	27.801	59.067	0.471	0.638
Months fr 1st OL Fee 1	1.111	64.551	0.017	0.986
Months fr 1st OL Fee 2	-12.807	61.936	-0.207	0.836
Months fr 1st OL Fee 3	-19.782	66.454	-0.298	0.766
Months fr 1st OL Fee 4	-0.584	73.941	-0.008	0.994
Months fr 1st OL Fee 5	14.811	72.944	0.203	0.839
Months fr 1st OL Fee 6	7.599	76.015	0.100	0.920
Months fr 1st OL Fee 7	23.915	77.299	0.309	0.757
Months fr 1st OL Fee 8	26.927	86.044	0.313	0.754
Months fr 1st OL Fee 9	29.846	80.670	0.370	0.711
Months fr 1st OL Fee 10	50.832	82.491	0.616	0.538
Months fr 1st OL Fee 11	44.161	93.798	0.471	0.638
Months fr 1st OL Fee 12+	29.420	99.559	0.296	0.768
Balance^3	0.000	0.000	1.743	0.081
Balance^2	0.000	0.000	-1.492	0.136
Balance	0.224	0.038	5.951	0.000
Credit Limit^3	0.000	0.000	0.704	0.482
Credit Limit^2	0.000	0.000	0.660	0.509
Credit Limit	-0.054	0.030	-1.793	0.073
Utilization^3	-1.465	4.873	-0.301	0.764
Utilization^2	-32.852	38.394	-0.856	0.392
Utilization	-80.675	54.694	-1.475	0.140
Charge-off Rate^3	-567.594	351.370	-1.615	0.106
Charge-off Rate^2	465.901	390.281	1.194	0.233
Charge-off Rate	-404.561	127.763	-3.166	0.002
Monthly Purchase^3	0.000	0.000	-1.177	0.239
Monthly Purchase^2	0.000	0.000	2.191	0.028
Monthly Purchase	0.178	0.015	11.776	0.000
R^2	0.452			
Number of observations	234,232			
Number of accounts	17,606			

Note: OLS regression with cluster standard errors clustered by account and month. Prediction plot from the model is illustrated in Figure 10.

Table A17: Fixed effects OLS estimates account purchases in months before and after last over-limit fee

	β	S.E.	t-value	p-value
Months fr last OL Fee -11	-15.272	14.744	-1.036	0.300
Months fr last OL Fee -10	-17.791	20.098	-0.885	0.376
Months fr last OL Fee -9	-45.072	20.841	-2.163	0.031
Months fr last OL Fee -8	-25.193	26.058	-0.967	0.334
Months fr last OL Fee -7	-43.142	29.312	-1.472	0.141
Months fr last OL Fee -6	-42.070	34.087	-1.234	0.217
Months fr last OL Fee -5	-45.233	38.390	-1.178	0.239
Months fr last OL Fee -4	-41.833	41.597	-1.006	0.315
Months fr last OL Fee -3	-51.284	47.101	-1.089	0.276
Months fr last OL Fee -2	-56.075	51.121	-1.097	0.273
Months fr last OL Fee -1	-0.589	53.794	-0.011	0.991
Months fr last OL Fee 0	92.407	59.620	1.550	0.121
Months fr last OL Fee 1	-262.439	61.088	-4.296	0.000
Months fr last OL Fee 2	-239.912	62.500	-3.839	0.000
Months fr last OL Fee 3	-227.456	66.372	-3.427	0.001
Months fr last OL Fee 4	-224.859	69.521	-3.234	0.001
Months fr last OL Fee 5	-225.571	70.426	-3.203	0.001
Months fr last OL Fee 6	-221.846	75.502	-2.938	0.003
Months fr last OL Fee 7	-218.180	77.199	-2.826	0.005
Months fr last OL Fee 8	-204.942	81.131	-2.526	0.012
Months fr last OL Fee 9	-209.027	81.713	-2.558	0.011
Months fr last OL Fee 10	-208.088	86.063	-2.418	0.016
Months fr last OL Fee 11	-186.031	92.339	-2.015	0.044
Months fr last OL Fee 12+	-203.980	99.428	-2.052	0.040
Balance^3	0.000	0.000	5.220	0.000
Balance^2	0.000	0.000	-7.668	0.000
Balance	0.324	0.021	15.730	0.000
Credit Limit^3	0.000	0.000	1.810	0.070
Credit Limit^2	0.000	0.000	-0.409	0.682
Credit Limit	0.024	0.024	1.015	0.310
Utilization^3	-3.450	4.327	-0.797	0.425
Utilization^2	56.488	37.082	1.523	0.128
Utilization	-247.259	43.418	-5.695	0.000
Charge-off Rate^3	-8,881.306	628.072	-14.141	0.000
Charge-off Rate^2	11,430.993	604.921	18.897	0.000
Charge-off Rate	-3,909.626	156.447	-24.990	0.000
R^2	0.547			
Number of observations	234,232			
Number of accounts	17,606			

Note: OLS regression with cluster standard errors clustered by account and month. Prediction plot from the model is illustrated in Figure 11.

Table A18: Fixed effects OLS estimates account cash advances in months before and after last over-limit fee

	β	S.E.	t-value	p-value
Months fr last OL Fee -11	0.007	0.005	1.276	0.202
Months fr last OL Fee -10	0.009	0.007	1.313	0.189
Months fr last OL Fee -9	0.010	0.006	1.595	0.111
Months fr last OL Fee -8	0.010	0.007	1.450	0.147
Months fr last OL Fee -7	0.010	0.008	1.223	0.221
Months fr last OL Fee -6	0.017	0.010	1.716	0.086
Months fr last OL Fee -5	0.015	0.011	1.363	0.173
Months fr last OL Fee -4	0.022	0.012	1.825	0.068
Months fr last OL Fee -3	0.028	0.013	2.100	0.036
Months fr last OL Fee -2	0.037	0.015	2.514	0.012
Months fr last OL Fee -1	0.053	0.017	3.191	0.001
Months fr last OL Fee 0	0.080	0.017	4.785	0.000
Months fr last OL Fee 1	-0.018	0.016	-1.108	0.268
Months fr last OL Fee 2	-0.016	0.017	-0.967	0.334
Months fr last OL Fee 3	-0.009	0.019	-0.498	0.619
Months fr last OL Fee 4	-0.012	0.021	-0.597	0.551
Months fr last OL Fee 5	-0.008	0.021	-0.406	0.685
Months fr last OL Fee 6	-0.012	0.022	-0.529	0.597
Months fr last OL Fee 7	-0.008	0.022	-0.365	0.715
Months fr last OL Fee 8	-0.006	0.024	-0.252	0.801
Months fr last OL Fee 9	-0.008	0.024	-0.312	0.755
Months fr last OL Fee 10	-0.010	0.026	-0.384	0.701
Months fr last OL Fee 11	-0.011	0.027	-0.407	0.684
Months fr last OL Fee 12+	-0.011	0.029	-0.373	0.709
Balance^3	0.000	0.000	1.775	0.076
Balance^2	0.000	0.000	-0.794	0.427
Balance	0.000	0.000	-0.737	0.461
Credit Limit^3	0.000	0.000	2.806	0.005
Credit Limit^2	0.000	0.000	-3.980	0.000
Credit Limit	0.000	0.000	8.218	0.000
Utilization^3	0.000	0.001	0.081	0.936
Utilization^2	-0.007	0.006	-1.220	0.222
Utilization	0.004	0.008	0.452	0.651
Charge-off Rate^3	4.290	0.609	7.045	0.000
Charge-off Rate^2	-4.932	0.642	-7.688	0.000
Charge-off Rate	1.048	0.153	6.839	0.000
Monthly Purchase^3	0.000	0.000	2.889	0.004
Monthly Purchase^2	0.000	0.000	-3.516	0.000
Monthly Purchase	0.000	0.000	6.189	0.000
R^2	0.347			
Number of observations	234,232			
Number of accounts	17,606			

Note: OLS regression with cluster standard errors clustered by account and month. Prediction plot from the model is illustrated in Figure 11.