How Do Consumers Avoid Penalty Fees? Evidence From Credit Cards

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December 11, 2019

Abstract

Using data from multiple card issuers, we show that the most common penalty fee type incurred by credit card holders – late payment fees – declines sharply over the first few months of card life. This phenomenon is wholly due to some consumers adopting automatic payments after a late payment event, thereby insuring themselves against future late payment fees. Non-adopters, who remain on manual-only payments, experience an unchanged high likelihood of future fees, despite exhibiting ample levels of available liquidity. Our results show that heterogeneity in adopting account management features of financial products, such as automatic payments, is important for understanding who avoids financial mistakes.

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

JEL Codes: D10, D12, D4, G21

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This work was supported by Economic and Social Research Council (ESRC) grants ES/K002201/1, ES/N018192/1, ES/P008976/1, Sakaguchi's ESRC PhD studentship award reference 1499648, and Leverhulme grant RP2012-V-022.

1. Introduction

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

In this paper, we investigate how consumers avoid contingent fees and charges on their credit cards arising due to late payment. For credit cards, negative feedback takes the form of a penalty fee that appears on a credit card statement and deprives the consumer of marginal utility. Late payments result in modest direct monetary fees and, more significantly, worsening credit card terms (such as penalty interest rates) and deterioration in the card holder's credit score which can restrict access to future credit and make future credit more costly. Credit cards are the most common consumer unsecured borrowing product and late payment fees are the most common type of penalty fee, which may be an important source of profits for banks (especially in a low interest rate environment).[3] How consumers respond to these fees, and the mechanisms consumers use, are important issues and may improve our understanding of the origins of suboptimal behavior (Agarwal et al., 2008).

We shed new light on consumer responses to credit card late payment fees using individual level card data on 250,000 new card openings across five card issuers from the United Kingdom, a nation with a high level of credit card penetration similar to that of the United States.[4] Our

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

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

[3] Fees could represent significant rents for credit card issuers, especially as card issuers target products to consumers based on their behavioral characteristics (Ru and Schoar, 2016). 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.

[4] 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

data span a two-year period. Our data cover approximately 2.6 million card-months, and includes granular card level information. A feature of our data is that we observe rich information on how consumers manage their card repayments, such as whether they pay their card manually each month, or also use an automatic instruction ("autopay") to pay part or all of the bill. Autopay allows consumers to set an automatic payment for their credit card bill while retaining the freedom to made additional manual payments.[5] We show that this additional information on how consumers manage their payments is crucial for explaining whether and how consumers avoid late payment fees.

We find that late payment fees are front-loaded, peaking in the first month of card life and then declining sharply over the following months. These patterns are not attributable to survivorship bias (i.e., cards closing or falling dormant following the occurrence of a fee). The decline in late payment fees with tenure is also predicted from a rich multivariate regression model that includes a broad range of time-varying card level controls plus card and calendar time fixed-effects.

Why do fees decline over time? We show that the *average* decline in late payment fees across all consumers over time is wholly attributable to a subset of consumers who activate autopay in the month following a late payment. By adopting autopay, these card holders override the need to remember to pay the minimum payment, therefore avoiding future late payment events. While adopting autopay all but eliminates the likelihood of future fees, we find that among non-adopters the probability of fee payment remains as high as it was before these consumers incurred their first fee, at approximately 20% *per month*.[6]

Hence, those consumers who react to the late payment by adopting autopay find an effective facility to insure themselves against future forgetting. However, those who do not (and instead continue to rely on memory alone to pay their bill on time) remain just as likely to pay a late payment fee again in future.[7]

Assets Survey 2012–2014).

[5] Card holders can set the level of autopay to be at any level between the minimum payment and the full balance. Once autopay is adopted, card holders can continue to make additional manual payments. Autopay was widely introduced in the UK from the 1990s onwards. All card issuers in our sample offer autopay on all of their products. Autopay is a more recent innovation in the United States credit card market.

[6] Adopting autopay does not completely eliminate future fees because card holders may have insufficient funds in their deposit accounts. However, missing a payment does to insufficient funds is extremely rare. The rate of missed payments due to insufficient funds is approximately 0.08% per month.

[7] In the first version of our paper, we suggested that this result shows how consumers do not "learn" to avoid late payment fees. However, the referees have rightly observed that adopting autopay could itself be considered a form of learning. In light of this, in this revised version of the paper we refrain from discussions over what constitutes "learning".

This result raises the question of why only *some* consumers adopt autopay in response to late payment. This result does not arise due to selection into products with differing autopay options, as all cards in our sample offer identical autopay facilities free of charge. Nor does this result arise due to selection into products with heterogeneity in fee levels across consumers, as fee levels are set at regulatory limits and therefore uniform across card issuers.

To address this question, we present additional analysis in which we compare the characteristics of adopters and non-adopters. The descriptive analysis reveals important differences between these two groups with respect to their credit card usage, economic circumstances, socio-economic characteristics, and spending patterns, although our data does not allow us to firmly establish causal links between individual characteristics, adoption of autopay and subsequent payment behavior. Specifically, we investigate four explanations for why some individuals do not adopt autopay.

First, we explore low card usage, which would reduce the benefits from adopting autopay. However, we find that non-adoption is not explained by some card holders making only occasional use of their cards. In fact, non-adopters have surprisingly similar usage patterns to adopters. Second, we explore liquidity constraints, which would negate the benefits of autopay if credit card holders have sufficient funds to make payments. Here, we show that non-adopters in our data actually have lower levels of debt, lower utilization and slightly *higher* average repayments compared with adopters, indicating that their failure to adopt autopay does not arise due to liquidity constraints.

Third, we explore differences in individual socio-economic characteristics between adopters and non-adopters. We match-in geographically granular census microdata to our credit card panel. Adopters are disproportionately drawn from local populations with higher incomes, home values and education, lower unemployment and lower social insurance dependency when compared with non-adopters. Adopters are also more likely to have obtained a low-cost promotional card, often with 0% APR, reducing the interest payments on borrowing. They are also more likely to hold a low APR balance-transfer facility, allowing them to refinance higher-APR debt from other cards onto a lower-APR card.

Fourth, analysis of spending patterns shows that non-adopters have, on average, a higher number, and monetary value, of spends in consumables, such as restaurants and bars, retail, clothing stores and food stores. These results suggest a role for myopia as a cause of non-adoption of autopay. 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 educated consumers (Andersen et al., 2015; Agarwal et al., 2016).[8]

In additional analysis, we also consider two other common contingent fees on credit cards: cash advance fees and over-limit fees. Cash advance fees also decline with card tenure. Our analysis suggests this arises due to liquidity constraints, with cash advances concentrated among higher risk customers in periods of high card utilization and high purchase volumes, with these periods coinciding with card openings. We also show that over-limit fees tend to occur during periods of persistently high purchases and low repayments, with consumers responding to over-limit fees by making one-time balloon repayments and subsequently lowering in month-on-month purchase volumes.

Our paper is closest to Agarwal et al. (2008), who also find that credit card fees are front-loaded in a sample of US credit card holders in the period 2002–2004, a period of time before the widespread introduction of autopay. They attribute the decline in late payments with card tenure as arising due to consumers remembering to repay on time (but also show a recency effect, whereby the likelihood of another fee increases with the distance in time since the first fee was incurred). Given the difference in institutional settings between the credit card markets in the early 2000s and today, we think that there may be different drivers of fee avoidance in our paper compared with Agarwal et al. (2008). It may be the case that the types of individuals who were better at remembering to avoid future mistakes in the early 2000s would nowadays be those more likely to adopt autopay.

We focus on credit cards because they offer a rich environment for studying consumer responses to negative feedback. As a high frequency product, credit cards provide fast feedback on recent behavior. Fees are prominently displayed on credit card statements, so the negative feedback from failing to repay on time is made salient to the consumer.[9] 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

[8] The cited 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).

[9] Credit card penalty fees and charges are also salient on card statements, and the card issuers in our UK data all write to consumers separately to notify them of charged fees. Consumers may be more likely to respond in settings where feedback is salient, such as credit card fees highlighted on card statements, compared with scenarios where the consequences of mistakes are not made salient to consumers, such as borrowing or repaying on the wrong credit card (Ponce et al., 2017; Gathergood et al., 2019).

et al., 2010; Andersen et al., 2015).

Our findings relate more broadly to the growing literature on the role of 'reminders' or 'prompts' to improve behavior (Karlan et al., 2016; Carlin et al., 2017). To some extent, automating flows – such as bill payment, debt payment or savings – negates the need for reminders to bring a financial need to the 'top of the mind' and prompt a manual action. However, at the same time, automating payments may result in lower-bound default effects, whereby consumers no longer pay attention to their cards. In the case of credit cards, if consumers choose to set up autopay at the minimum payment amount and do not make additional manual payments, they may reduce average payments. Hence, adopting autopay may increase interest charges while reducing late payment fees. While this is not the focus of our paper, we present descriptive analysis from our data consistent with this effect.

Recent papers emphasize that minimum payments may give rise to default effects in debt repayment (Keys and Wang, 2019; Sussman and Bartels, 2018), including a suppressing effect on average repayments over time (Sakaguchi et al., 2018).[10] Views differ on the relative benefits of autopay as a mean of avoiding late payment fees against the possibility that consumers who use autopay neglect to pay attention to their card balances. Recently, this has provoked regulatory interest of the UK financial regulator, but has attracted surprisingly little academic research.[11]

This paper contributes to the growing literature on consumer behavior in the credit card market. A large literature documents that consumer choices in the credit card market appear sub-optimal (Agarwal et al., 2009; Gross and Souleles, 2002; Stango and Zinman, 2009; Meier and Sprenger, 2010; Ponce et al., 2017; Gathergood et al., 2019; Jorring, 2018). Credit card companies also exploit consumer inertia and naïvete (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., 2018; Liberman, 2016).

The structure of the remainder of our paper is as follows. In Section 2, we describe the credit card data we use in this study and present summary data. We introduce our main results in Section 3 by showing the decline in credit card fees with tenure. In Section 4, we show the role

[10] We return to these issues in more detail in Section 6.

[11] In the UK, the Financial Conduct Authority's (FCA) current 'Credit Card Market Study' has focused upon automatic credit card repayment, in particular automatic credit card repayment of the minimum payment only, as a potential source of detriment to consumers (Financial Conduct Authority, 2016). We are not aware of any academic research on how consumers use autopay facilities. The response of consumers to credit card fees has been an important issue for regulation, including fee limits introduced by the 2009 US CARD Act.

of autopay in explaining the decline in fees and explore heterogeneity in who adopts autopay. Section 5 presents extensions exploring responses to second late payments, spillover effect on other cards, and other credit card fee types. We discuss the implications of our results for credit card issuers in Section 6, with the final Section 7 concluding the paper.

2. Data

The data we use are provided by five UK credit card issuers, who together comprise 40% of the UK credit card market by number of cards. The UK credit card market has many similarities with the US credit card market, with cards offering the same features and fee structures. Some UK card issuers are subsidiaries of US firms and card issuance is dominated by the mainstream networks Mastercard and Visa. The credit card market mostly comprises general purpose credit cards, often with purchases rewards programs, teaser rate deals and balance transfer facilities. The issuers in our sample serve a broad range of market segments from 'prime' low-APR cards, which focus on revenue accrual through interchange fees to 'sub-prime' cards issued with high APRs.

We source the data via Argus Information and Advisory Services, who collate and harmonize data from credit card issuers.[12] Argus provided us with card level data for a random sample of 10% of consumers who held at least one card among the five credit card issuers in the period between January 2013 and December 2014. Our data are an unbalanced panel in which we observe card openings and closures.

The total data sample comprises 1.4 million customers, 1.8 million individual credit cards, and approximately 48 million card-months. The data include transaction level records (categorized spending and repayments) alongside card-month summary records (including credit limits, purchases and repayments, average daily balances, revolving balances, interest and charges). We also observe the opening date of each card in the sample, which allows us to calculate card tenure. In addition, Argus provides geocodes in the form of 4-digit UK postcodes.[13]

Our focus in this paper is on patterns in fee payments early in the life of new cards. We therefore restrict the sample to cards that open within our two-year sample period. This

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

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

sample restriction gives us approximately 243,000 cards and 2.7 million card-months of data. Summary statistics for this baseline sample for our analysis 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%).

Many cards 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 card-month observations having an APR of 0%. Figure A.1 Panel A illustrates slight growth in new card openings over the sample period, with some evidence of seasonality in card openings. Figure A.1 Panel B shows that the average credit score (measured in the data set by the predicted likelihood of charge-off within the next six months) is steady over the sample period.

2.1. Late Payments

Our analysis focuses on the most common fee type: late payment fees. Late payment fees are incurred when the consumer fails to make at least the required minimum repayment on the card by the statement bill due date. The required minimum payment is a fixed amount or a percentage of the card balance, whichever is higher (e.g., £25 or 2% of the balance). In additional analysis, shown in Section 5.3 and Appendix B, we also explore patterns in cash advance fees and over-limit fees, which are the next two most common fee types.[14]

Table 2 summarizes fees in our sample, showing summary data at the card level. Fees are quite common within our sample, with 34% of cards incurring a fee at least once within the sample period. Late payment fees are most common with 24% of cards incurring a late payment fee at least once. Cash advance and over-limit fees are less common, with 13% of cards incurring a cash advance fee and 7% of cards incurring an over-limit fee in the sample. Late payment fees are not concentrated among a small set of cards, which might distort our analysis. Figure A.2 illustrates the distribution of fees-per-card over the sample period, showing that the modal number of late payment fees incurred by cards that incur a fee is one.

2.2. Are Late Payments Costly to Cardholders?

Late payments are costly to cardholders via three channels: a modest direct penalty fee, a deterioration in credit card terms, and restricted access to future credit (including other forms of credit).

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

First, a late payment event results in a penalty fee. Late payment fees are modest in size, capped by regulation at a maximum £12 per month with no limit on the number of successive months in which a consumer can incur the fee. All card issuers in our dataset set the fee at the £12 regulatory limit.[15]

Second, a late payment results in a deterioration in credit card terms. Individuals who incur late payments may trigger APR increases (known as "penalty rates"), the loss of promotional zero-percent APR periods, and credit limit reduction. Figure A.3 draws a subsample of cards from the baseline sample that incurred a late payment fee at least once. The figure illustrates each of these outcomes at work in an event-study of credit card terms around the month in which a card incurred a first late payment fee. The card APR jumps up in Panel A by approximately two percentage points on a baseline of six percent (an increase of close to 33%). The probability of the card having a promotional zero APR jumps down in Panel B by approximately one percentage point on a baseline of seven percent (a decrease of 14%). The likelihood of the card receiving a credit limit decrease rises in Panel C from 0.25 percent to 3.5 percent (a 14 fold increase).[16] Finally, the card holder's predicted charge-off rate jumps upwards in Panel D from 0.015 to 0.045 (a 3 fold increase).

Third, the worsening credit score affects broader access to credit through the impact on future credit availability across the credit market via flags on credit files. The negative effects of fee payments therefore extend beyond the immediate modest fee imposed by the credit card issuer. We cannot quantify these directly due to the devolved credit scoring models used by lenders in the UK, and there is no mainstream credit score in the UK analogous to a US FICO score.[17] However, lenders and credit bureaus warn that credit card late payment fees lead to worsening credit bureau credit scores[18], can jeopardize mortgage applications[19], and remain on credit files for seven years after the fee is incurred.[20]

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

[16] Among cards that experienced a reduction in credit limit in the month following their first late payment fee, the average reduction was 33%, from £3600 to £2400).

[17] Instead, lenders compute proprietary credit scores. The impact of a late payment fee on a consumer's credit score will therefore differ by credit issuer.

[18] See `https://www.experian.co.uk/consumer/guides/late-payments.html`.

[19] See, for example, `https://www.landc.co.uk/insight/2015/03/can-late-payments-affect\-a-mortgage-application`.

[20] See `https://www.experian.com/blogs/ask-experian/how-long-past-due-remains`.

2.3. Background on Autopay

In this subsection, we describe how the autopay facility functions with a credit card. Manual repayments involve a customer receiving a bill each payment cycle, either electronically or in the mail, which must be repaid manually for example by electronic bank transfer, by mailing a depositor's check, or by making a payment via the telephone. Under autopay, the customer authorizes his or her bank to automatically make a payment by direct debit each month. The customer continues to receive a bill each payment cycle and can continue to make additional manual payments.

Credit card holders can choose to set the autopay amount to be the minimum amount due, the full balance, or a set money amount.[21] Hence, part, and sometimes all, of the bill is paid automatically, and additional manual repayments can still be made on top. Autopay therefore removes the need for the customer to be attentive to their bill and repayment (at least for the avoidance of late payment fees), conditional upon having sufficient funds in their deposit account.[22] The option to use autopay is available on all credit cards in the UK by law and is offered for free.[23] This is important in our analysis, as we can rule out the possibility that fee patterns differ across consumers due to selection into cards with or without the autopay option.

Most card holders set the autopay to be the minimum amount due. Figure A.4 Panel A illustrates the distribution of autopay levels among card-months in which the card balance was first paid by autopay. Approximately 60% of card-months are at the minimum due, with approximately 15% at full payment.[24] Figure A.4 Panel B illustrates the rate of adoption of autopay over the first months of card life, with about 40% of cards having autopay after the first year and only a small increase thereafter.

[21] In cases where card holders choose a set money amount or proportion of the balance, the amount taken via direct debit will never be lower than the minimum amount due or higher than the full balance.

[22] In the UK, autopay instructions are commonly used for a range of recurring payments, including mortgage payments, utility bills, cell phone bills and municipal taxes. Autopay is setup via a one-time instruction to the credit card company, often on the telephone or internet. Under UK law, an autopay instruction requires the consumer's consent. Autopay is guaranteed by the government against failure of the payments system to clear the transaction. In the UK, autopay is commonly referred to as "Direct Debit". To make a direct debit instruction, the customer has to complete a paper or online form detailing their deposit account details and providing their consent. Direct debit cannot be set up by proxy or as a trigger within a contingent contract. The direct debit mandate guarantees the customer against failed payments in the event of electronic of other failure of the payments system. It does not guarantee the payment in case of insufficient funds in the customer's deposit account.

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

[24] Note that a small fraction of autopay payments are "missed". These are cases in which the card holder's deposit account from which the direct debit is sourced had insufficient funds to meet the minimum payment.

3. Late Payments Decline With Tenure

We begin our main results by showing that credit card late payment fees decline with card tenure.[25] Figure 1 illustrates the late payment fees decline with tenure, both in the raw data and in a prediction from a rich multivariate model.

Figure 1 Panel A shows the raw data plot using the baseline sample. The proportion of cards incurring late payment fees falls from 6% to in the first month to 2.5% by month 23. The decline in fees is fastest over the first few months of card tenure. The sample used in Figure 1 Panel A is an unbalanced panel. Therefore, the observed pattern of fee decline could potentially arise due to selective attrition, or 'survivorship bias', if cards which incur a fee are more likely to close or fall dormant after the fee event. For this reason, in Figure A.5 we restrict the sample to cards that open within our sample period and remain open and active for at least 15 months, though results are not sensitive to changing this cut-off value.[26] This balanced panel includes 46% of observations in the main sample. Figure A.5 shows a very similar pattern of fee decline over tenure as that seen in the unbalanced panel. Summary statistics for this balanced panel sample can be found in Tables A1 and A2.

Figure 1 Panel B shows predicted fees from a multivariate model. The pattern of fee decline we observe could potentially be caused by time-varying card characteristics, or strong calendar time events which might dominate a period within our two-year panel. To the extent that fee events change subsequent behavior, card usage might be negatively autocorrelated over time with fee events. To control for time-varying card characteristics, card fixed effects and calendar time fixed effects, we estimate a linear probability model, similar to Agarwal et al. (2008). We then plot the predicted probability of incurring a fee over tenure. The equation we estimate is:

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

where fee is a dummy variable that is 1 if a late payment fee is paid on card i at tenure t. The probability of incurring a fee is modelled as a function of vectors of tenure dummies (Ω_t, indicating the age of the card in months), month dummies (ψ_{month}), card fixed effects (ϕ_i) and

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

[26] 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 cards and ii) restricting to 24 months implies a panel of cards all of which open in January 2013, which might highlight calendar month effects, though we see no strong seasonality in card openings. We see identical patterns of fee decline if we further shorten the panel length to 12 months or 10 months.

time-varying card level controls ($\beta(X)_{i,t}$).[27] Standard errors are clustered by card. Predictions are shown at covariate medians. The prediction plot in Figure 1 Panel B shows a very similar pattern to that in the raw data. The likelihood of late payment fees falls steeply over the first few months of card tenure.[28] Table A3 reports the model estimates.[29]

Before exploring the reasons why these patterns exist, we note one implication of these patterns in fee behavior: revenue streams from late payment fees are front-loaded for card issuers (this is also the case for other fee types, as we explore later in the paper). This might present another incentive for card issuers to acquire new customer accounts, especially if initial fees are the result of mistakes by 'good' credit types and not due to high credit risk (which would make accounts less attractive to card issuers). In the UK credit card market, as in the US, credit card issuers aggressively compete for customers via initial incentives such as teaser rate deals (zero or low APR promotional periods), cash-back rewards and other joining incentives. One reason for this strong competition over acquisition may be the initial fee concentration captured by the card issuer.

4. Late Payment Fees and Autopay

The focus of our paper is on why late payment fees decline with tenure. In this section we show that the tenure-profile of late payment fees differs markedly across card types by whether they adopt autopay. Strikingly, we find *all* of the decline in late payment fees with tenure is attributable to the subset of cards that open with manual repayment regime and then adopt autopay after incurring a fee. In contrast, the subset of cards that do not adopt autopay after incurring a fee experience no decline in fees. This leads us to focus on autopay as central to how consumers avoid future penalty fees.

To show the importance of autopay in explaining the pattern of decline in late payments among new cards, Figure 2 reproduces Figure 1 Panel B for three card types: cards that adopt autopay from card opening onwards (Panel A, 14.4% of cards); cards that open without autopay,

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

[28] Figure A.5 Panel B plots predictions for the balanced panel sample, in which the decline in late payment fees is sharper, confirming again that the modelled patterns we see in the prediction plots are not attributable to attrition. The patterns in the model plots (Panel B) are not sensitive to extending or shortening the time window out from 15 months. We also see identical patterns from estimates of Equation 1 in which we include a dummy variable to control for whether the card carries a balance, and therefore has a non-zero minimum payment due. This shows that selective card inactivity does not account for our results. Throughout the remainder of the analysis presented in the paper, we find no difference in econometric estimates when including this dummy variable or not.

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

i.e. are manual repayment cards, and keep this regime through the sample period (Panel B 64.1% of cards); and cards that open with a manual repayment regime but adopt autopay during the sample period (Panel C, 21.4% of cards).[30] These plots are obtained by estimating Equation 1 separately for each card type.[31]

The late payment fee patterns differ markedly across the panels of Figure 2. Unsurprisingly, among cards which have an autopay instruction from inception, shown in Panel A, the probability of a late payment fee is close to zero throughout the sample period (because at least the minimum amount is automatically repaid on time). Hence, a late payment fee is incurred only when the customer's deposit account has insufficient funds, a very rare event. Among cards which never have an autopay instruction, by contrast, the probability of late payment fees is consistently around 7%, with no decline over card tenure. All of the decline in fees with tenure is seen among cards that adopt autopay after opening, in Panel C. Among these cards, the probability of incurring a fee is close to 18% at the point of opening, but quickly declines and reaches 0% after a few months.

The results strongly suggest that the decline in late payments fees is attributable to adopting autopay. The rate of late payment fees among non-adopters exhibits no decline through the sample period. However, those who do not adopt autopay (and hence continue to rely on memory along to pay their bill on time) remain just as likely to pay a late payment fee again in the future. We present a series of robustness and sensitivity tests for this first result in Appendix A.

4.1. Adopting Autopay After a Late Payment Fee

Adopting autopay appears to be the driver of declining late payment fees. To further explore this, we conduct an event-study analysis to examine the relationship between late payment fees and adopting autopay. The event-study approach allows us to focus on changes in fee accrual at the timing of the first late payment fee incurred on a card. We estimate an event study model, given by Equation 2 below, which incorporates a set of time-varying card characteristics to capture changes in purchase or repayment behavior, or changes in credit risk, which might occur at the

[30] We use 15 months here to avoid calendar month effects which would arise from using a 24-month time period because this would restrict the sample to cards opening in January 2013. We also exclude from the sample a smaller number of cards that change autopay status multiple times during the period.

[31] We show corresponding scatter plots of fees in Figure A.6. Tables A4 to A6 report the model estimates.

same time as a late payment fee. We estimate the following event-study equation:

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

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

In Figure 3 we show plots of the predicted probability of incurring a late payment fee, where the x-axis is event-time elapsed since the first fee, for all cards that are manually repaid throughout (Panel A) and those that adopt autopay (Panel B).[32] By construction, the plots only show months after the first late payment fee event.

Panel A illustrates that among always non-autopay cards the fee likelihood is persistently 20% per month in the months following the first fee event. Among cards that adopt autopay, shown in Panel B, the fee likelihood reduces immediately in the month after incurring the first fee to 10%, and falls to 0% in the following months.[33]

To show fee dynamics around the adoption of autopay, Figure 4 plots the proportion of cards incurring a late payment fee, where the x-axis is event time since the first autopay payment. The figure confirms that late payment fees are a strong trigger of adopting autopay. In the months before adopting, the fee rate among adopters is approximately 8%, this spikes to 16% in the month before adoption. Following the setup of an autopay instruction, the proportion of cards incurring a late payment fee falls to nearly 0%.

These results illustrate in an event-study time analysis that the decline in late payment fees over tenure occurs due to a subset of customers changing their repayment behavior by adopting autopay. The sharp decline in subsequent fees also strongly suggests that the late payment fees incurred by these customers were one-time mistakes. If late payment fees were due to persistent liquidity constraints, then adopting autopay would not reduce the late payment fee. Remarkably, customers who do not adopt autopay show a persistently high likelihood of future

[32] We show corresponding scatter plots in Figure A.14. Tables A7 and A8 report the model estimates. Less than 1% of cards incur a late payment fee while already being repaid by autopay, an additional small number of cards change autopay status more than once in the sample period.

[33] The decline in fees is not immediately to zero as i) not all cards adopting autopay following a late payment fee do so in the month immediately following the first fee event; ii) cards may continue to incur late payment fees due to insufficient funds in the consumer's deposit account.

fees. For these customers – who need to remember each month to make their card payments in order to avoid late payment fees – purely "remembering" to pay in future appears to be an ineffective strategy for reducing the likelihood of future fees.

These results suggest that the late payment fee acts as a "call to action" for consumers to adopt autopay. When we examine the timing of fees and adoption of autopay, we see in Figure 5 that the vast majority of consumers who adopt autopay following a late payment fee do so in the months immediately following the late payment fee. Figure 5 takes the sample of all cards which incur at least one fee and illustrates the probability of a card adopting autopay over the months after the first fee is incurred. Adoption occurs soon after the fee, either in the same month as the fee (month 0 for individuals who adopt autopay and bring their account up-to-date with the first autopay payment), or in the following month.

4.2. Who Adopts Autopay?

The results on late payment fees raise the question of why only *some* card holders adopt autopay after incurring a fee, while others do not. This distinction is important because, as discussed above, late payment events are costly to cardholders through a variety of channels.[34] Given that autopay is available to all cardholders, and can be set at a variety of levels, it is perhaps puzzling as to why it is not more widely adopted after a late payment fee.

We consider four explanations for why some individuals adopt autopay, but others do not: i) *occasional card usage*, ii) *liquidity constraints*, iii) *socio-economic characteristics*, iv) *card characteristics and spending patterns.* The descriptive analyses reveal important differences between adopters and non-adopters, though we cannot firmly establish causal links between individual characteristics, adoption of autopay and subsequent payment behavior.

In Table 3 we compare card characteristics for individuals who do and do not adopt autopay following the incursion of a first late payment fee using information from the Argus data, and also matched data on consumer characteristics using geocodes. In Panel A, we compare adopters and non-adopters by their card usage and in Panel B by their card characteristics. The availability of geocodes also allows us to match-in a rich set of socio-economic covariates, by which we compare adopters and non-adopters in Panel C. Other recent studies using matched

[34] A calculation of the direct late payment fee cost is that, among non-adopters, the fee probability persisting at 20% per month implies that a card will incur a £12 late payment fee every five months; while among adopters this likelihood is approximately 2%, implying a card will incur a late payment fee every 50 months. Hence, over reasonable time periods, non-adopting cards will incur 10 times more late payment fees compared to adopting cards. While these direct fee costs are moderate, this is an underestimate of the total difference in the economic costs of fees, which also includes the indirect costs arising from markers added to credit files.

census data, based on US zip codes, include Mian and Sufi (2009) and Chetty et al. (2013).[35] We also compare spending patterns across merchant categories with results shown in Figure 6.

Occasional Card Usage. One potential reason for not adopting autopay is that customers have low levels of card activity, so the need to repay in the future is low, and hence late payment fees are very occasional events. However, a comparison of card characteristics suggests that non-adopters do not avoid adopting because they have low card activity (and hence low likelihood of future fees). On average, non-adopters revolve around £1,600 in balances and have a positive balance in 86% of card-months. Non-adopters also have higher monthly purchases compared with adopters (£170 compared to £150) and also have higher monthly repayments (£260 compared to £185). These similarities in card activity also suggest that inattention is unlikely to be a cause of not adopting autopay.

Liquidity Constraints. Consumers might not adopt autopay if they are financially constrained and cannot make repayments. Autopay does not provide perfect insurance against failure to pay if the consumer's deposit account contains insufficient funds to meet the repayment due, in which case the consumer would incur penalty charges on the deposit account as well as on the credit card. However, non-adopters do not appear on average liquidity constrained in the data. First, card utilization among non-adopters is actually lower compared to adopters (48% compared with 59%). Monthly purchases by non-adopters are also only approximately 10% of the spare capacity on the card, suggesting that non-adopters on average are not moving towards a liquidity constraint on their credit card. Second, non-adopters make *higher* average repayments each month compared to adopters (£260 compared to £185), despite being more likely to miss payments, also suggesting that lack of available funds in their deposit account does not drive this behavior.[36] We cannot observe the deposit account position of card holders in our sample, and expect that in some cases not adopting autopay may arise due to lack of liquidity in the deposit account. However, the higher average repayments among non-adopters suggest that they are not on average constrained by low available funds in other accounts.

Socio-economic Characteristics. Adopters and non-adopters might also differ in their

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

[36] Figure A.16 illustrates mean payment amounts by non-adopters in the months before and after their first late payment fee.

socio-economic characteristics. The matched geodata indicates that adopters are drawn from localities with higher median house prices, lower jobless claimants, higher weekly incomes, higher proportions of individuals in the locality with post-high school educational qualifications and a lower proportion of children in the locality entitled to free school meals. They also have lower ACORN scores, a postcode-level affluence score constructed by the UK statistics authority, indicating a higher degree of affluence. The differences in means across groups are all statistically significant at the 1% level.[37]

Card Characteristics and Spending Patterns. Differences in card characteristics between adopters and non-adopters suggest that adopters have a higher propensity to hold cards with 0% introductory merchant APR and are also more likely to hold cards with a balance transfer facility. Figure 6 compares the spending behavior of adopters and non-adopters. The figure compares the average number of transactions in each merchant category code (Panel A), the average spend in each merchant category code (Panel B) and the average spend as a proportion of total spend in each merchant category code (Panel C).[38] The plots show that non-adopters tend to have a larger number, and monetary value, of spends in consumables, such as restaurants and bars, retail, clothing stores and food stores. Tests of the equivalence of means between the two groups for the number of transactions and average spend indicate these differences are statistically significant at the 1% level.[39]

Taken together, these results show that differences in adopting autopay cannot be explained by liquidity constraints or low levels of card usage. Instead, the analysis of socio-economic characteristics reveals differences in education, income and spending on consumables across the two groups. The analysis of spending patterns suggests a role for consumer myopia as a cause of non-adoption of autopay.

5. Extensions

In this section we extend our main analysis to consider responses to second late payments, spillover effects from late payments on one card onto behavior on other cards, and also extend our analysis to over-limit and cash advance fees.

[37] 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.

[38] A caveat to this variable is that credit card spending is most likely only a share of total spending for the majority of individuals in the sample. Unfortunately, we do not have data on the timing of spending within the month, so cannot analyse the relationship between timing of income receipt and timing of spending, as in Hastings and Shapiro (2018).

[39] Summary data, together with results from t-tests, are reported in Tables A10 to A12.

5.1. Extension I: Responses to Second Late Payments

The patterns of responses to second late payments may differ from those to first fees if, for example, second fees have a strong reinforcement effect. Among those cards that incur a first late payment, 36.2% of cards incur a second late payment within the sample period. To show how consumers respond to second late payment, Figure 7 replicates the analysis of first late payments by showing responses to late payments among cards that do and do not adopt autopay after their incursion of a *second* late payment. The pattern in the figure is the same as in the first late payment analysis. Notably, there is no evidence of fee decline among consumers who continue with manual payments after the second late payment. Of those incurring a second late payment, approximately one quarter adopt autopay while three-quarters persist with manual repayment. The month-by-month likelihood of incurring a second late payment remains high at more than 20% through the ten months following the second late payment.[40]

5.2. Extension II: Spillover Effects to Other Cards

The effects of late payments may spill over to other cards held by the individual. In this subsection we explore this in an event-study analysis of outcomes on other cards. For simplicity, we restrict to cardholders holding two cards in the month in which they incur the first late payment fee on one of the cards (among the sample of card holders for whom we see multiple cards, 91.4% hold two cards, with the remaining 8.6% holding more than two cards). In Figure A.17 we denote the card on which the first late payment event occurs as Card A and plot, on the y-axis, characteristics of the other card, which we call Card B.

Panel A shows that there is a positive correlation in late payments across cards: 25% of individuals incurring a first late payment on Card A also incur a late payment on Card B in the same month. Panel B shows that adoption of autopay on Card B increases in the months following the late payment on Card A. Panel C shows that balances on Card B decline in the months following the late payment fee on Card A, but interest paid increases (this is due to a fraction of Card B cards that incur a late payment fee experiencing an increase in interest rates

[40] To explore heterogeneity in adopting autopay after the second late payment event, Table A13 replicates Table 3 for the sample of consumers that incur a second late payment. In keeping with our results from the analysis of the first late payment event, non-adopters do not appear to be only occasional card users or more likely liquidity constrained: they have lower utilization, higher purchases and higher payments than adopters. Instead, adopters have a range of indicators of being more financially sophisticated than non-adopters: they are drawn from localities with higher median house prices, lower jobless claimants, higher weekly incomes, higher proportions of individuals in the locality with post-high school educational qualifications and a lower proportion of children in the locality entitled to free school meals.

to the penalty interest rate).[41]

5.3. Extension III: Over-limit and Cash Advance Fees

We also extend our analysis to over-limit and cash advance fees, the next two most common fee types after late payment fees. While our focus in this paper is on late payment fees and the adoption of autopay, other fee also present direct and indirect real costs to consumers. Appendix B presents the analysis in full, which we summarize here.

Cash advance fees show a similar pattern of steep decline over the first few months of card life to those seen for late payments. The probability of a card incurring a cash advance fee falls from approximately 3 percent to 1 percent over the first year of card life. Further analysis suggests that this pattern is due to liquidity constraints focused around the time of card openings: spells of use of cash advances occur on average during periods of high purchase transactions, rising revolving balances and rising utilization. Cash advance fees are also concentrated among higher-risk cards.

Over-limit fees, in contrast, steadily increase in the first few months of card life.[42] However, conditional on tenure of the first fee, over-limit fees decline in subsequent months. On average, over-limit events occur after the balance has accrued over a series of months and are, on average, followed by a one-time balloon payment to bring the balance below the limit.

6. Should Firms Mandate Autopay?

Our results may have implications for how credit card issuers manage the repayment options offered to their customers. One possibility is that card issuers should encourage, or even mandate, that customers use autopay in order to avoid the negative effects of late payments. Given that autopay can be set at a variety of payment amounts, mandating a minimum payment autopay could be a mean of effective insurance against card holders forgetting to make repayments without imposing high repayment burdens on card holders.

However, one potentially negative side-effect of the use of autopay set to the minimum payment due is that this may implicitly discourage higher repayments either through a recom-

[41] In Figure A.18 we show patterns in other card characteristics in event study time around the adoption of autopay. Again, we restrict to cardholders holding two cards in the month in which the first card adopted autopay. We denote the card which adopted autopay as Card A and plot, on the y-axis, characteristics of the other card, which we call Card B. The panels show no changes in characteristics of Card B around the time of the adoption of autopay on Card A in automatic payment, balances, interest on late payments on Card B.

[42] This finding is in contrast to Agarwal et al. (2009), who show that over-limit fees (as well as late payment and cash advance fees) peak in the first month of card life and then steadily decline.

mendation effect, or by making consumers inattentive to their card balances. In our data, we see that the majority of card holders using autopay choose an automatic minimum payment (see Figure A.4). We further observe that, after adopting autopay, the fraction of the balance repaid each month falls. Additional analysis in Figure A.19 shows that the fraction of the balance repaid falls from approximately 55% to approximately 28% after the adoption of autopay (Panel A). This arises due to a large increase in the proportion of cards paying exactly the minimum payment each month, which increases from approximately 25% to almost 50%, despite an increase in the proportion of cards paying in full from approximately 13% to 16% (see Panels B and C of Figure A.19). Hence, descriptively, the adoption of autopay is associated with lower future payments, and therefore higher future interest charges.[43]

These descriptive patterns of course do not imply that adopting autopay causes a reduction in payments, consequent increase in balances and increase in interest payments. Also, the effects of mandating autopay for those who do not currently adopt autopay may differ from the descriptive analysis of those who choose to adopt. Indeed, we observe that those not adopting autopay make, on average, larger monthly payments compared with those who do adopt. If individuals who make larger average payments were instead to adopt automatic minimum payments, the negative effects arising from reduced payments would be larger. The overall effects of a policy mandating automatic minimum payments is therefore a topic for future research.

In the UK, the Financial Conduct Authority (FCA) has identified persistent automatic minimum payments as a potential source of excess interest charges to card holders and has sought to nudge card holders towards higher payments.[44] In a collaborative study with the FCA involving a co-author of this paper, Adams et al. (2018) conduct a field trial in which card holders are nudged towards a higher-than-minimum automatic payment at card opening, with mixed effects. While encouraging higher autopay amounts increases automatic payments, the authors find that card holders decrease their additional payments, resulting in no net increase in debt repayment.[45]

[43] Figure A.20 illustrates the distribution of repayment amounts, by card balance, before and after the switch to autopay. As can be seen in the figure, the adoption of autopay all but eliminates missed payments. However, the adoption of autopay increases the fraction of minimum payments, especially at higher balances. The net effect of the changing distribution of payments shown in the figure is that the mean fraction of balance repaid falls.

[44] This issue is also examined in a working paper by Sakaguchi et al. (2018), involving some of the co-authors of this paper, which seeks to establish the causality between adoption of automatic minimum payments and patterns in future payment amounts.

[45] Adams et al. (2018) implement an intervention that shrouds the option to automatically pay the contractual minimum at the end of each pay cycle. This increases the salience of the other autopay option: cardholders can select a fixed monthly payment, which is typically more than the contractual minimum. The intervention results in a very large increase in the amounts consumers select for autopay. However, it has no effect on other, more

7. Conclusion

In this paper, we examine patterns in credit card late payments among newly opened credit card accounts. In a large sample of cards from five credit card issuers, we show that late payments peak in the first month of card life and then decline sharply. We show that the decline in fees is wholly attributable to a subset of customers who adopt automatic payments after incurring a late payment fee. Individuals who do not adopt automatic payments see their likelihood of future fees remain high and unchanged. Our analysis of adopters and non-adopters suggests that non-adopters have on average lower education and income and may be more myopic, with adoption not appearing to be driven by occasional borrowing needs or liquidity constraints.

Our findings may have important implications for understanding how consumers respond to feedback – in the most general sense of the word – in financial markets. With their prominent fees and short time cycles, credit cards are a very promising financial product for adapting behavior. Our core finding –that people only avoid fees when they act to change their ongoing repayment behavior by adopting automatic payment – is important for understanding which consumers gain from financial innovations (such as automatic payments) and the costs to consumers who do not embrace additional features of financial products. The heterogeneous responses across customers in our data also implies that losses from incurring fees are unevenly distributed among consumers. The benefits from innovation in payments technology, such as automatic payment, may be unevenly distributed across consumers who do and do not adopt these new technologies.

important outcomes: total debt repayments (including both automatic and nonautomatic – ie manual – payments), credit card spending, borrowing costs or debt net of payments. These null effects arise primarily because consumers in the treatment group offset their increased automatic payments by reducing the value of their (infrequent) manual payments. The intervention also causes a modest reduction in consumers selecting any type of autopay, which leads to a small increase in arrears.

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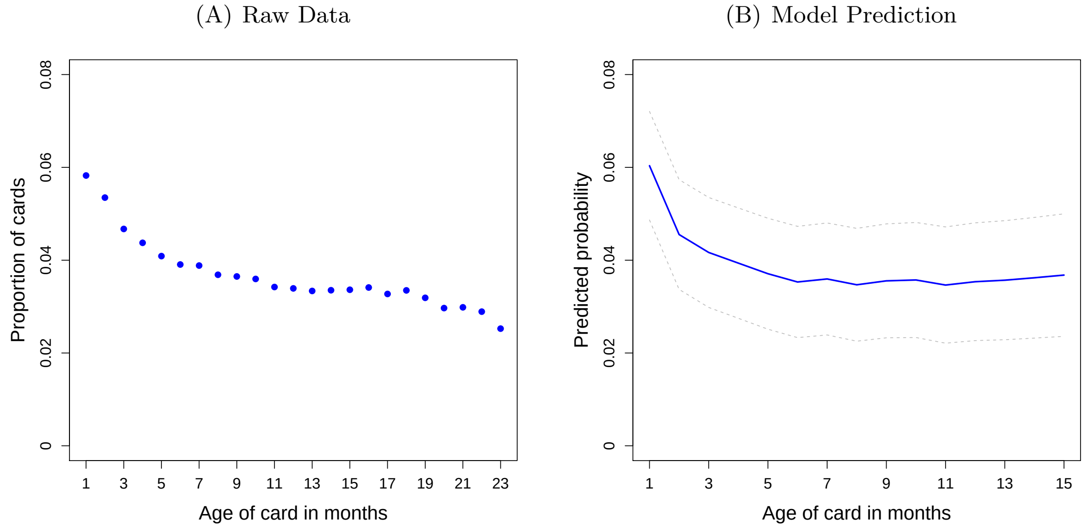
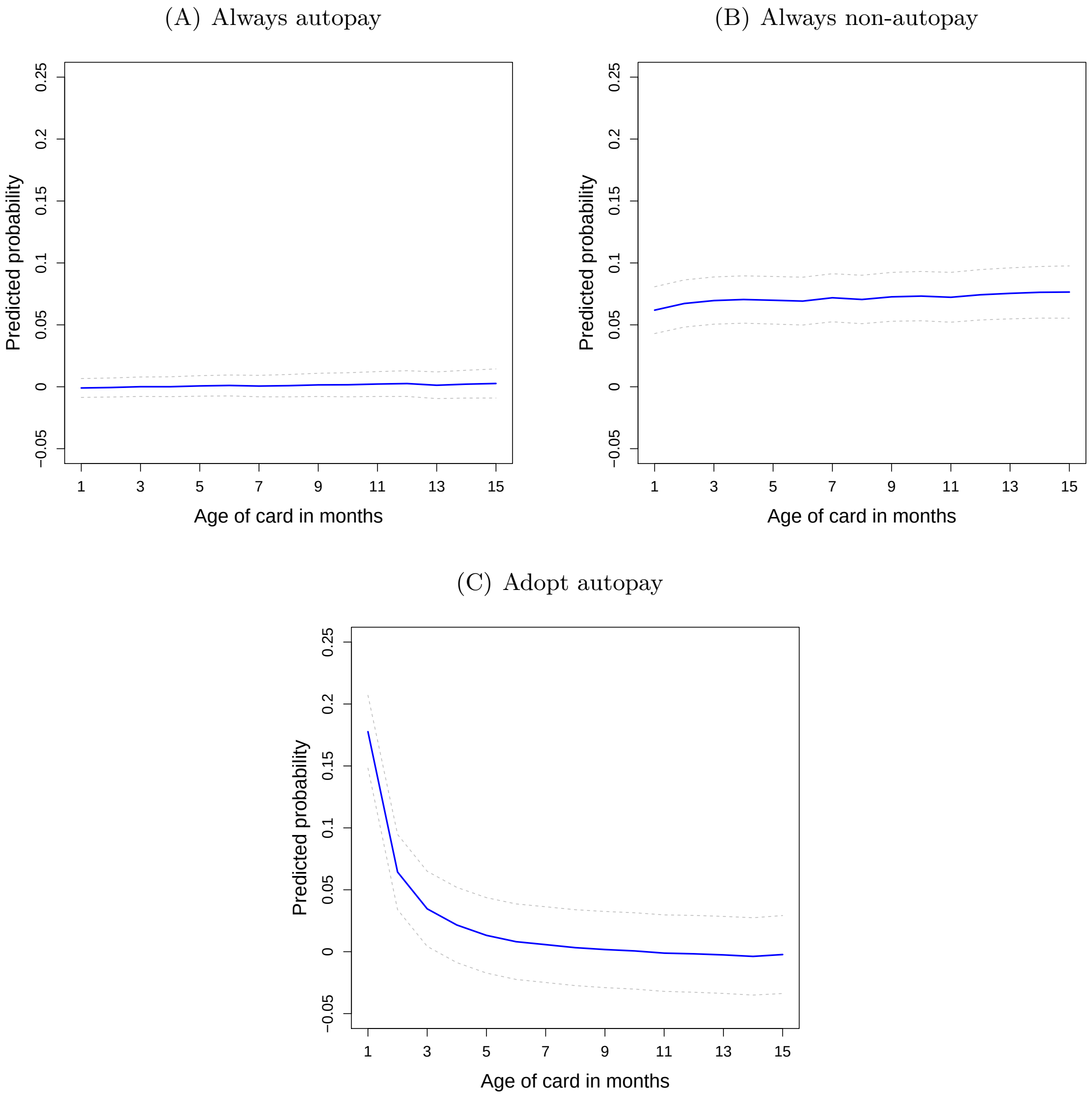
Figure 1: Late Payment Fees and Card Tenure



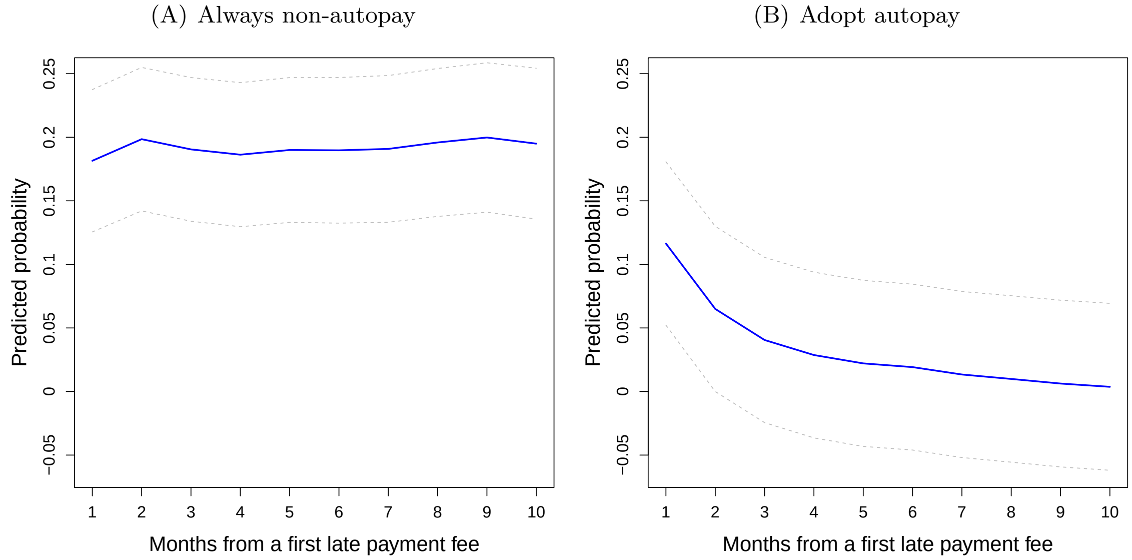
Note: Figures show late payment fees by age of card in months (card tenure). Panel A plots the mean of the y-axis variable (dummy variable indicating whether the card incurred a late payment fee) by units of the x-axis variable (age of the card in months). The x-axis variable is adjusted one month forward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

Figure 2: Probability of Late Payment Fee by Autopay Status



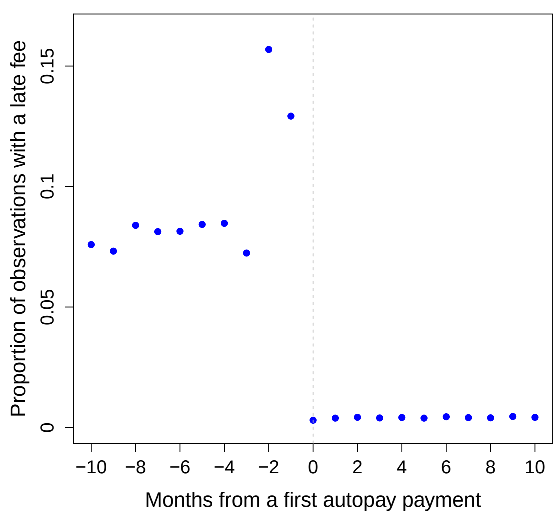
Note: Figures show the predicted probability of cards incurring a late payment fee in the next period by the age of the card in months. Predictions are from a linear probability model at covariate medians (Equation 1). The panels show three mutually exclusive groups of cards: cards which were subject to an autopay instruction from card opening onwards; cards which were never subject to an autopay instruction; and cards which adopt autopay after card opening. 95% confidence intervals are illustrated by the dashed lines. The corresponding scatter plots of fees over tenure for each group are shown in Figure A.6. Tables A4 to A6 report the model estimates.

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



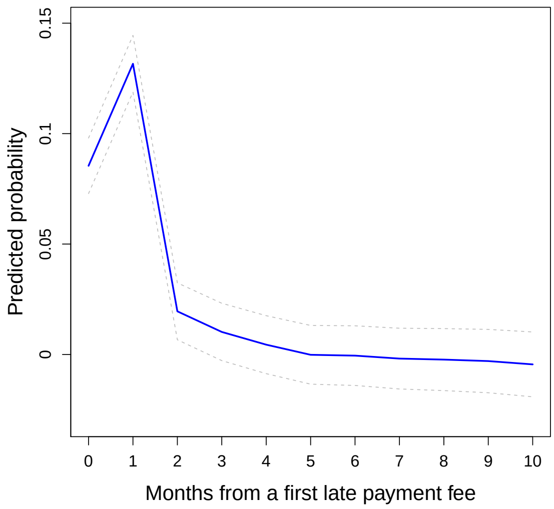
Note: Figures show the predicted probability of cards incurring a late payment fee in months after the first late payment fee is incurred (month zero). Predictions are from a linear probability model at covariate medians (Equation 2). The panels show two mutually exclusive groups: cards which were never subject to an autopay instruction throughout the sample period; and cards which adopt autopay within the sample period. All cards 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 A.14. Tables A7 and A8 report the model estimates.

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



Note: Figure shows the proportion of cards incurring a late payment fee before and after adopting autopay. The sample comprises cards which adopt autopay within the sample period. Month zero on the x-axis denotes the month in which the card was first repaid using autopay.

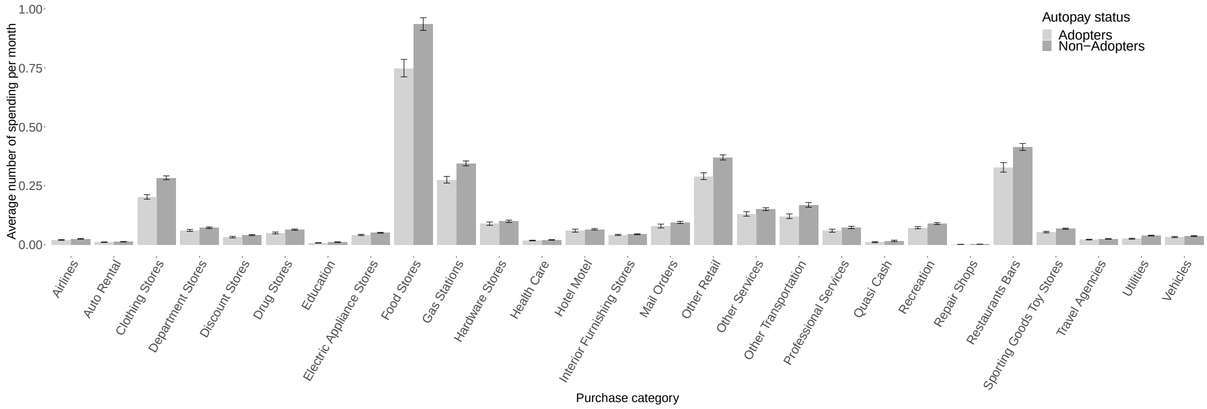
Figure 5: Probability of Cards Adopting Autopay by Month After First Late Payment Fee



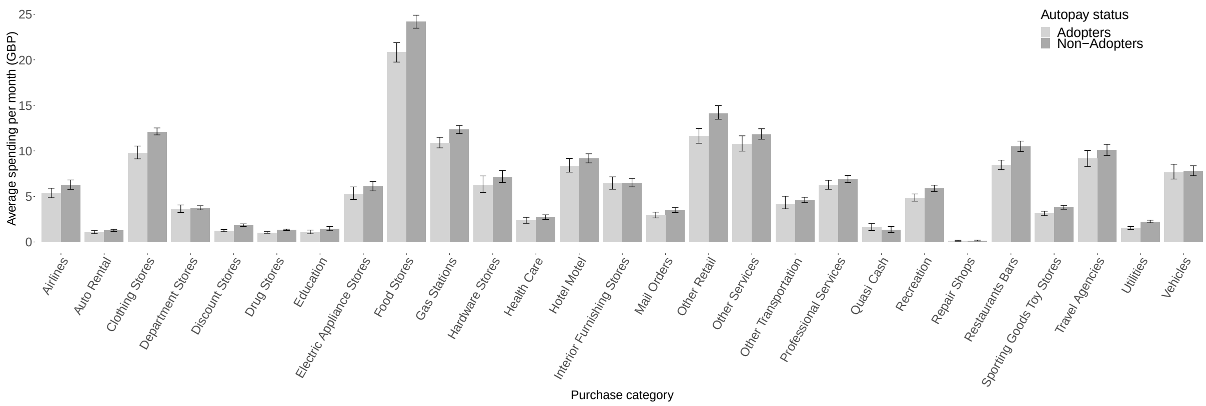
Note: Figure shows the probability of cards adopting autopay by months from the first late payment fee (month zero). Sample is all cards with at least one late payment fee. Table A9 reports the model estimates.

Figure 6: Card Purchase Patterns for Adopters vs. non-Adopters

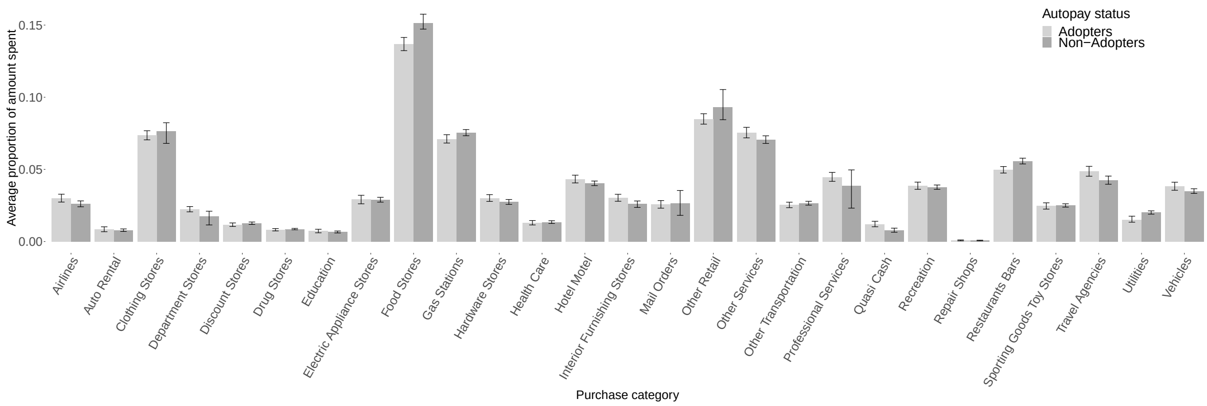
(A) Number of Purchases per Month



(B) Value of Purchases

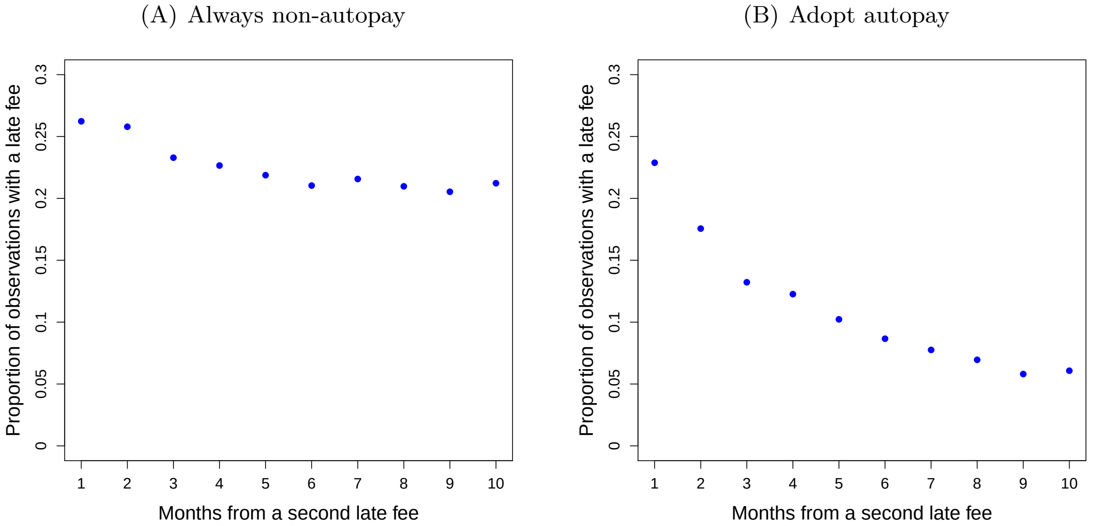


(C) Purchases as a Proportion of Monthly Spend



Note: Figures show spending patterns in card × months following the first late payment fee for those who adopt autopay (light grey shading) compared with those who do not adopt autopay (dark grey shading). Categories on the x-axis represent merchant category codes created by Argus. Panel A shows average number of spends per card per month in each category. Panel B shows average spend in pounds per card per month in each category. Panel C shows average spending in each category as a proportion of total spend of each card.

Figure 7: Late Payment Fees in Months Following a Second Fee, by Autopay Status



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

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 cards	242,899						
Number of card-months	2,669,259						

Note: Table shows summary data for the sample of new card openings (cards which open at or after January 2013). The unit of data is a card × month. APR denotes Annualized Percentage Rate. Merchant APR refers to APR on revolving balances incurred from purchases. Cash APR refers to APR on balances incurred from cash advances. Utilization is calculated by dividing the balance by the credit limit, expressed in percent of the credit limit. Charge-off Rate is the predicted probability of charge-off within the next sixth months. SD denotes standard deviation.

Table 2: Fee Summary Statistics

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

Note: Table shows card-level summary data for fees incurred by fee type. Sample of cards which open at or after January 2013.

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

	All Mean	Non-Adopters Mean	Adopters Mean	t score	p value
Panel A					
Card Usage					
Mean balance (£)	1,842.59	1,553.33	2,406.46	-134.03	0.0000
Mean utilization (%)	51.32	47.61	58.57	-96.32	0.0000
Mean monthly purchase (£)	162.20	170.38	146.27	16.58	0.0000
Mean repayment|given balance>0 (£)	234.43	261.87	185.97	38.27	0.0000
Proportion of card-months with balance>0	0.89	0.86	0.95	-104.69	0.0000
Panel B					
Card Characteristics					
Has 0% intro APR (0/1)	0.79	0.76	0.88	-36.60	0.0000
Mean Merchant APR (%)	7.85	9.08	4.85	48.28	0.0000
Mean Cash APR (%)	25.11	25.05	25.27	-7.70	0.0000
Has Balance Transfer (0/1)	0.60	0.57	0.67	-21.19	0.0000
Panel C					
Socio-Economic Characteristics (Postcode)					
Mean house price (£)	206,490	204,718	211,194	-4.69	0.0000
Jobless claimants (%)	2.626	2.664	2.528	6.36	0.0000
Mean weekly income (£)	744.69	740.63	755.46	-7.53	0.0000
Education level 4+ (%)	28.294	28.110	28.782	-6.31	0.0000
Mean Acorn category	3.246	3.264	3.197	8.43	0.0000
Free-school meal (%)	13.036	13.225	12.535	7.84	0.0000

Note: Table shows card-level summary data for the sample of cards which open at or after January 2013 and incur at least one late payment fee over the subsequent two years. "Non-Adopters" consist of cards that never adopt autopay, "Adopters" consist of cards that adopt autopay", and "All" consist of all cards in the two sub-samples. The units of analysis and sample sizes are: Card usage variables (Panel A) are measured at the card × month level. Sample size for card characteristics: Non-Adopters 288,977; Adopters 148,237. Card characteristics (Panel B) and socio-economic characteristics (Panel C) are measured at the card holder level. The sample sizes differ by variable. For house price, weekly income and educational level: Non-Adopters 24,677; Adopters 9,299. For jobless claimants: Non-Adopters 15,846; Adopters 6,054. For Acorn category: Non-Adopters 26,400; Adopters 9,921; For free school meals: Non-Adopters 23,338; Adopters 8,818. Socio-economic characteristics are matched from the UK Office for National Statistics ACORN database, which provides observations of postcode-level characteristics derived from census data.

Appendix

Online-Only Appendix accompanying "How Do Consumers Avoid Penalty Fees? Evidence From Credit Cards" by John Gathergood, Hiroaki Sakaguchi, Neil Stewart and Jörg Weber, forthcoming in Management Science. Acceptance date 2 December 2019.

A. Late Payment Fee Sensitivity Analysis and Robustness Checks

We present a sensitivity analysis for our main result, shown in Figure 2. We show the sensitivity of the main model estimates of Equation 1 to variation in the set of controls, set of fixed effects, regression functional form and panel length. We present this battery of sensitivity tests in Figure A.7 in a "specification curve" (as suggested by Simonsohn et al., 2015). A specification curve is a visualization of how coefficient magnitudes and precision vary across specifications of econometric models. In Figure A.7, each dot represents an estimate of the coefficient on the dummy variable for tenure in Equation 1 at tenure month 10. This month is chosen as there are clear differences in fee likelihoods at this month across the panels in Figure 2. The unfilled dots show estimates for always non-autopay cards and the filled dots show estimates for cards that adopt autopay. Each column presents estimates for a separate equation, with the rows in the bottom panel indicating the combination of sample, control variables, fixed effects and functional forms used in the models. Results show that across the wide variety of models the coefficient estimate on the tenure = month 10 dummy among the sample of adopted-autopay cards is always below that of the always non-autopay cards, and both sets of estimates are stable across specifications.[46]

Second, we vary the panel length to ascertain whether there is any evidence of fee decline over longer time horizons for always non-autopay cards. We do this because results could potentially be sensitive to the time period in our main analysis. Therefore, in Figure A.8 we restrict our baseline sample to cards which provide a balanced panel of observations from the month of card opening onwards for 6-months (shortening the horizon) and for 18-months (lengthening the horizon). We see the same patterns as in our main analysis.[47]

We also further extend the panel length by drawing on the larger sample of non-new cards. When we expand the sample to all card-months up to 48 months from opening (bringing

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

[47] Figure A.9 shows accompanying scatter plots.

into the analysis cards that are already open at the start of the sample period) in Figure A.10, we see that the likelihood of always non-autopay cards paying late payment fees at four years of age is not lower than after one year.[48]

Third, we estimate the slope in Figure 2 Panel B. The plot in Figure 2 Panel B shows coefficients on the tenure dummies. These suggest there is no download slope. To estimate the slope, we replace the tenure dummies term in Equation 1 with a linear tenure-trend variable. We re-estimate the model, showing in Figure A.11 that the slope of the fitted line is flat in the baseline sample, as well as in the 6-month and 18-month balanced panel samples. The flatness of the fitted line implies no decline in fees with tenure.

We also focus on cards which open with a high risk of incurring a late payment, and hence have more scope to show a reduction in late payment fees. We do this because the likelihood of fees in the baseline sample might not be sufficiently high such that we could detect fee decline (given that fees present as integer units). We therefore restrict the baseline sample to higher-risk cards, drawing cards which open with an above-median credit risk score. The results in Figure A.12 show that among always non-autopay cards, the predicted probability of a late payment fee in month one is 10% in this sample (compared with approximately 6% in the main sample). The figure also shows that there is again no decline in the predicted probability of incurring a fee with card age, even in this higher-risk sample.[49]

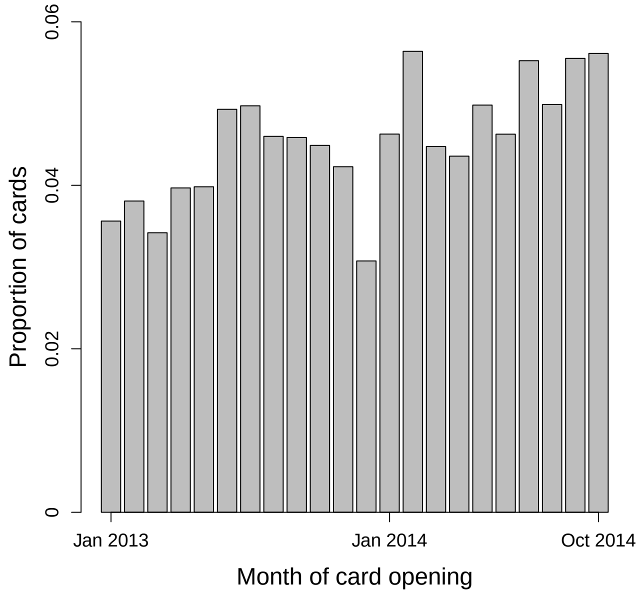
In addition, we present sensitivity analysis of the result shown in Figure 3. We again use a specification curve to show the sensitivity of these model estimates to variation in the set of controls, set of fixed effects, regression functional form and panel length in Figure A.15. Each dot shows an estimate of the coefficient on the dummy variable for 5 months after the first fee from Equation 2. This month is chosen as there are clear differences in fee likelihoods at this month in Figure 3. The unfilled dots show estimates for always non-autopay cards and the filled dots show estimates for the cards adopting autopay. Results show that the coefficient estimate on the dummy variable among the sample of cards adopting autopay is always below that in the non-adopting cards, and both sets of estimates are persistently different across specifications. The estimates are slightly sensitive to the inclusion of combinations of card and calendar month fixed effects (which are all included in our main estimates of Equation 2).

[48] Figure A.10 shows plots for always-autopay and always non-autopay cards in the months in which we observe them in the data. We are unable to show an equivalent plot for cards that adopt autopay as we cannot observe the point of adoption for cards opening before the start of the sample period.

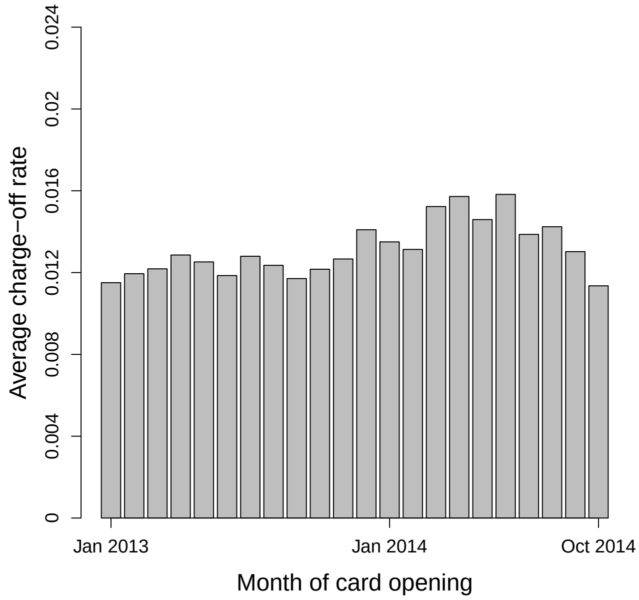
[49] Figure A.13 shows accompanying scatter plots.

Figure A.1: Card Openings by Calendar Month

(A) Frequency of Card Openings

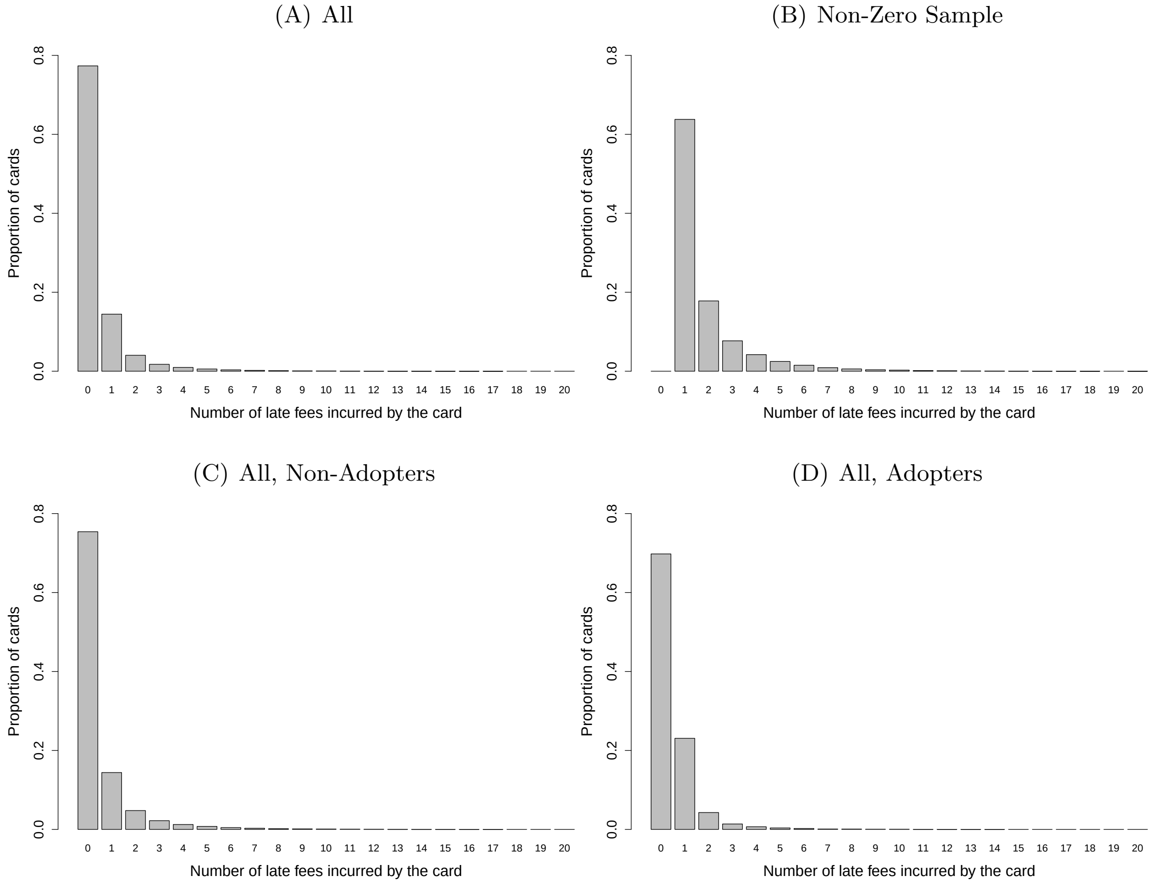


(B) Mean Charge-Off Rate



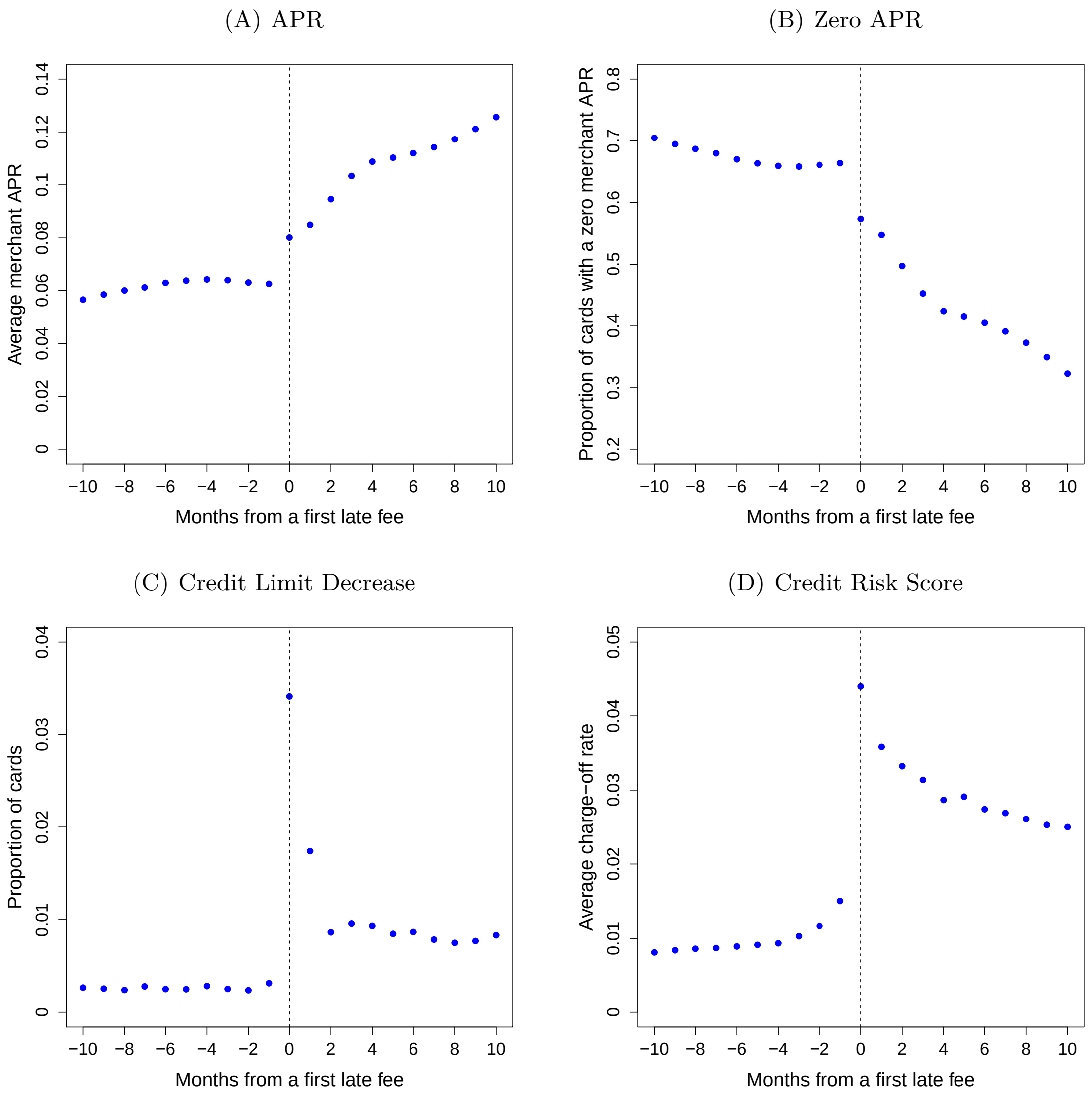
Note: Figure shows the volume of card openings and the mean charge-off rate by calendar month. Panel A shows bar plot of proportion of total sample of new cards opened each month. Panel B illustrates the mean predicted charge-off rate among cards opened each month. Sample of new cards opened at or after January 2013.

Figure A.2: Distribution of Late Payment Fees Across Cards



Note: Figure shows histograms of the number of late payment fees incurred by cards over the sample period. The unit of analysis is a card. The x-axis variable is the number of late payment fees incurred by the card over the sample period, could take a maximum value of 24 if the card were to incur a late payment fee in every month. Panel A shows sample of all cards, Panel B restricts to cards incurring at least one fee, Panel C restricts to cards that do not adopt autopay over the sample period and Panel D restrict to cards that adopt autopay over the sample period.

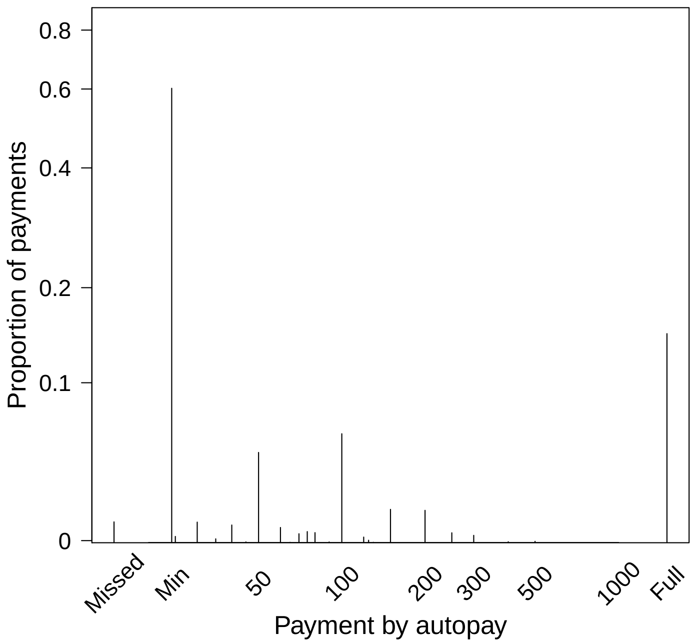
Figure A.3: Card Characteristics Late Payment Fee Event Study



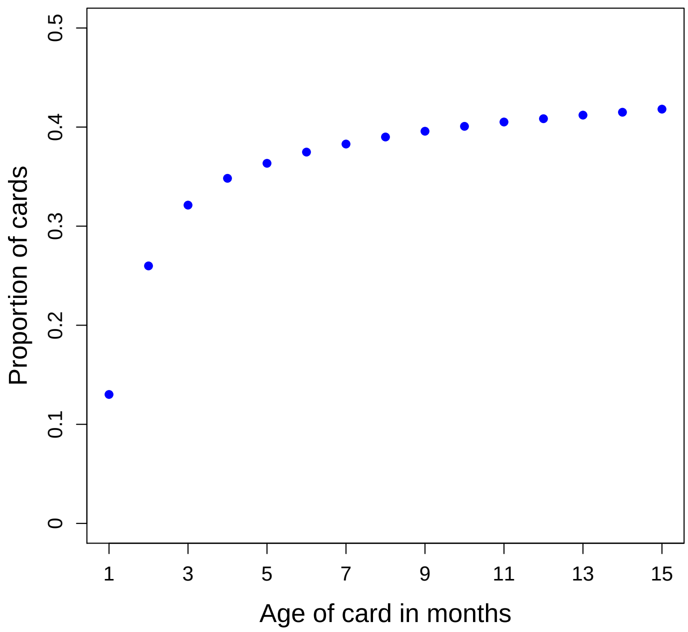
Note: Figure shows scatter plots of card characteristics before and after the month in which the card first incurred a late payment fee (shown as month zero on the x-axis). The sample consists of cards opening in the sample period and incurring at least one late payment fee, and the panels are unbalanced. Panel A shows the Annualized Percentage Rate (APR) on purchase balances. Panel B shows the proportion of cards with a promotional zero percent APR on purchases. Panel C shows the proportion of cards which experience a credit limit decrease. Panel D shows the credit risk score (specifically, the predicted charge-off rate within the next six months).

Figure A.4: Autopay Characteristics

(A) Automatic Payment Levels

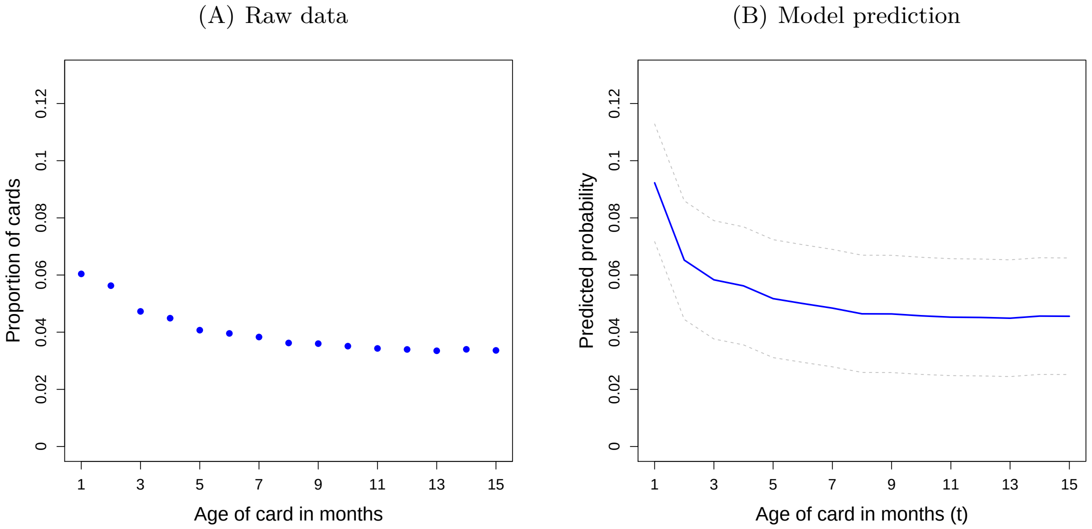


(B) Proportion of Cards Ever Making Automatic Payment



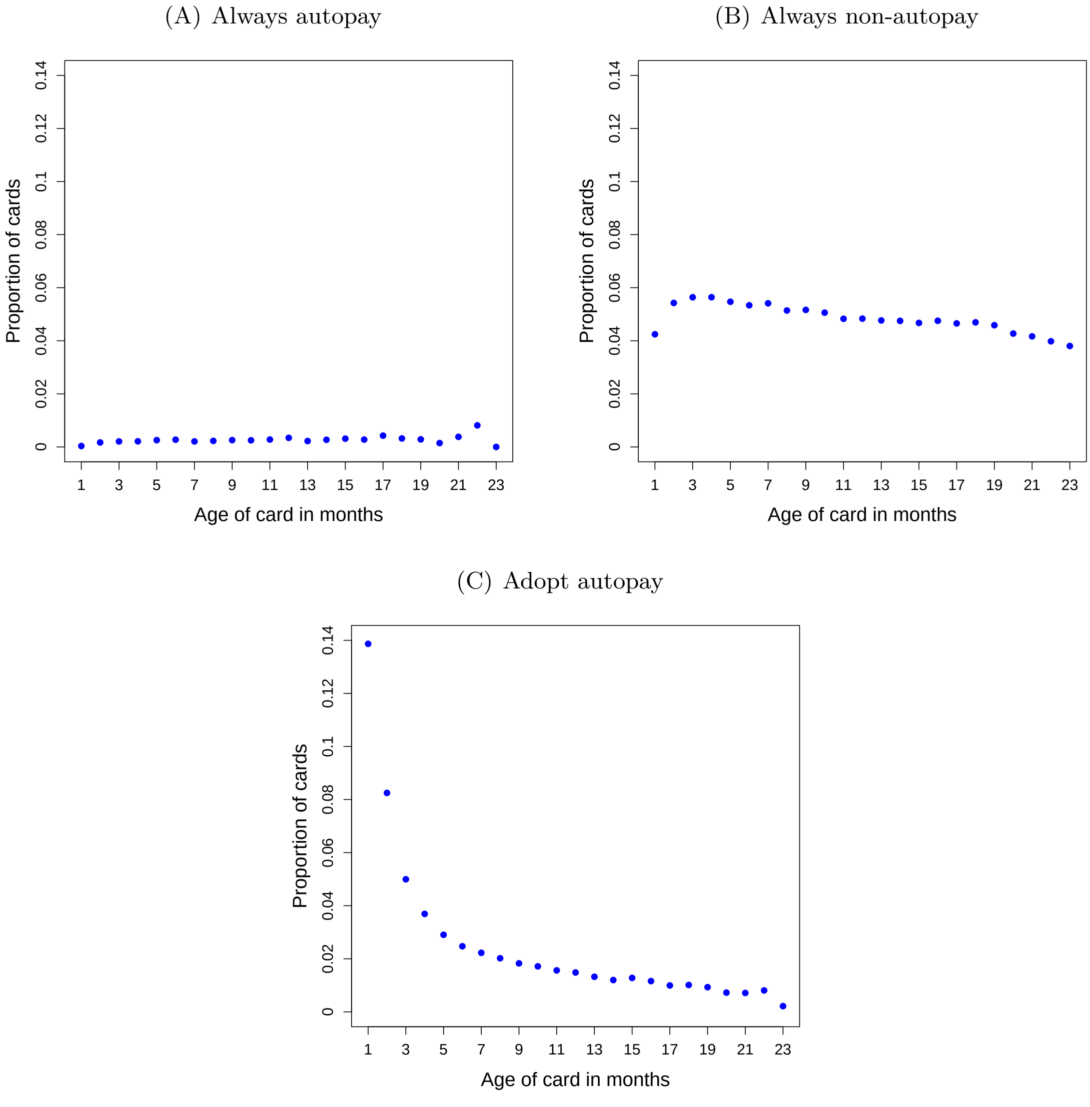
Note: Figures show levels of automatic payment and the growth of cards ever making an automatic payment by card age. Panel A shows the level of automatic payment (in £, with £amounts corresponding to a missed payment, minimum payment and full balance payment shown on the x-axis) for card × months in which the card balance was first paid by autopay. Panel B shows a scatter plot of the proportion of cards ever making an automatic payment by the age of the card in months

Figure A.5: Late Payment Fees and Card Tenure, Balanced Panel



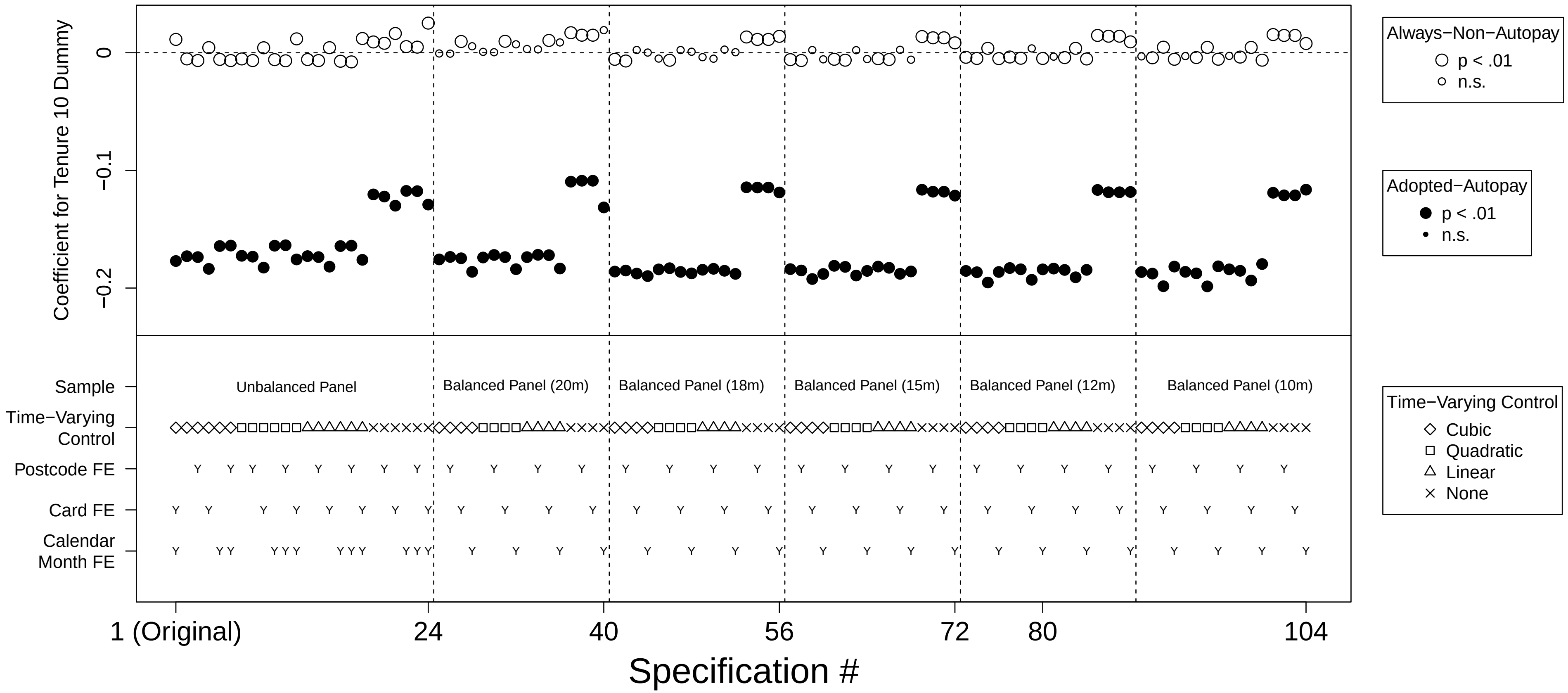
Note: Figure shows late payment fees by card tenure for a balanced panel of cards. The figure reproduces the plots in Figure 1 but with the data restricted to a balanced panel of cards which open within the sample period, beginning January 2013, and remain open for at least the following 15 months.

Figure A.6: Late Payment Fees and Card Tenure by Autopay Status



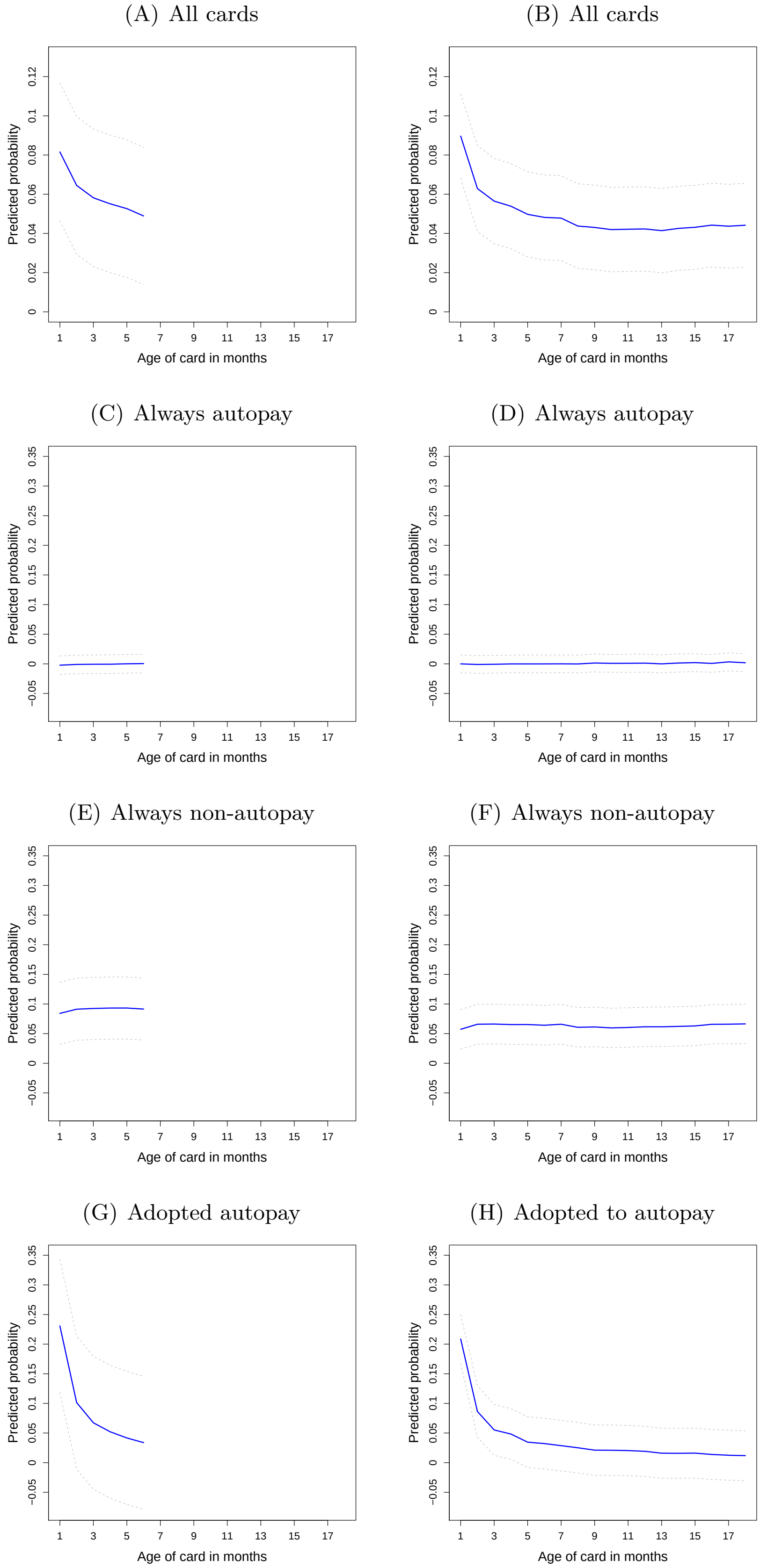
Note: Figure shows the proportion of cards incurring a late payment fee in the next period by age of card in months. The panels show three mutually exclusive groups: cards which were always subject to an autopay instruction from card opening onwards; cards which were never subject to an autopay instruction;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

Figure A.7: Specification Curve Illustrating Estimates from Equation 1 (Fee Decline With Tenure)



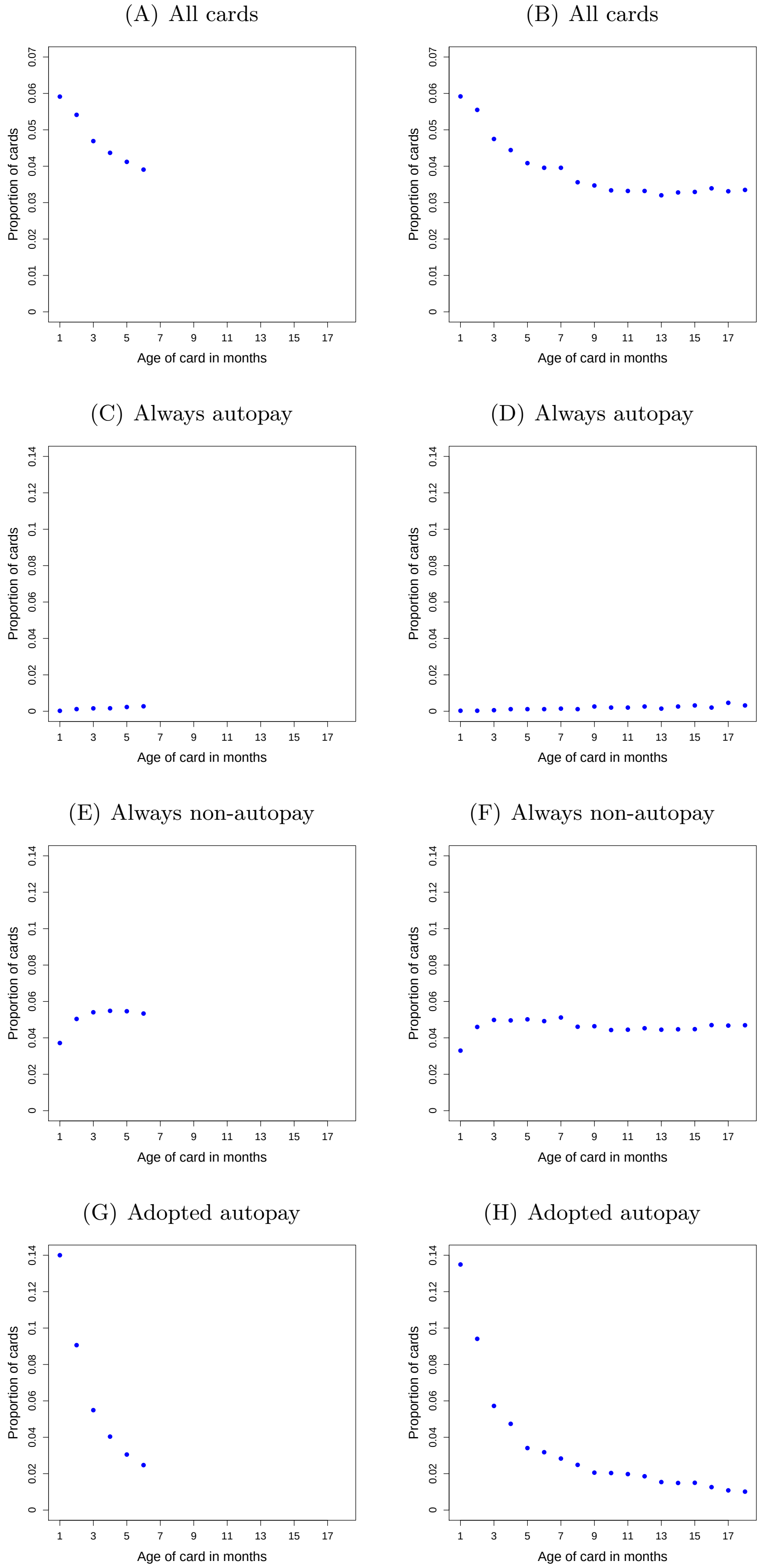
Note: Figure shows coefficient estimates (dots) and p-values (dot sizes) of the card tenure = 10 months dummy from estimates of Equation 1 for cards that were always subject to an autopay instruction from card opening onwards and cards which adopted autopay within the sample. Each column shows estimates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

Figure A.8: Late Payment Fees and Card Tenure, 6-Month and 18-Month Panels



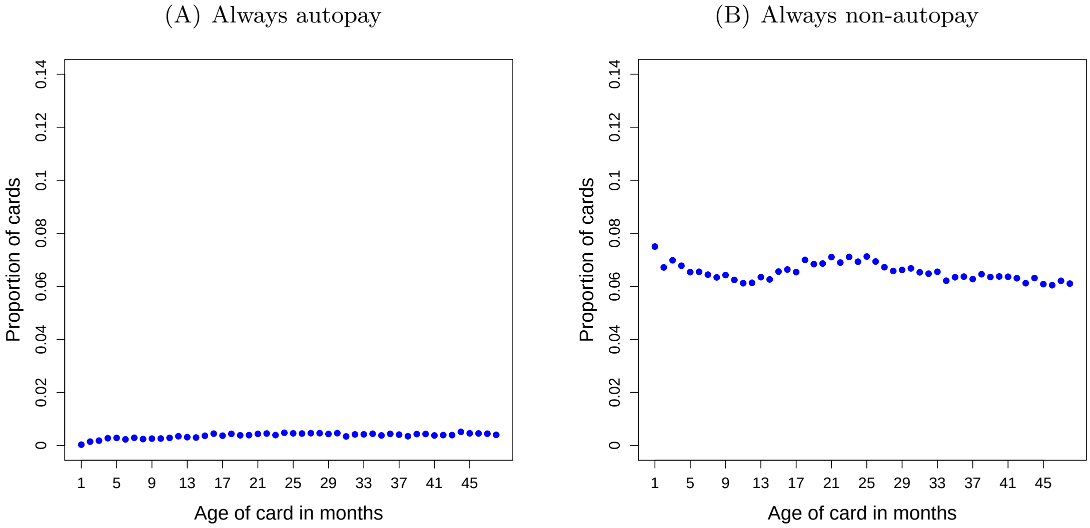
Note: Figure shows late payment fees by card tenure for balanced panels of cards of 6-months (left-side plots) and 18-months (right-side plots). The figure reproduces the plots in Figure 1 Panel B and Figure 2 for the two sub-samples. Both sub-samples draw cards that open within the sample period, beginning January 2013, and then remain open for at least 6 months and at least 18 months respectively.

Figure A.9: Late Payment Fees and Card Tenure, 6-Month and 18-Month Panels



Note: Figure shows late payment fees by card tenure for balanced panels of cards of 6-months (left-side plots) and 18-months (right-side plots). The figure reproduces the plots in Figure 1 Panel A and Figure A.6 for the two sub-samples. Both sub-samples draw cards that open within the sample period, beginning January 2013, and then remain open for at least 6 months and at least 18 months respectively.

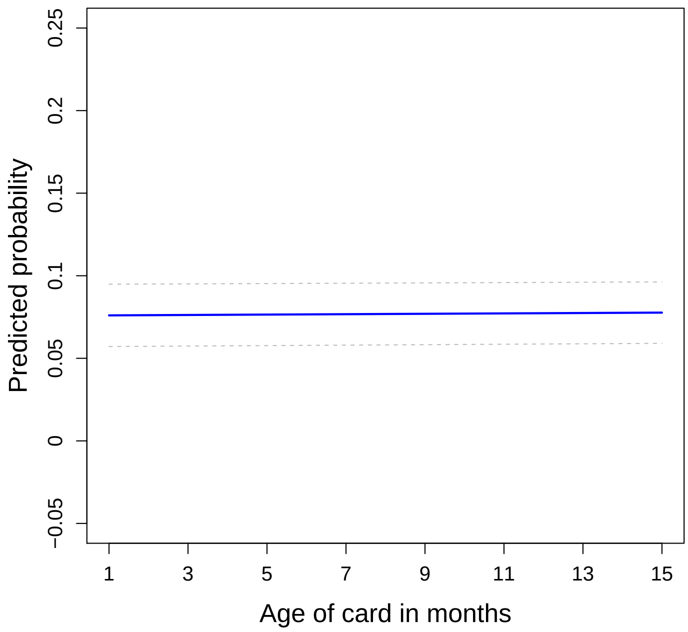
Figure A.10: Late Payment Fees and Card Tenure by Autopay Status for All Cards



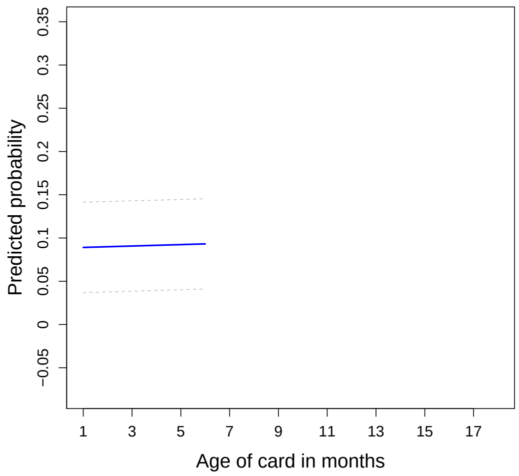
Note: Figure shows a scatter plot of the proportion of cards incurring a late payment fee in the next period by age of card in months. Sample includes all card × months up to 48 months in age with a positive balance (not restricting only to new cards, as in the main analysis).

Figure A.11: Late Payment Fees and Card Tenure, Linear Plots for Always Non-Autopay Cards

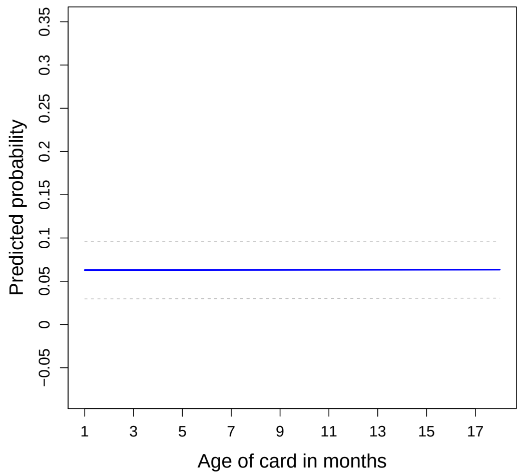
(A) Main Sample



(B) 6-Month Balanced Panel

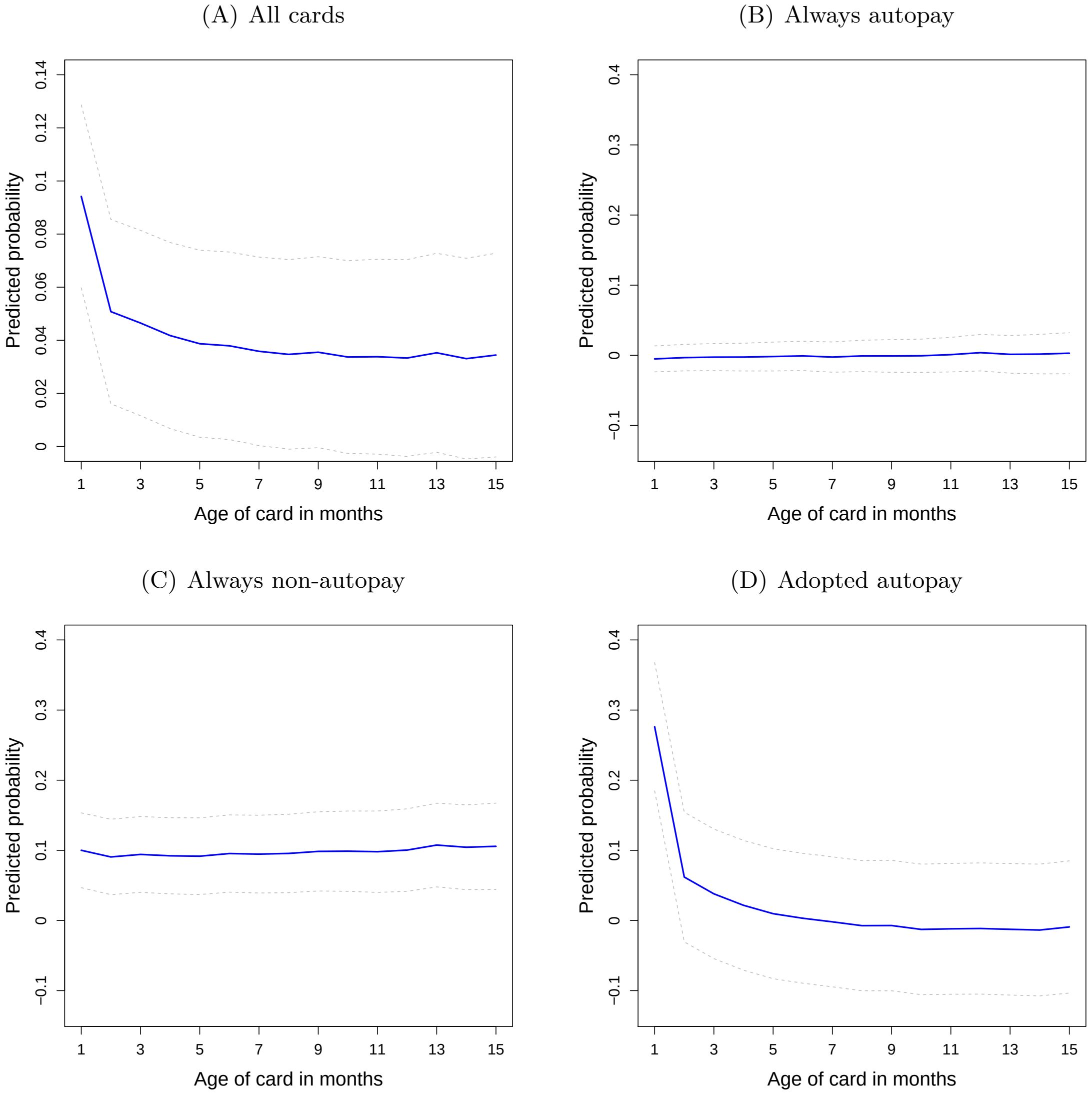


(C) 18-Month Balanced Panel



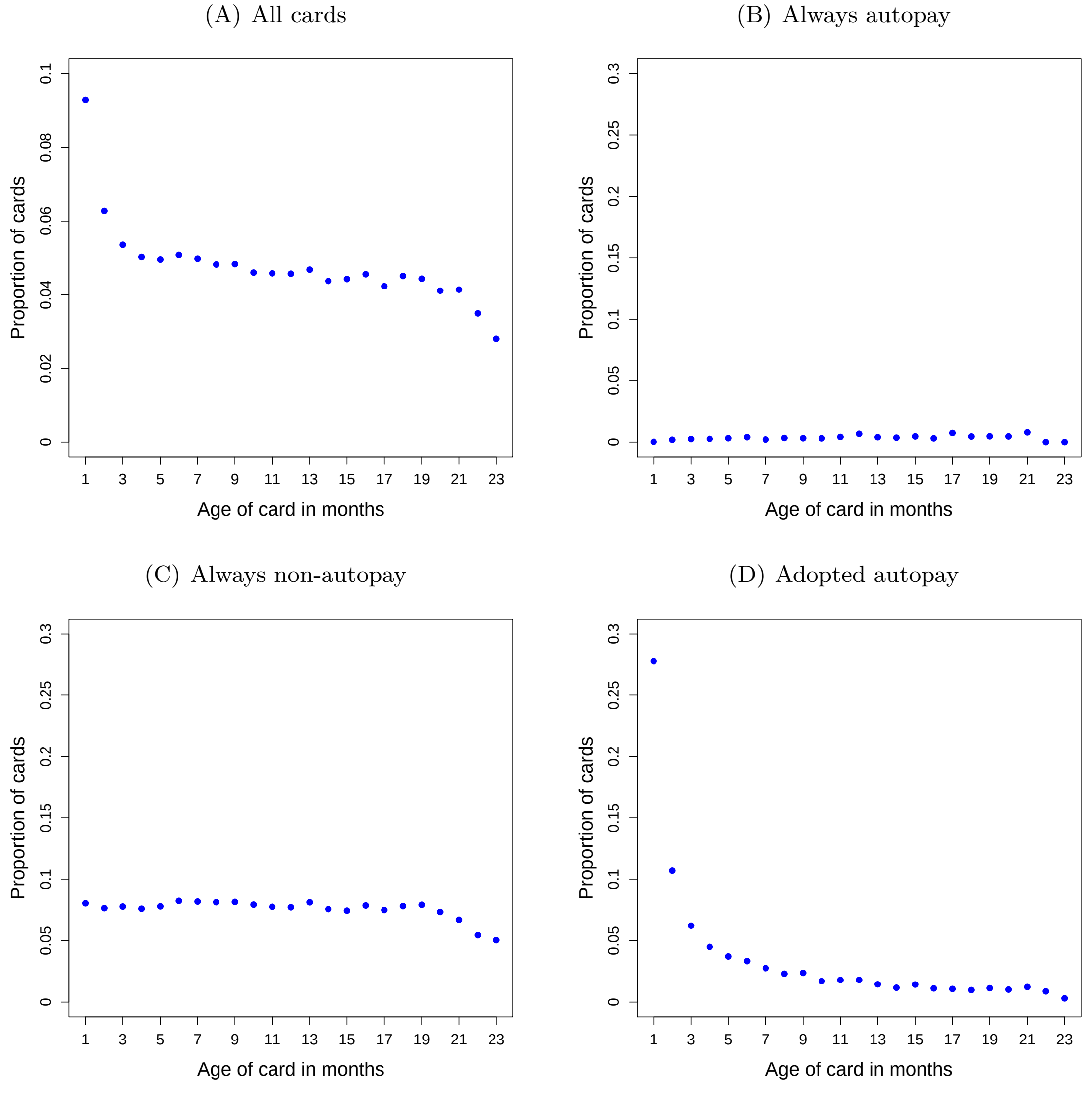
Note: Figure shows prediction plots of the tenure-trend in late payment fees among cards that are always non-autopay during the sample period. The prediction model is a variant of the model in Equation 1 in which tenure dummies are replaced with a linear tenure trend. Panel A show the sample of all cards that are always non-autopay and exist in the data for at least 15 months since opening, Panel B restricts to a six-month balanced panel and Panel C restricts to an eighteen-month balanced panel.

Figure A.12: Late Payment Fees and Card Tenure – Cards with High Risk of Charge-Off (Predicted probability)



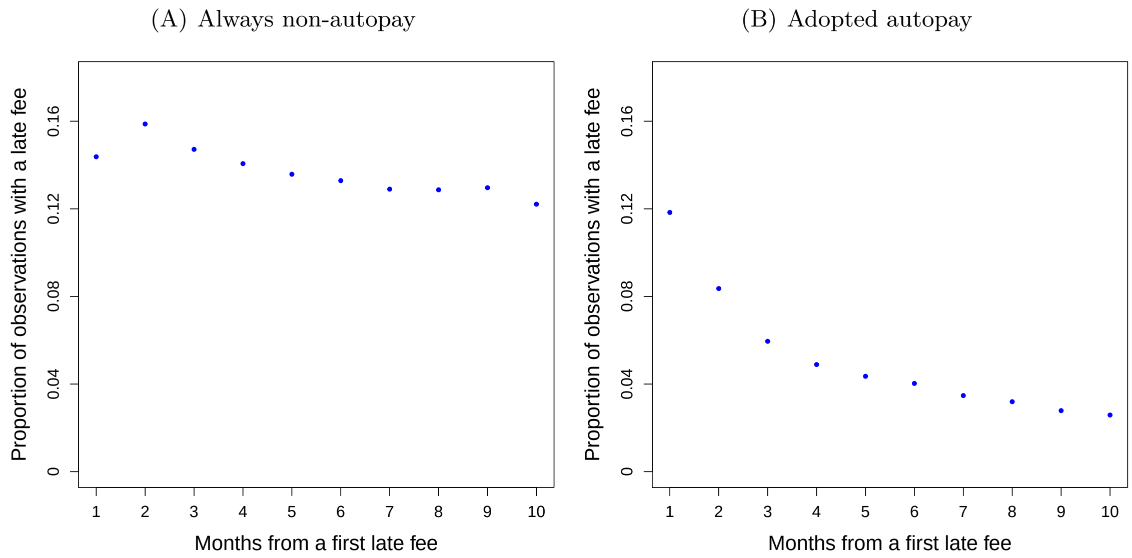
Note: Figure shows the predicted probability of cards incurring a late payment fee in the next period by the age of the card in months. Predictions are from a linear probability model at covariate medians (Equation 1). Panel A shows all cards. Panels B-D restrict to three mutually exclusive sub-samples: cards which were subject to an autopay instruction from card opening onwards; cards which were never subject to an autopay instruction; and cards which adopted autopay after card opening. All samples are further restricted to cards with above-median credit risk score at card opening. 95% confidence intervals are illustrated by the dashed lines.

Figure A.13: Late Payment Fees and Card Tenure – Cards with High Risk of Charge-Off (Proportion)



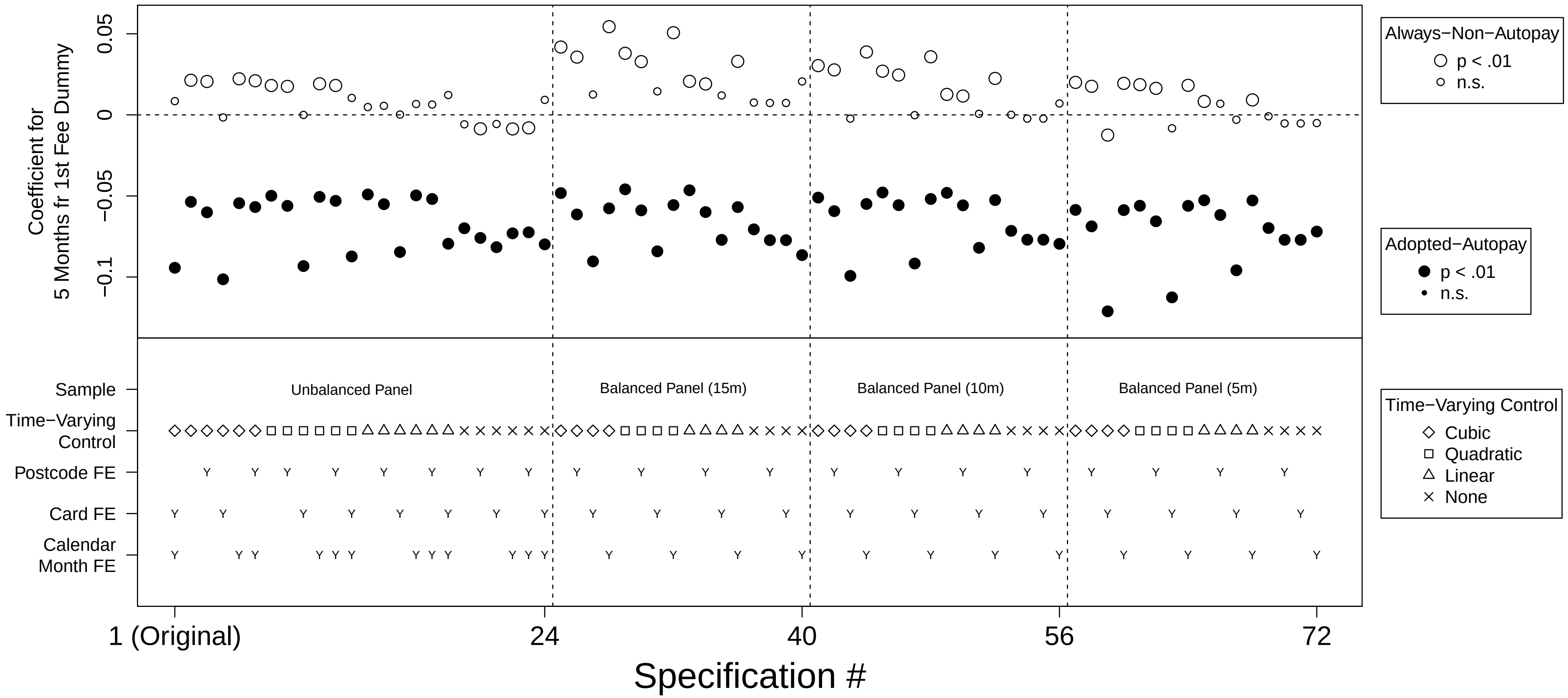
Note: Figure shows a scatter plot of the proportion of cards incurring a late payment fee in the next period by the age of the card in months. Panel A shows all cards. Panels B-D restrict to three mutually exclusive sub-samples: cards which were subject to an autopay instruction from card opening onwards; cards which were never subject to an autopay instruction; and cards which adopted autopay after card opening. All samples are further restricted to cards with above-median credit risk score at card opening.

Figure A.14: Late Payment Fees in Months Following a First Fee, by Autopay Status



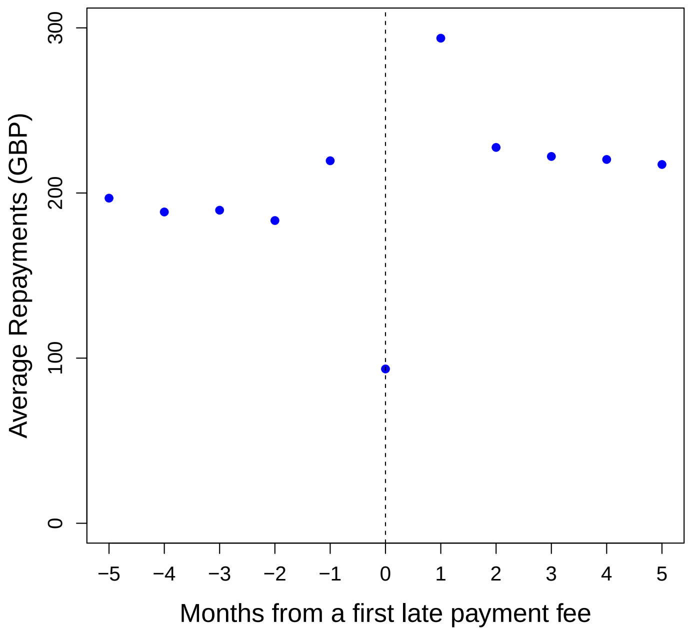
Note: Figures plot the proportion of cards incurring a late payment fee in months after the first late payment fee incurred (month zero). The panels show two mutually exclusive groups: cards which were never subject to an autopay instruction throughout the sample period; and cards which adopted autopay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

Figure A.15: Specification Curve Illustrating Estimates from Equation 2 (Fees After First Late Payment Fee)



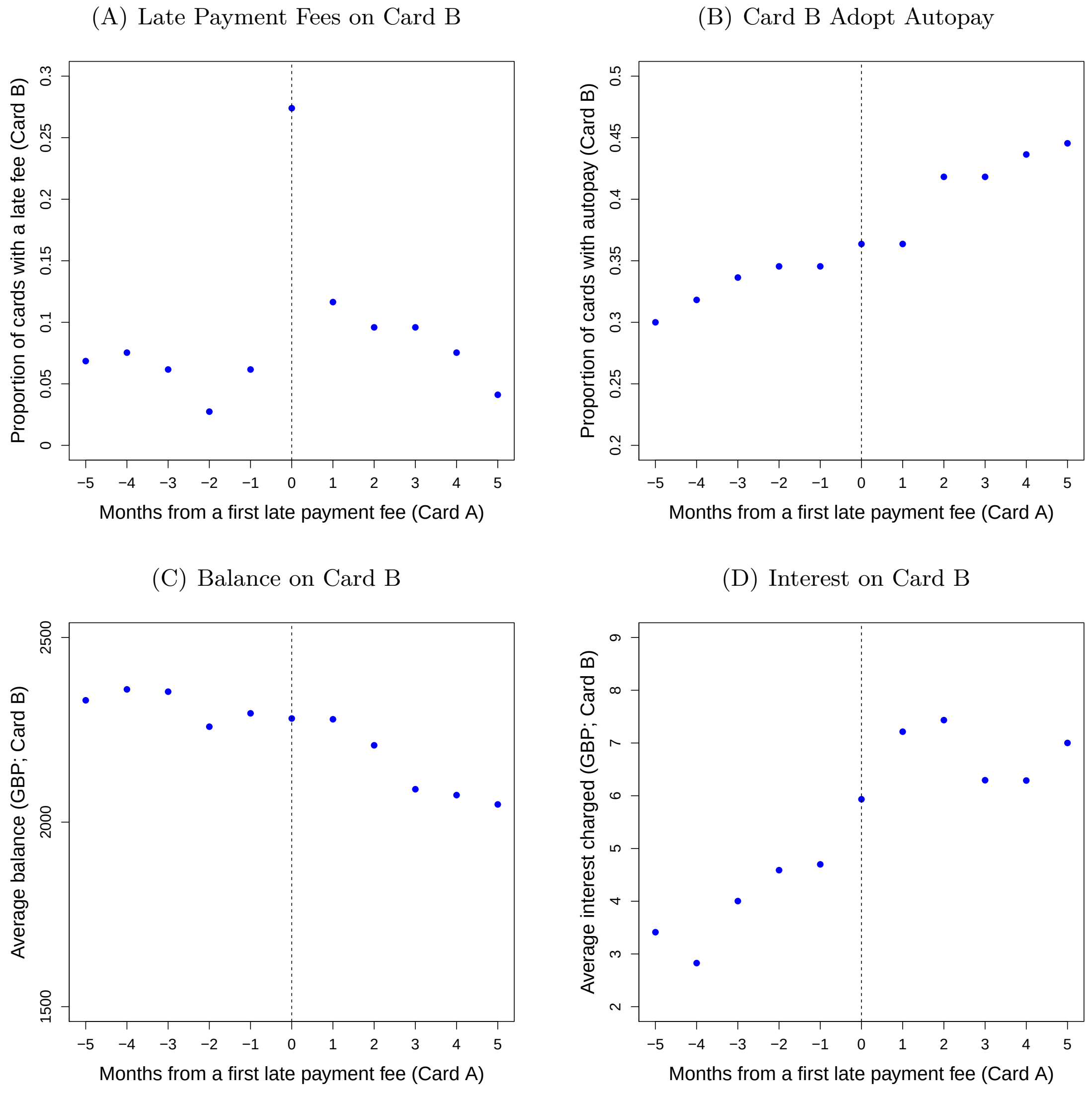
Note: Figure shows coefficient estimates (dots) and p-values (dot sizes) of the time dummy for month = 5 months after 1st late payment fee from estimates of Equation 2 for cards that were always subject to an autopay instruction from card opening onwards and cards which adopted autopay within the sample.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

Figure A.16: Repayments by Non-Autopay Cards in Months Before and After First Late Payment Fee



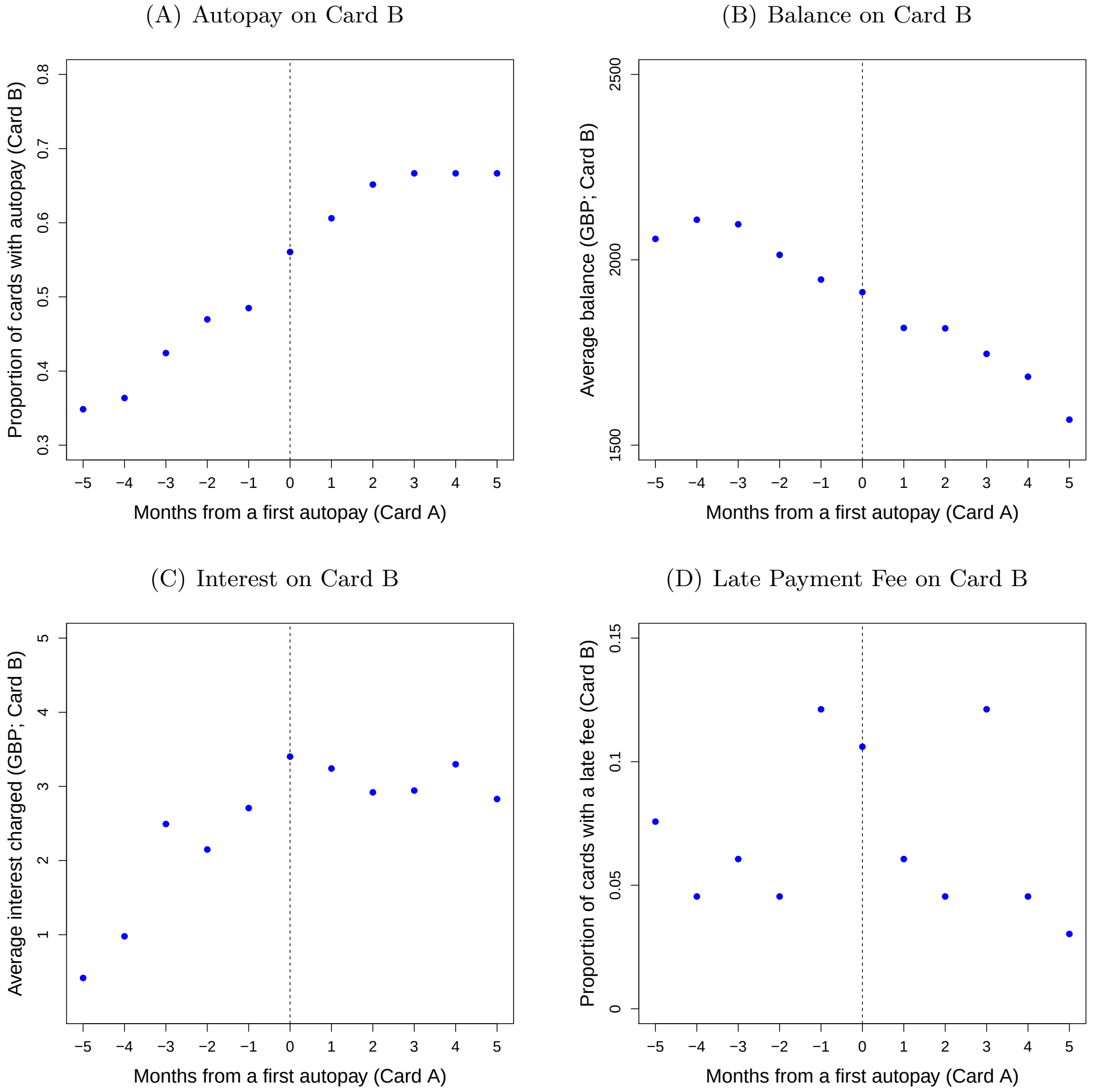
Note: Figure shows the mean monthly repayment among cards that do not adopt autopay in the months before and after the card incurs a first late payment fee. Sample is restricted to cards that open within the sample period (at or after January 2013) and incur a late payment fee.

Figure A.17: Late Payment Fees and Outcomes on Second Card



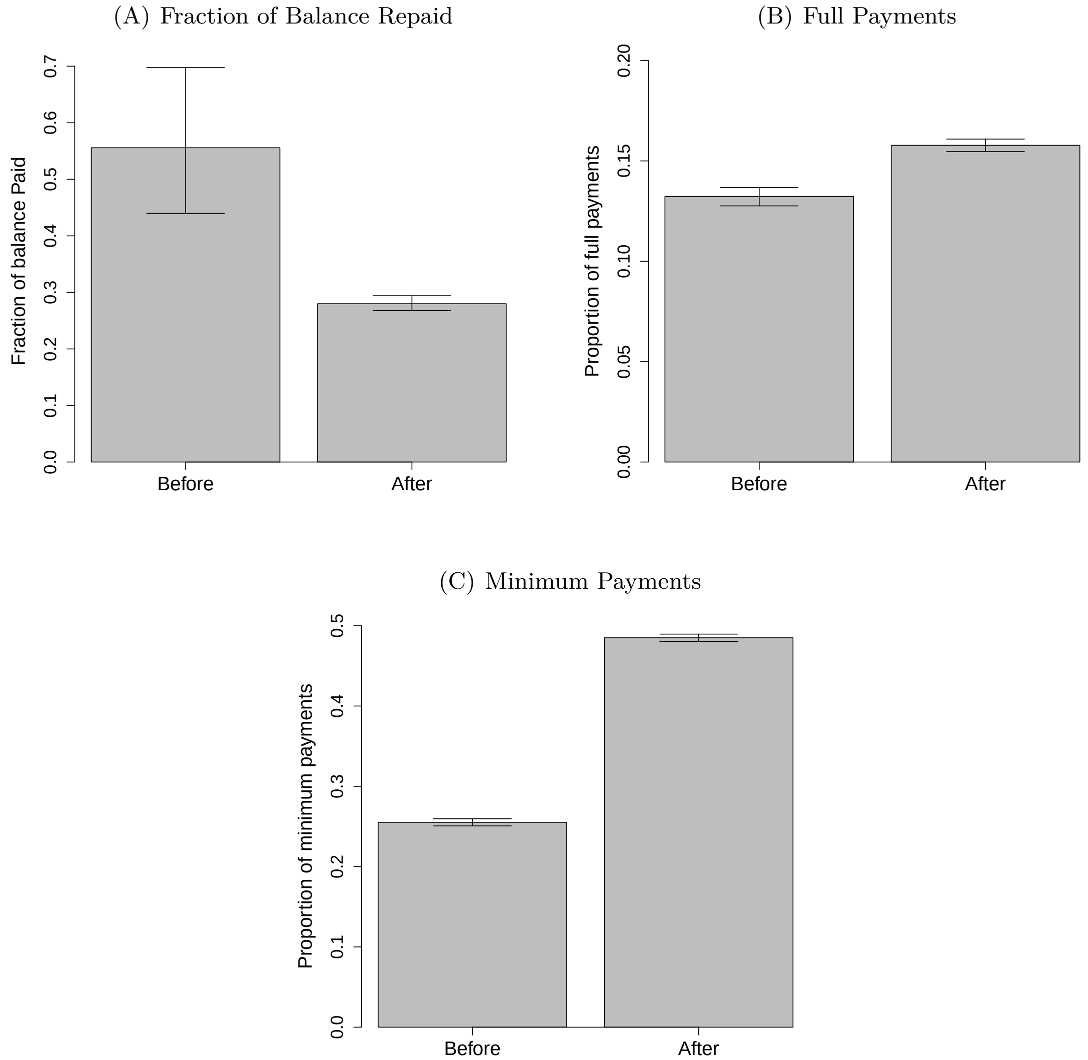
Note: Figures show event-studies around months from a first late payment fee on Card A (shown as month 0 on the x-axis) with characteristics of a second card held by the same individual, called Card B, shown in the y-axis. Sample restricted to individuals with two credit cards in the month in which the first late payment fee occurs. Card A is defined as the card on which the first late payment fee occurred.

Figure A.18: Adopting Autopay and Outcomes on Second Card



Note: Figures show event-studies around months from a Card A adopting autopay (shown as month 0 on the x-axis) with characteristics of a second card held by the same individual, called Card B, shown in the y-axis. Sample restricted to individuals with two credit cards in the month in which the adoption of autopay occurs. Card A is defined as the card which adopted autopay.

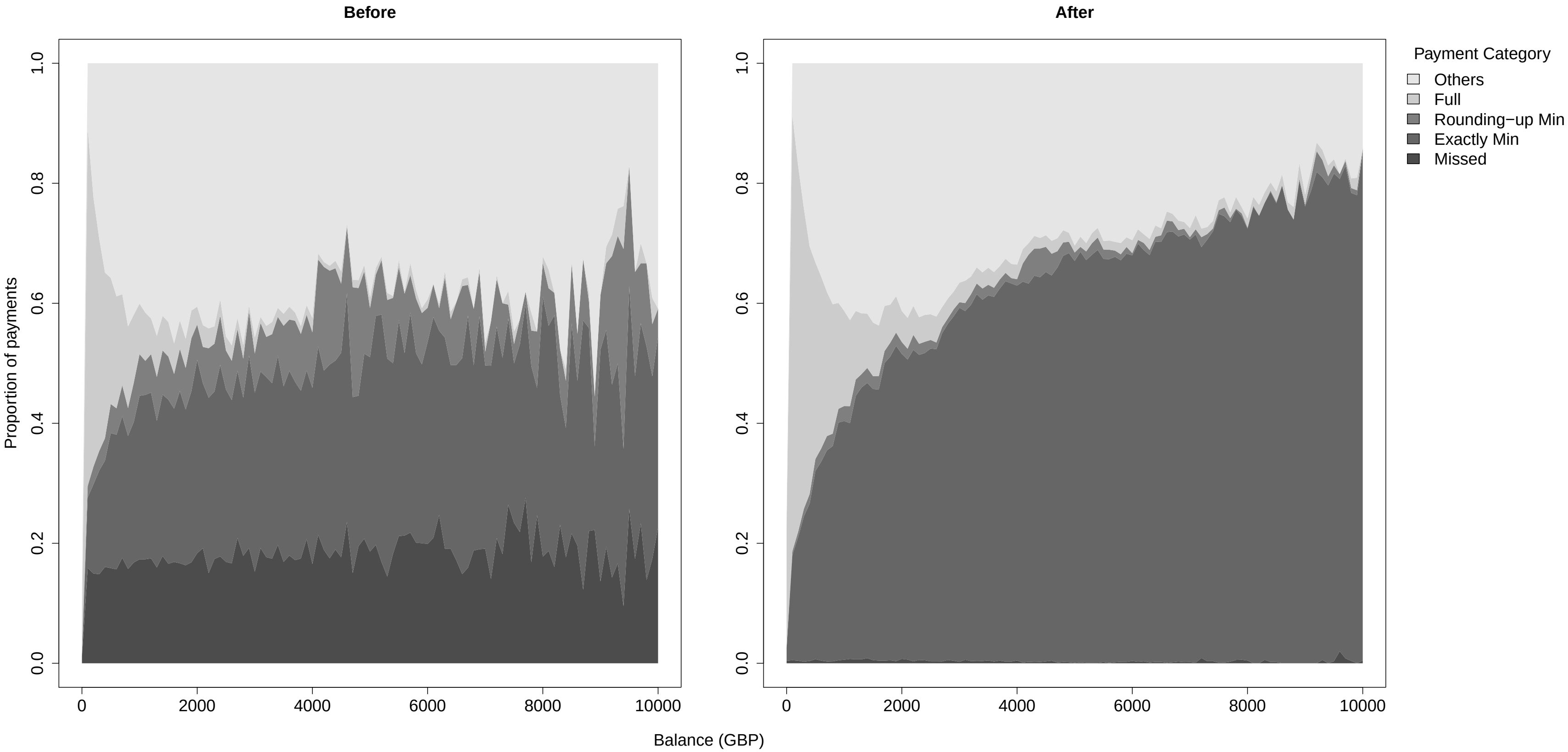
Figure A.19: Payments Before and After Adopting Autopay



Note: Figures show payments before and after adopting autopay in the sample of card × months drawn from those adopting autopay in the sample period. Panel A shows the mean fraction of outstanding card balance paid. Panel B shows the proportion of card × months in which the full balance is paid. Panel C shows the proportion of card × months in which the only minimum payment due is paid. Error bars illustrate 95% confidence intervals.

Figure A.20: Payment Categories Before and After Adopting Autopay

(A) Fraction of Balance Repaid



Note: Figures show payments before and after adopting autopay in the sample of card × months drawn from those adopting autopay in the sample period. Payments are categorized as i) missed (payment is lower than the minimum payment due), ii) exactly min (exactly the minimum payment due), iii) rounding-up min (payment amount is the minimum payment rounded upward to the nearest £1, £5, or £10), iv) full (payment is the full balance amount), v) other.

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 cards	82,661						
Number of card-months	1,239,915						

Note: Table shows summary data for the sample of new card openings (cards which open at or after January 2013) restricted to cards which exist in the data for 15 consecutive months. Unit of data is a card × month. APR denotes Annualized Percentage Rate. Merchant APR refers to APR on revolving balances incurred from purchases. Cash APR refers to APR on balances incurred from cash advances. Utilization is calculated by dividing the balance by the credit limit, expressed in percent of the credit limit. Charge-off Rate is the predicted probability of charge-off within the next sixth months. SD denotes standard deviation.

Table A2: Fee Summary Statistics – Balanced Panel

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

Note: Table shows card-level summary data for fees incurred by fee type. Sample of new card openings (cards which open at or after January 2013) restricted to cards which exist in the data for 15 consecutive months.

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

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

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

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

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

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

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

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

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

Table A6: Fixed Effects OLS Estimates Late Payment Fees and Tenure, Adopted Autopay Cards

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

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

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

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

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

Table A8: Fixed Effects OLS Estimates Late Payment Fees in Months Following a First Fee, Adopted Autopay Cards

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

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

Table A9: OLS Estimates Probability of Cards Adopting Autopay by Month After First Late Payment Fee

	β	S.E.	t-value	p-value
Months fr 1st Late Fee 1	0.046	0.001	39.201	0.000
Months fr 1st Late Fee 2	-0.066	0.001	-48.620	0.000
Months fr 1st Late Fee 3	-0.075	0.002	-47.194	0.000
Months fr 1st Late Fee 4	-0.081	0.002	-43.300	0.000
Months fr 1st Late Fee 5	-0.086	0.002	-39.439	0.000
Months fr 1st Late Fee 6	-0.086	0.002	-34.514	0.000
Months fr 1st Late Fee 7	-0.087	0.003	-30.929	0.000
Months fr 1st Late Fee 8	-0.088	0.003	-27.707	0.000
Months fr 1st Late Fee 9	-0.088	0.004	-25.171	0.000
Months fr 1st Late Fee 10	-0.090	0.004	-23.279	0.000
Months fr 1st Late Fee 11	-0.091	0.004	-21.433	0.000
Months fr 1st Late Fee 12+	-0.091	0.005	-17.636	0.000
Balance^3	0.000	0.000	0.299	0.765
Balance^2	0.000	0.000	0.017	0.987
Balance	0.000	0.000	-1.391	0.164
Credit Limit^3	0.000	0.000	-0.896	0.370
Credit Limit^2	0.000	0.000	1.221	0.222
Credit Limit	0.000	0.000	-4.312	0.000
Utilization^3	0.000	0.000	0.514	0.607
Utilization^2	0.005	0.003	1.925	0.054
Utilization	-0.013	0.004	-2.998	0.003
Charge-off Rate^3	1.834	0.083	22.001	0.000
Charge-off Rate^2	-2.330	0.085	-27.329	0.000
Charge-off Rate	0.813	0.022	36.230	0.000
$\text{Monthly Purchase}^3$	0.000	0.000	2.963	0.003
$\text{Monthly Purchase}^2$	0.000	0.000	-4.448	0.000
Monthly Purchase	0.000	0.000	10.714	0.000
R^2	0.185			
Number of observations	492,453			
Number of cards	55,019			

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

Table A10: Monthly Spending Counts: Autopay Adopters and Non-Adopters

	All Mean	Non-Adopters Mean	Adopters Mean	t score	p value
Airlines	0.02	0.03	0.02	3.96	0.0001
Auto Rental	0.01	0.01	0.01	2.37	0.0179
Clothing Stores	0.26	0.28	0.20	12.67	0.0000
Department Stores	0.07	0.07	0.06	4.27	0.0000
Discount Stores	0.04	0.04	0.03	4.77	0.0000
Drug Stores	0.06	0.06	0.05	5.98	0.0000
Education	0.01	0.01	0.01	3.19	0.0014
Electric Appliance Stores	0.05	0.05	0.04	5.45	0.0000
Food Stores	0.88	0.94	0.75	8.17	0.0000
Gas Stations	0.32	0.34	0.28	7.80	0.0000
Hardware Stores	0.10	0.10	0.09	2.38	0.0175
Health Care	0.02	0.02	0.02	3.07	0.0022
Hotel Motel	0.06	0.07	0.06	1.67	0.0953
Interior Furnishing Stores	0.04	0.04	0.04	1.58	0.1132
Mail Orders	0.09	0.10	0.08	3.26	0.0011
Other Retail	0.35	0.37	0.29	8.82	0.0000
Other Services	0.14	0.15	0.13	3.82	0.0001
Other Transportation	0.15	0.17	0.12	6.61	0.0000
Professional Services	0.07	0.07	0.06	3.27	0.0011
Quasi Cash	0.01	0.02	0.01	2.99	0.0028
Recreation	0.08	0.09	0.07	5.98	0.0000
Repair Shops	0.00	0.00	0.00	2.06	0.0392
Restaurants Bars	0.39	0.41	0.33	6.46	0.0000
Sporting Goods Toy Stores	0.06	0.07	0.05	6.94	0.0000
Travel Agencies	0.02	0.02	0.02	3.11	0.0019
Utilities	0.04	0.04	0.03	8.87	0.0000
Vehicles	0.04	0.04	0.03	2.79	0.0052

Note: Table shows card-level summary data for all observations in the sample of cards which open at or after January 2013 and incur at least one late payment fee over the subsequent two years. "Non-Adopters" consist of cards that never adopt autopay, "Adopters" consist of cards that adopt autopay", and "All" consist of all cards in the two sub-samples. The unit of analysis is a card $\times$ month. The table reports average number of spends in each category in each month for card $\times$ months for each group in the months following the first late payment fee.

Table A11: Monthly Spending Amounts: Autopay Adopters and Non-Adopters

	All Mean	Non-Adopters Mean	Adopters Mean	t score	p value
Airlines	6.00	6.27	5.34	2.46	0.0141
Auto Rental	1.21	1.26	1.07	1.90	0.0571
Clothing Stores	11.44	12.12	9.79	5.65	0.0000
Department Stores	3.71	3.74	3.63	0.47	0.6411
Discount Stores	1.67	1.84	1.24	6.65	0.0000
Drug Stores	1.25	1.34	1.04	5.02	0.0000
Education	1.35	1.46	1.10	2.32	0.0205
Electric Appliance Stores	5.86	6.10	5.27	1.87	0.0610
Food Stores	23.21	24.19	20.84	5.01	0.0000
Gas Stations	11.92	12.35	10.88	3.82	0.0001
Hardware Stores	6.90	7.17	6.25	1.62	0.1047
Health Care	2.62	2.72	2.38	1.61	0.1065
Hotel Motel	8.92	9.16	8.36	1.74	0.0822
Interior Furnishing Stores	6.48	6.50	6.42	0.19	0.8512
Mail Orders	3.33	3.49	2.95	2.56	0.0106
Other Retail	13.39	14.12	11.63	4.58	0.0000
Other Services	11.51	11.80	10.79	2.05	0.0404
Other Transportation	4.49	4.61	4.22	1.01	0.3121
Professional Services	6.71	6.89	6.27	1.83	0.0668
Quasi Cash	1.44	1.36	1.61	-1.01	0.3119
Recreation	5.59	5.88	4.88	3.78	0.0002
Repair Shops	0.15	0.15	0.13	0.75	0.4507
Restaurants Bars	9.90	10.49	8.48	4.93	0.0000
Sporting Goods Toy Stores	3.60	3.80	3.13	4.13	0.0000
Travel Agencies	9.82	10.09	9.18	1.66	0.0979
Utilities	2.04	2.24	1.54	6.34	0.0000
Vehicles	7.75	7.79	7.64	0.30	0.7647

Note: Table shows card-level summary data for all observations in the sample of cards which open at or after January 2013 and incur at least one late payment fee over the subsequent two years. “Non-Adopters” consist of cards that never adopt autopay, “Adopters” consist of cards that adopt autopay”, and “All” consist of all cards in the two sub-samples. The unit of analysis is a card $\times$ month. The table reports average spending amounts (in pounds) for card $\times$ months for each group in the months following the first late payment fee.

Table A12: Spending as a Proportion of Total Spend: Autopay Adopters and Non-Adopters

	All Mean	Non-Adopters Mean	Adopters Mean	t score	p value
Airlines	0.03	0.03	0.03	-2.12	0.0341
Auto Rental	0.01	0.01	0.01	-0.70	0.4849
Clothing Stores	0.08	0.08	0.07	0.70	0.4844
Department Stores	0.02	0.02	0.02	-1.68	0.0922
Discount Stores	0.01	0.01	0.01	1.32	0.1853
Drug Stores	0.01	0.01	0.01	0.92	0.3593
Education	0.01	0.01	0.01	-0.94	0.3483
Electric Appliance Stores	0.03	0.03	0.03	-0.18	0.8570
Food Stores	0.15	0.15	0.14	4.23	0.0000
Gas Stations	0.07	0.08	0.07	2.37	0.0180
Hardware Stores	0.03	0.03	0.03	-1.71	0.0873
Health Care	0.01	0.01	0.01	0.56	0.5736
Hotel Motel	0.04	0.04	0.04	-1.86	0.0627
Interior Furnishing Stores	0.03	0.03	0.03	-2.47	0.0137
Mail Orders	0.03	0.03	0.03	0.21	0.8328
Other Retail	0.09	0.09	0.08	1.44	0.1512
Other Services	0.07	0.07	0.08	-2.03	0.0428
Other Transportation	0.03	0.03	0.03	0.95	0.3431
Professional Services	0.04	0.04	0.04	-0.88	0.3787
Quasi Cash	0.01	0.01	0.01	-3.49	0.0005
Recreation	0.04	0.04	0.04	-0.67	0.5008
Repair Shops	0.00	0.00	0.00	-0.21	0.8309
Restaurants Bars	0.05	0.06	0.05	3.94	0.0001
Sporting Goods Toy Stores	0.02	0.03	0.02	0.24	0.8076
Travel Agencies	0.04	0.04	0.05	-2.73	0.0064
Utilities	0.02	0.02	0.02	4.23	0.0000
Vehicles	0.04	0.03	0.04	-2.02	0.0439

Note: Table shows card-level summary data for all observations in the sample of cards which open at or after January 2013 and incur at least one late payment fee over the subsequent two years. "Non-Adopters" consist of cards that never adopt autopay, "Adopters" consist of cards that adopt autopay", and "All" consist of all cards in the two sub-samples. The unit of analysis is a card × month. The table reports average spending in each category as a proportion of the total spend on the card for each group in the months following the first late payment fee.

Table A13: Matched Characteristics of Autopay Adopters and Non-Adopters After Second Fee

	All Mean	Non-Adopt Mean	Adopt Mean	t score	p value
Panel A					
Card Usage					
Mean balance (£)	1,788.73	1,635.58	2,290.14	-50.87	0.0000
Mean utilization (%)	58.99	56.73	66.36	-39.85	0.0000
Mean monthly purchase (£)	123.92	130.14	103.55	11.40	0.0000
Mean repayment|given balance>0 (£)	204.35	221.68	151.86	20.52	0.0000
Proportion of card-months with balance>0	0.91	0.89	0.96	-50.28	0.0000
Panel B					
Card Characteristics					
Has 0% intro APR (0/1)	0.77	0.75	0.86	-15.29	0.0000
Mean Merchant APR (%)	10.54	11.09	8.19	15.77	0.0000
Mean Cash APR (%)	25.31	25.26	25.53	-5.29	0.0000
Has Balance Transfer (0/1)	0.60	0.60	0.63	-3.40	0.0007
Panel C					
Socio-Economic Characteristics (Postcode)					
Mean house price (£)	207,521	206,082	214,376	-2.78	0.0055
Jobless claimants (%)	2.635	2.662	2.506	3.76	0.0002
Mean weekly income (£)	743.06	740.48	755.38	-3.82	0.0001
Education level 4+ (%)	28.302	28.156	28.997	-4.01	0.0001
Mean Acorn category	3.259	3.269	3.208	3.93	0.0001
Free-school meal (%)	13.172	13.290	12.613	3.92	0.0001

Note: Table shows card-level summary data for the sample of cards which open at or after January 2013 and incur at least one late payment fee over the subsequent two years. "Non-Adopters" consist of cards that never adopt autopay, "Adopters" consist of cards that adopt autopay", and "All" consist of all cards in the two sub-samples. The units of analysis and sample sizes are: Card usage variables (Panel A) are measured at the card × month level. Sample size for card characteristics: Non-Adopters 103,158; Adopters 31,508. Card characteristics (Panel B) and socio-economic characteristics (Panel C) are measured at the card holder level. The sample sizes differ by variable. For house price, weekly income and educational level: Non-Adopters 10,051; Adopters 2,110. For jobless claimants: Non-Adopters 6,496; Adopters 1,367. For Acorn category: Non-Adopters 10,672; Adopters 2,237; For free school meals: Non-Adopters 9,483; Adopters 2,006. Socio-economic characteristics are matched from the UK Office for National Statistics ACORN database, which provides observations of postcode-level characteristics derived from census data.

B. Analysis of Cash Advance and Over-limit Fees

In this we appendix explore the dynamics of cash advance fees and over-limit fees. Understanding the dynamics of these fees is important as they also represent significant flows of revenues for card issues, though below revenues accrued from late payment fees.[50] Also, in contrast with late payment fees, credit cards do not offer management features to consumers analogous to autopay that could provide an automatic facility for avoiding these fee types.

B.1. Fee Types

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% on average. Furthermore, interest is charged on cash advances from the day of the advance, even if the consumer repays the cash advance by their next payment due date. Cash advances are also reported on credit files.

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

B.2. Analysis of Cash Advance Fees

Figure B.1 illustrates the evolution of cash advances with card tenure, showing analogous illustrations to those shown for late payment fees in Figure 1. Panel A shows a scatter plot of the raw data, with Panel B showing estimates of Equation 1. As with late payments, we observe a sharp decline in the proportion of cards incurring cash advance fees over the first few months of card life. This pattern is also seen in Panel B of Figure B.1.[51]

Why do cash advance fees decline with tenure? The use of this high-cost cash borrowing facility might reflect a customer facing a binding liquidity constraint. With other sources of cash unavailable (e.g. deposit account balances) and present consumption needs requiring cash

[50] In the US, prior to the introduction of the CARD ACT over-limit fees and cash advance fees together summed to approximately half of the revenues received from late payment fees.

[51] Figure B.6 further shows identical patterns when we restrict the data to be a balanced panel.

payments, customers might draw upon this alternative source of funds by taking a new credit card. If so, we would expect cash advances to be concentrated among higher risk, liquidity constrained customers. These patterns appear to be at play in our data.

First, we show that the decline in cash advance fees with tenure is concentrated in higher risk cards. The riskiest 10% of cards incur 38% of all cash advance fees in our sample. In the Argus data, the credit risk of a card is measured by the probability of charge-off (six consecutive missed payments). The probability variable is provided by the card issuers on a harmonized scale common across issuers in the Argus dataset. Figure B.2 illustrates predicted probability plots from estimates of Equation 1, in which models are fitted separately for cards with high and low probability of charge-off (split at the median).[52] The figure illustrates that among high probability of charge-off cards the likelihood of fee incursion drops from approximately 7% at card opening to 3% after 15 months, whereas for low probability of charge-off cards the likelihood is steady at 2% throughout the first 15 months of card life.

Second, we also find that cash advances appear much more common among customers who appear liquidity constrained. We cannot directly observe liquidity constraints in our data. Instead, we use proxy measures of card balances and card utilization. Figure B.3 shows the average balance among cards in the months before, during and after the card incurs consecutive cash advance fees. Each card contributes to one of the panels in the figure, depending on the number of consecutive cash advance fees within the first spell of the card's history in which a cash advance is incurred.[53] Cards 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 B.4 confirms that higher balances translate to higher utilization.

This effect could, of course, occur mechanically through cash advances adding to balances and so raising card utilization. However, Figure B.5 illustrates that the onset of a spell of cash advances occurs in the same month as an upswing in card purchases, which remain persistently high through the spell of cash advances. The panels illustrate that most spells of cash advances show large average increases in purchases in the month in which the spell of cash advances begins.

[52] The corresponding scatter plots of fees over tenure for each group are shown in Figure B.7. Tables B.2 and B.3 report the model estimates. Sample sizes are smaller in these estimates because not all cards in the data include values for the probability of charge-off.

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

Purchases tend downwards through the spell of cash advances.

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

B.3. Analysis of Over-Limit Fees

Figure B.8 illustrates the evolution of over-limit fees with card tenure, showing analogous illustrations to those shown for late payment fees in Figure 1. Here we see that over-limit fees steadily increase in the first few months of card life. However, the wide confidence intervals in the probability plot show that this relationship is not precisely defined.[54] In our data, cards take time after opening to accrue balances. Among cards that incur an over-limit fee, the first fee is on average incurred at 8 months after opening. Very few cards immediately accrue a balance after opening that exceeds the card limit (fewer than 0.5% of cards in our sample). This pattern is unsurprising, as purchase levels are typically low relative to credit limits. However, our result here contrasts with that seen in Agarwal et al. (2008), who find in their US data the same pattern in over-limit fees as that seen in late payment fees and cash advance fees.[55]

The pattern seen in Figure B.8 does not mean that consumers do not respond to over-limit fee events. We do observe a decline in over-limit fees with tenure when we look at a set of cards incurring their first over-limit fee *at a given tenure*, illustrated in Figure B.12. We examine how consumers respond to a first over-limit fee. To do so, we estimate Equation 2 for over-limit fees and illustrate the predicted probability plots in Panel A of Figure B.9.[56] 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%

[54] The data also show that the proportion of cards incurring over-limit fees increases through the first months of tenure among both high and low risk of charge-off cards (see Figure B.13). Hence, the pattern in fees over tenure in our data suggests that consumers on average *do not* open credit cards and put them straight over limit, as if ignorant of the existence of a credit limit, even among higher risk cards that are likely to be held by less sophisticated consumers and have lower credit limits.

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

[56] The corresponding scatter plots of fees over tenure for each group are shown in Figure B.11 Tables B.5 to B.7 report the model estimates.

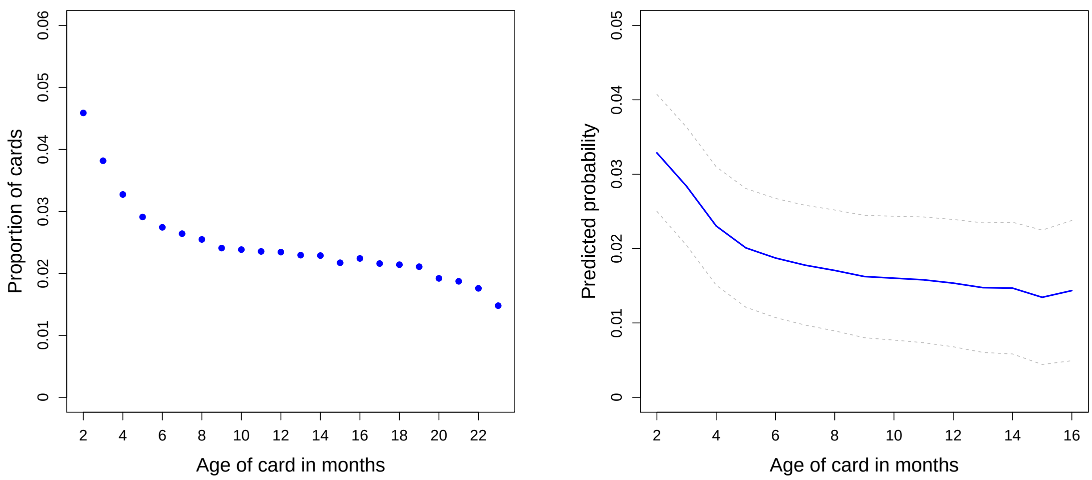
after two further months. Hence, there is low persistence in over-limit fees at the card level. This suggests that consumers on average adjust their behavior relatively quickly after an over-limit event. This pattern is consistent with the increase in the proportion of cards exhibiting over-limit fees over the first months of tenure. However, again here the wide confidence intervals in the probability plots show that these relationships are imprecisely estimated.

What drives customer responses to over-limit fees? In subsequent panels of Figure B.9, 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 cards exhibit successive months of higher purchases and declining repayments, with a spike in purchases in the month in which the fee is incurred. By contrast, in the period after the incursion of the over-limit fee, purchase volumes drop sharply, by approximately 55%, which persists over the 10 months following the first fee event.

Hence, the observed pattern of responses to an over-limit fee is that consumers on average take action to avoid future fees by cutting purchase volumes sharply, while leaving repayments unchanged. This is also consistent with the existence of individual liquidity constraints, as the reduction in balances when faced with a binding credit limit is concentrated in the current period through lower consumption purchases instead of higher repayments. As in the conclusions we draw from our analysis of cash advance fees, we expect that in the very few cases we observe in which customers open cards and immediately put the card over-limit, learning dynamics may be at play. However, our data suggest that this is not the main driver of the dynamics of over-limit fees.

Figure B.1: Cash Advance Fees and Card Tenure

(A) Raw data (B) Model prediction

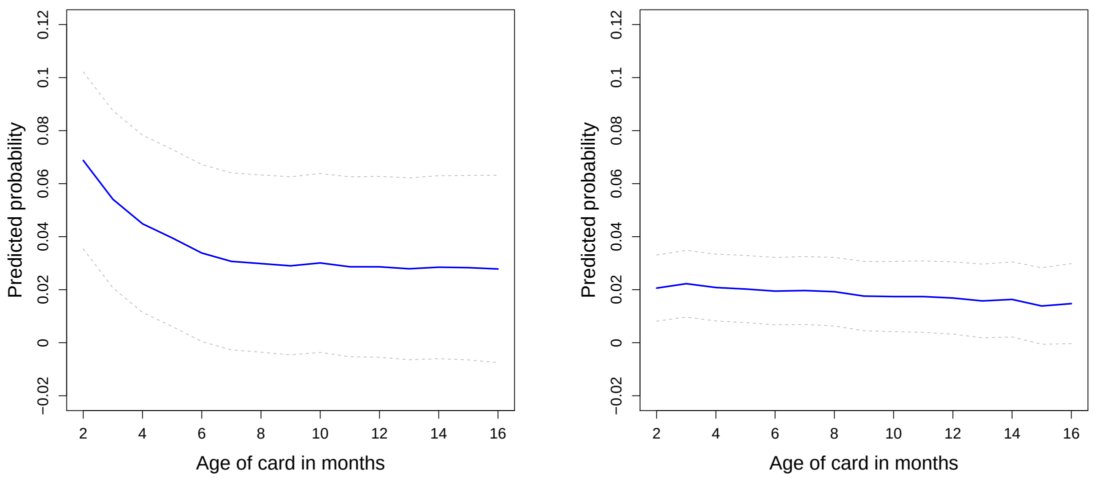


Note: Figure shows cash advance fees by card age. Panel A plots the mean of the y-axis variable (dummy variable indicating whether the card incurred a cash advance fee) by units of the x-axis variable (age of the card in months). The sample comprises all cards in the sample opened at or after January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

Figure B.2: Probability of Cash Advance Fees for High / Low Risk Cards

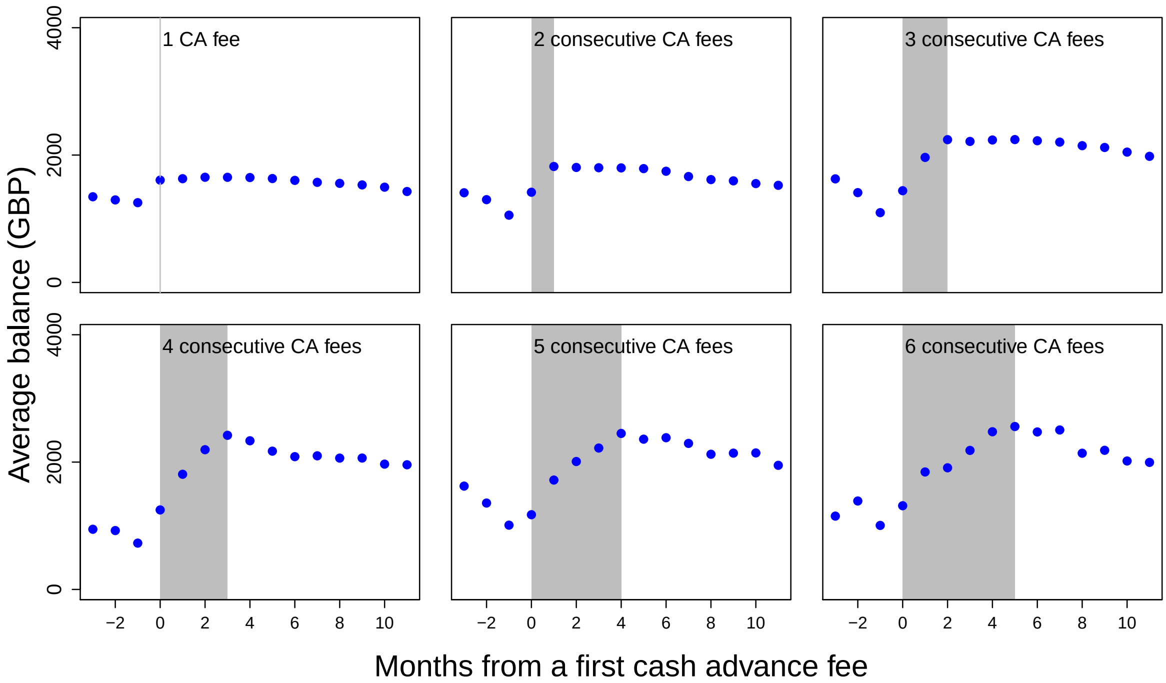
(A) High charge-off probability

(B) Low charge-off probability



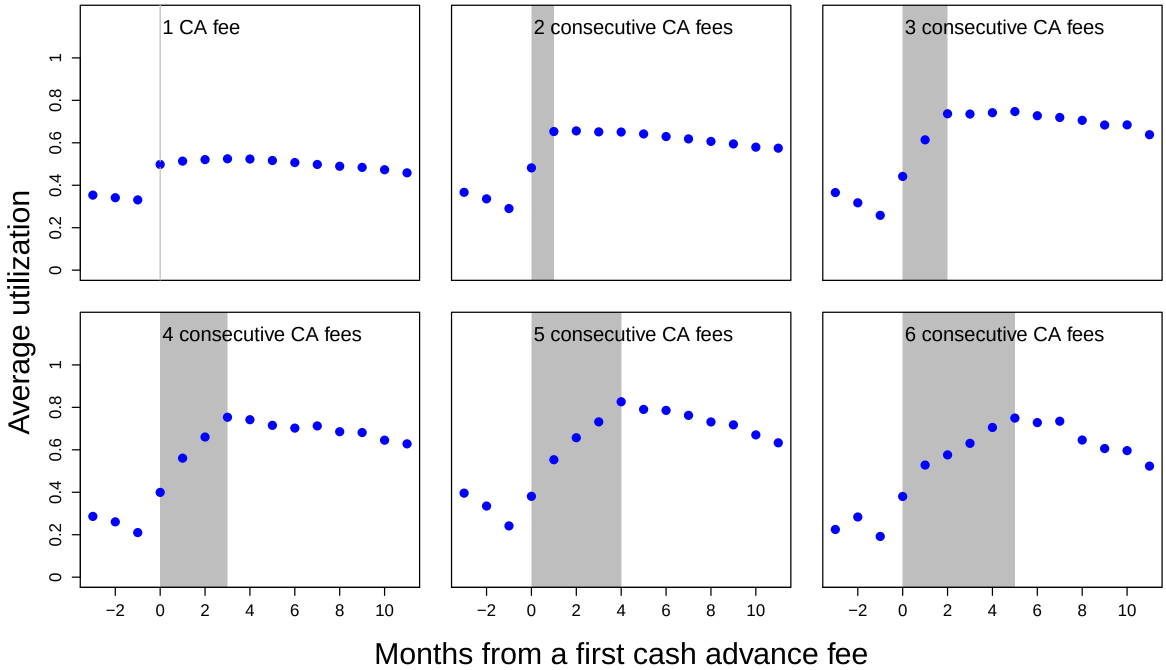
Note: Figure shows cash advance fees by card age for high and low risk cards. Plots show the predicted probability of cards incurring a cash advance fee by age of card. Predictions are from a linear probability model at covariate medians (Equation 1). The panels show plots from models estimated separately for cards with high (Panel A) and low (Panel B) probability of charge-off at card 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 B.7. Tables B.2 to B.3 report the model estimates.

Figure B.3: Credit Card Balances Through Spells of Cash Advance Fees



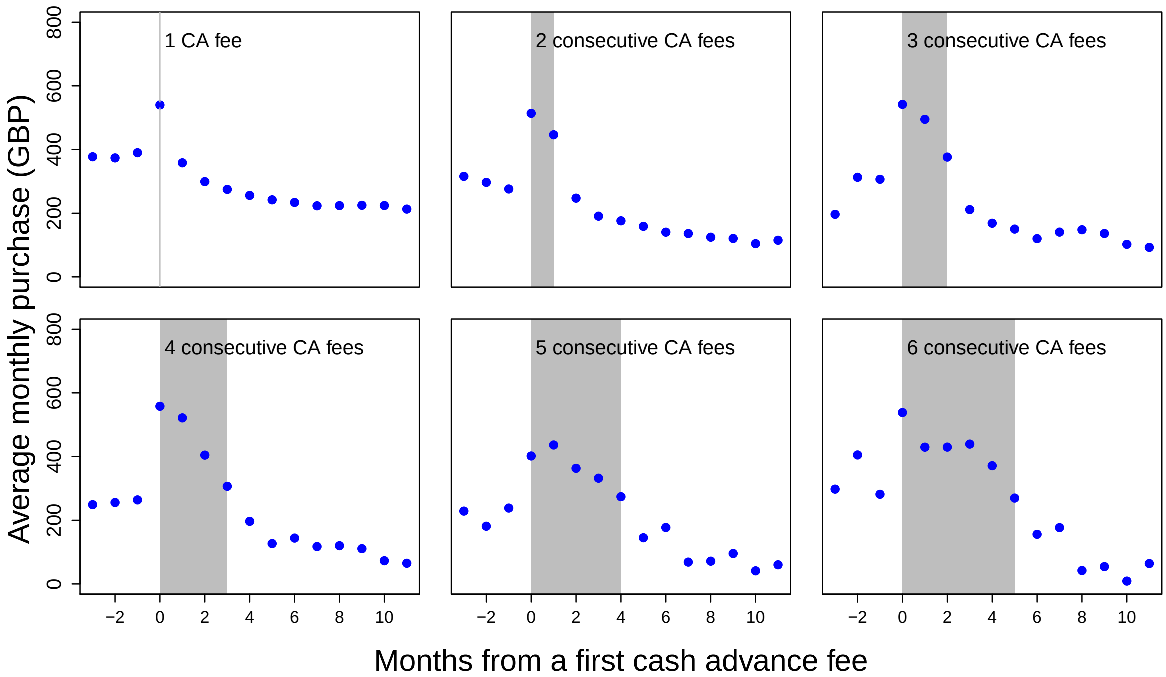
Note: Figure shows credit card balances through spells of cash advance fees, with panels showing spell length (in months). The plots show average credit card balances in each month by length of spell of consecutive months with at least one cash advance recorded on the card in each month. The x-axis ranges from three months before the first cash advance on the card through 11 months after.

Figure B.4: Credit Card Utilization Through Spells of Cash Advance Fees



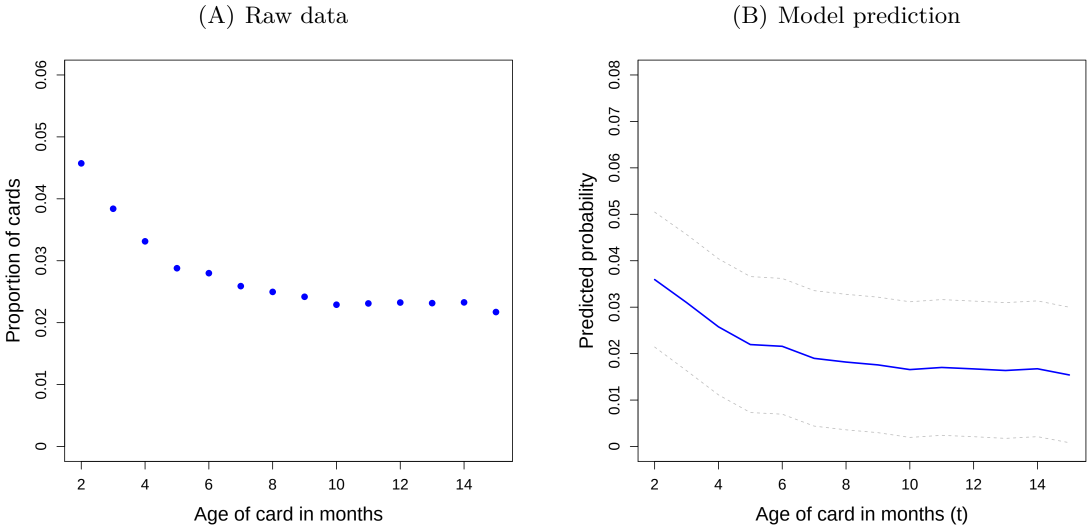
Note: Figure shows credit card utilization through spells of cash advance fees, with panels showing spell length (in months). Figure plots average utilization among cards by length of spell of consecutive months with at least one cash advance recorded on the card in each month. The x-axis ranges from three months before the first cash advance on the card through 11 months after.

Figure B.5: Credit Card Purchases Through Spells of Cash Advance Fees



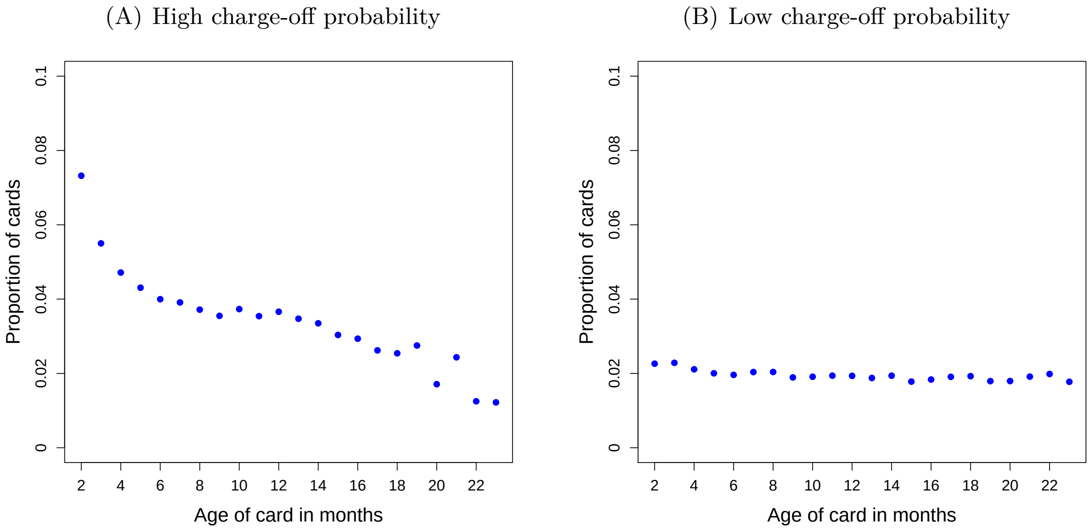
Note: Figure shows credit card purchases through spells of cash advance fees, with panels showing spell length (in months). Figure plots value of all credit card purchases within the month by length of spell of consecutive months with at least one cash advance recorded on the card in each month. The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

Figure B.6: Cash Advance Fees and Card Tenure, Balanced Panel



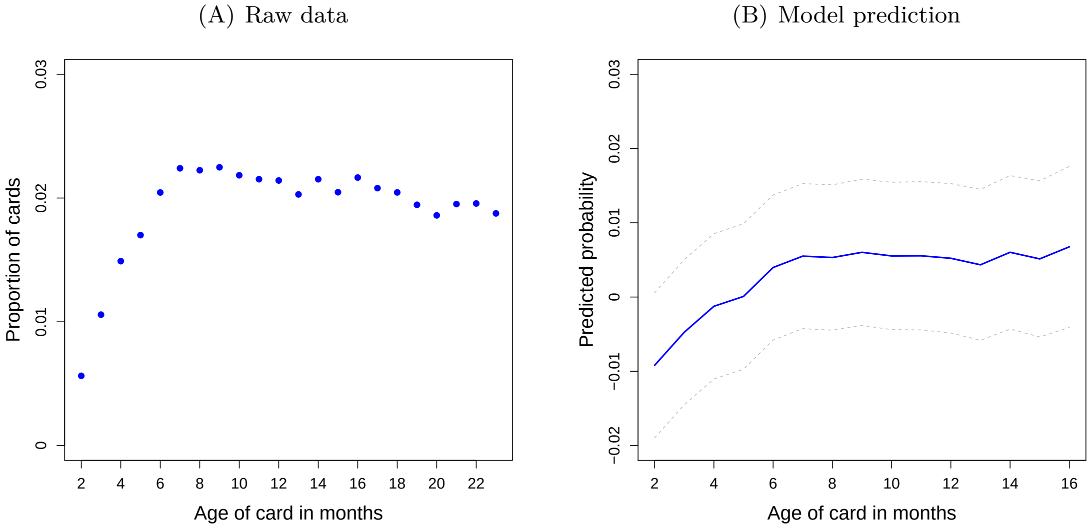
Note: Figure shows cash advance fees by age of card. The figure reproduces the plots in Figure B.1 when the data are restricted to a balanced panel of cards which open within the sample period and remain open for at least the following 15 months.

Figure B.7: Cash Advance Fees by Tenure, High/Low Charge-Off Probability Cards



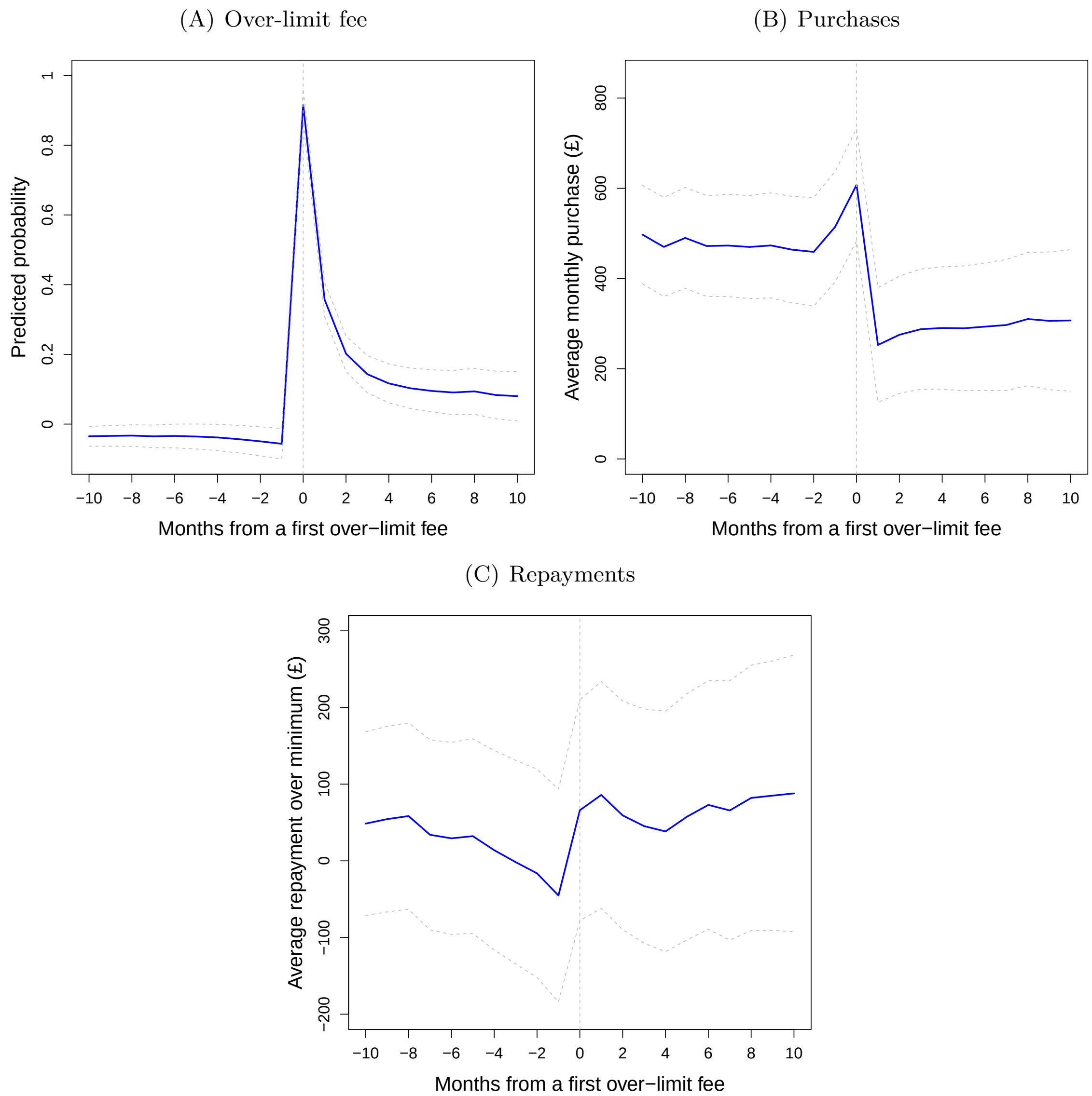
Note: Figure shows cash advance fees by tenure for high and low probability of charge-off cards. Figure plots the proportion of cards incurring a cash advance fee by age of card. The panels show plots from models estimated separately for cards with high (Panel A) and low (Panel B) probability of charge-off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

Figure B.8: Over-Limit Fees and Card Tenure



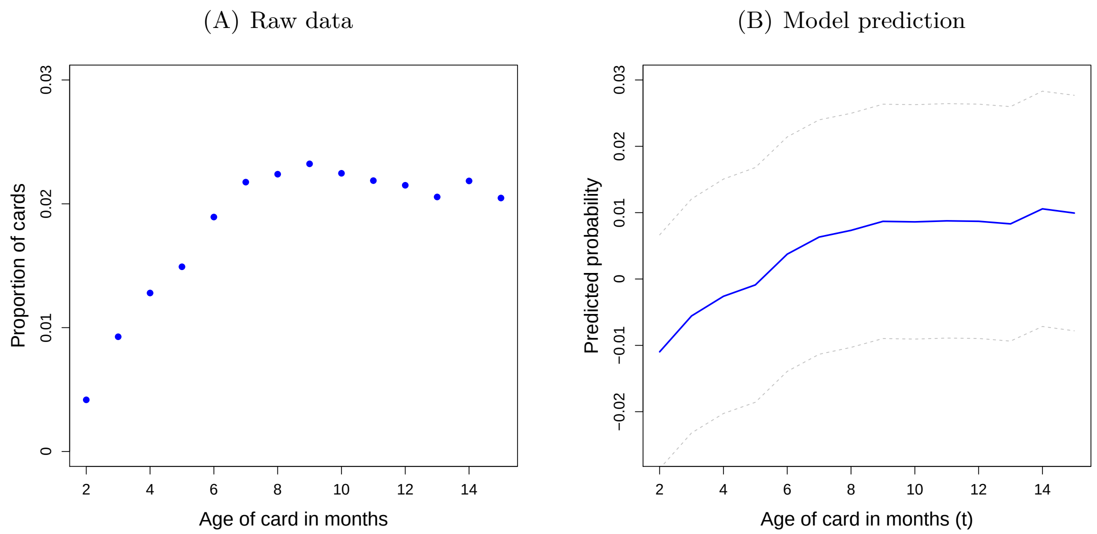
Note: Figure shows over-limit fees by card. Panel A plots the mean of the y-axis variable (dummy variable indicating whether the card incurred an over-limit fee) by units of the x-axis variable (age of the card in months). The sample comprises all cards in the sample opened at or after January 2013. Panel B plots the predicted probability of a card incurring an over-limit fee within the month based on estimates of (Equation 1). Predictions are from a linear probability model at covariate medians with clustered standard errors at card level. Full model estimates are reported in Table B.4. 95% confidence intervals are illustrated by dashed lines.

Figure B.9: Predicted Fees, Purchases and Repayments Around First Over-Limit Fee



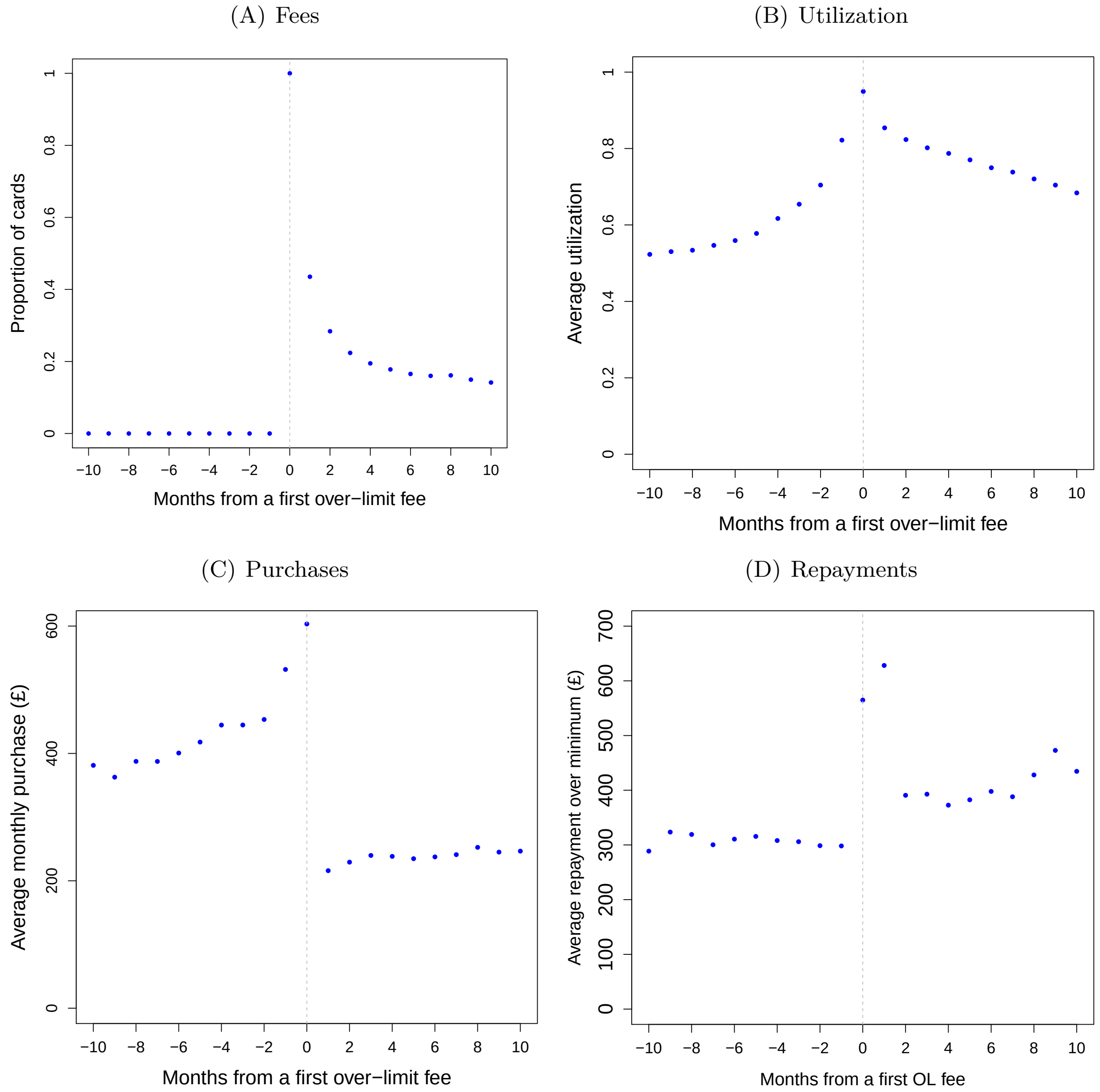
Note: Figure shows an event study of fees, purchases and repayments around the time of the first over-limit fee incurred by the card. Panels plot the predicted probability of cards incurring an over-limit fee in months before and after the over-limit fee is incurred (Panel A) and predicted average values of purchases and repayments (Panels B and C). Predictions are from a linear probability model at covariate medians (Equation 2). 95% confidence intervals illustrated by dashed lines. The corresponding scatter plots are shown in Figure B.11. Tables B.5 to B.7 report the model estimates.

Figure B.10: Over-Limit Fees and Card Tenure, Balanced Panel



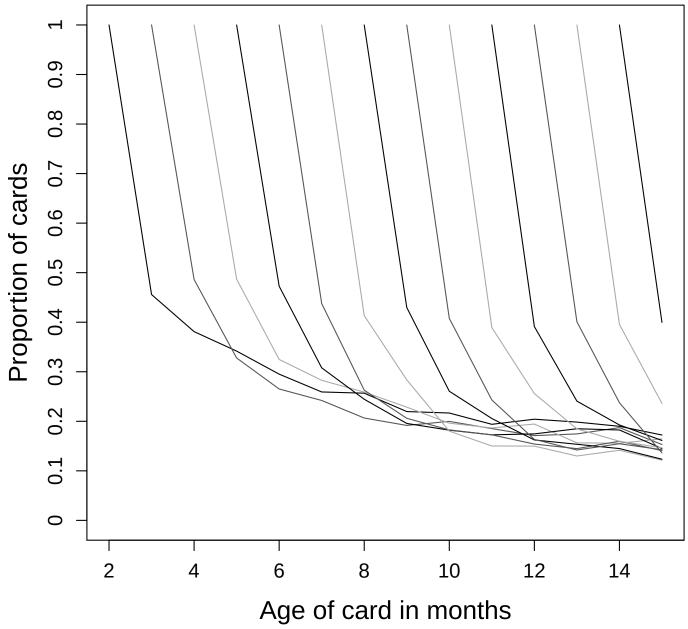
Note: Figure shows over-limit fees by card age. The figure reproduces the plots in Figure B.8 when the data are restricted to a balanced panel of cards which open within the sample period and remain open for at least the following 15 months. 95% confidence intervals are illustrated by the dashed lines.

Figure B.11: Purchases, Repayments and Utilization in Months Following First Over-Limit Fee



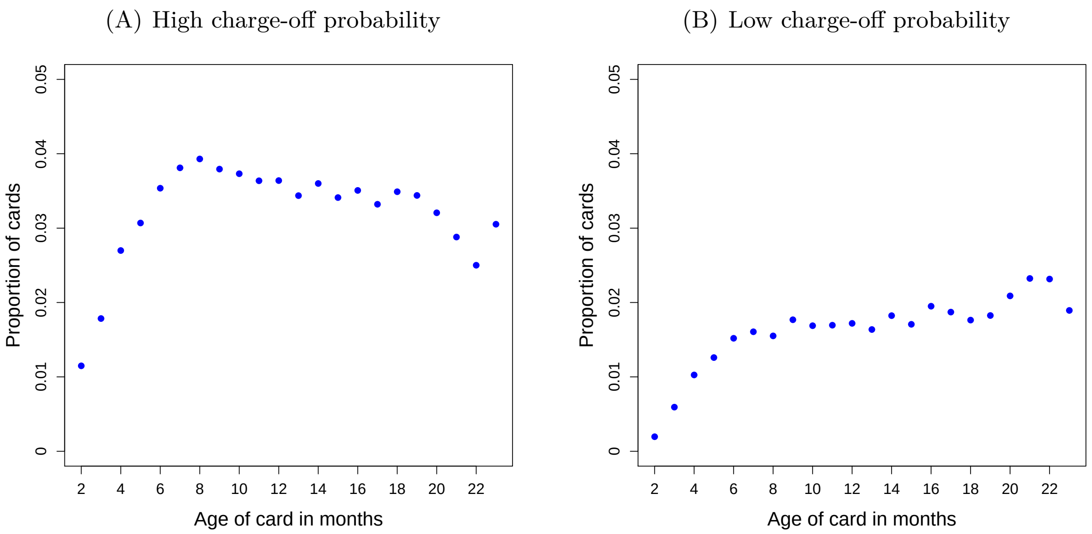
Note: Figure shows an event study of fees, utilization, purchases and repayments around the time of the first over-limit fee incurred by the card. Panels plot in Panel A average purchases (in £), in Panel B average repayment (in £) and in Panel C average utilization (balance expressed as a fraction of the credit limit) by number of months since the card first incurred an over-limit fee.

Figure B.12: Over-Limit Fees and Tenure, by Tenure of First Over-Limit Fee



Note: Figure shows the proportion of cards incurring an over-limit fee by card age in months, by month of the first over-limit fee. Each line plots the proportion of cards incurring an over-limit fee for a set of cards by month in which they incurred a first over-limit fee.

Figure B.13: Over-Limit Fees and Tenure for High and Low Charge-Off Probability Cards



Note: Figure shows over-limit fees by card age for high and low charge-off probability cards. Figures plots the proportion of cards incurring over-limit fees by tenure for high and low charge-off probability cards (median split)

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

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

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

Table B.2: Fixed Effects OLS Estimates Cash Advance Fees and Tenure, High Probability of Charge-Off Cards

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

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

Table B.3: Fixed Effects OLS Estimates Cash Advance Fees and Tenure, Low Probability of Charge-Off Cards

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

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

Table B.4: Fixed Effects OLS Estimates of Equation 1, Over-Limit Fees

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

Note: OLS regression estimates of Equation 1 in which over-limit fee dummy is dependent variable. Standard errors are clustered by card. The baseline for the tenure dummies is Tenure 2. Prediction plot from the model is illustrated in Figure B.8, Panel A.

Table B.5: Fixed Effects OLS Estimates Over-Limit Fees in Months Before and After First Over-Limit Fee

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

Note: OLS regression with clustered standard errors by card. Prediction plot from the model is illustrated in Figure B.9.

Table B.6: Fixed Effects OLS Estimates Purchases in Months Before and After First Over-Limit Fee

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

Note: OLS regression with clustered standard errors by card. Prediction plot from the model is illustrated in Figure B.9.

Table B.7: Fixed Effects OLS Estimates Repayments in Months Before and After First Over-Limit Fee

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

Note: OLS regression with clustered standard errors by card. Prediction plot from the model is illustrated in Figure B.9.