

How Do Consumers Avoid Penalty Fees? Evidence From Credit Cards

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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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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 make 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 due 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; Biliias

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 scores¹⁸, can jeopardize mortgage applications¹⁹, 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 or 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:

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

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:

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

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 fees 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 means 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.

mentation 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.

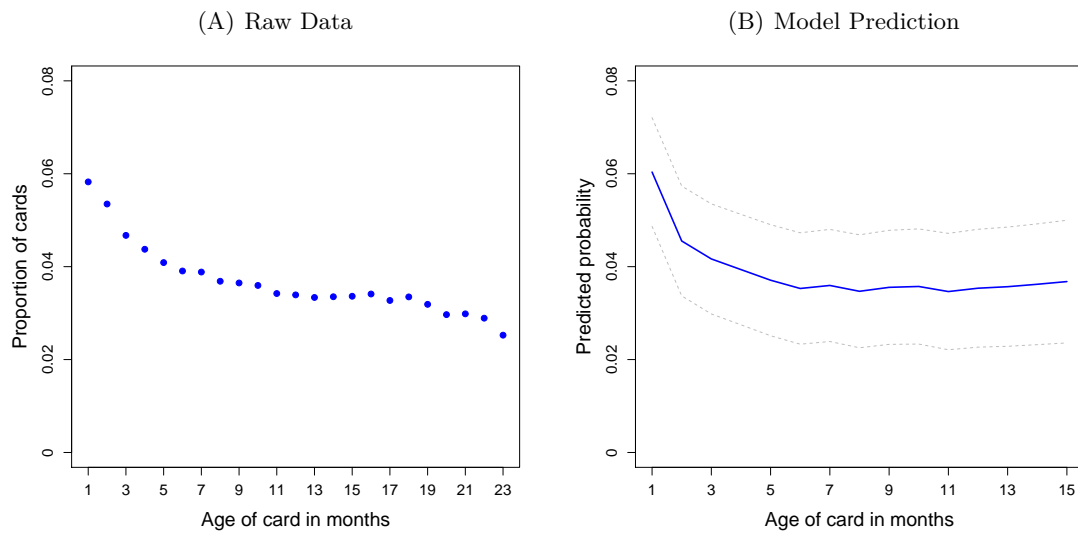
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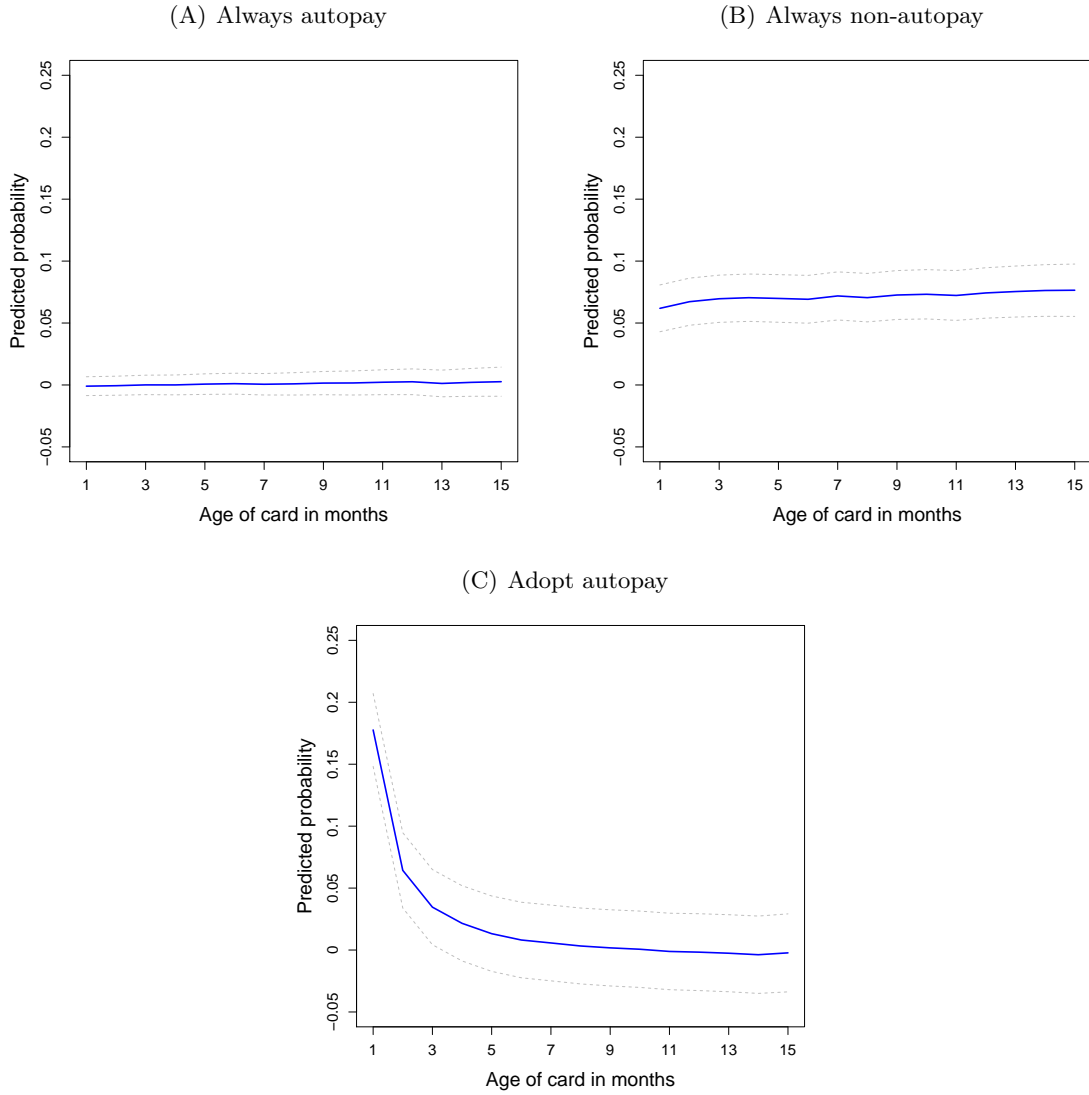
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Figure 1: Late Payment Fees and Card Tenure



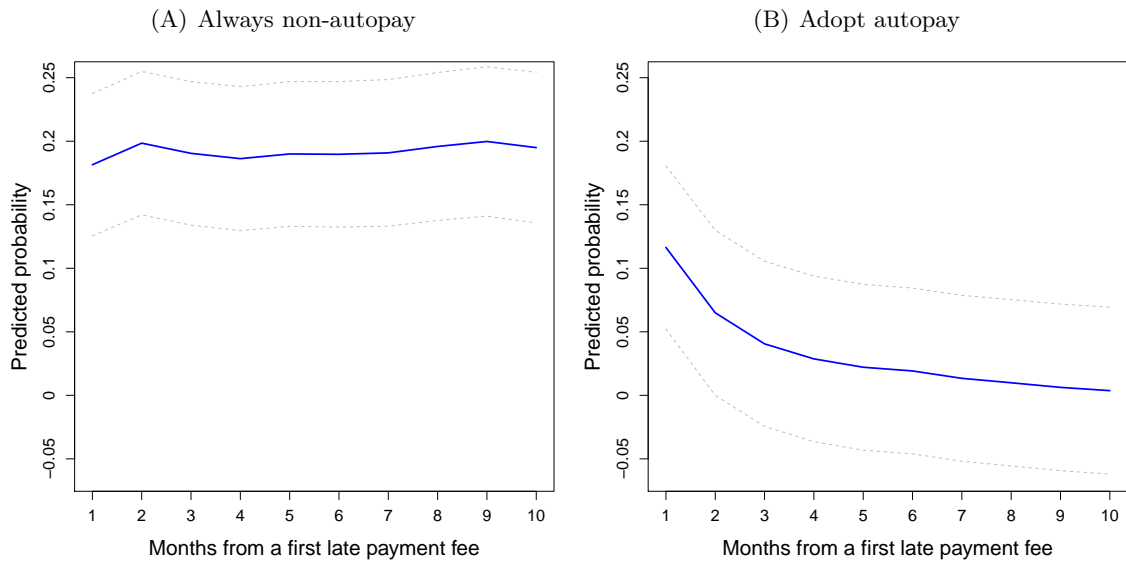
Note: Figures show late payment fees by age of card in months (card tenure). Panel A plots the mean of the y-axis variable (dummy variable indicating whether the card incurred a late payment fee) by units of the x-axis variable (age of the card in months). The x-axis variable is adjusted one month forward 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



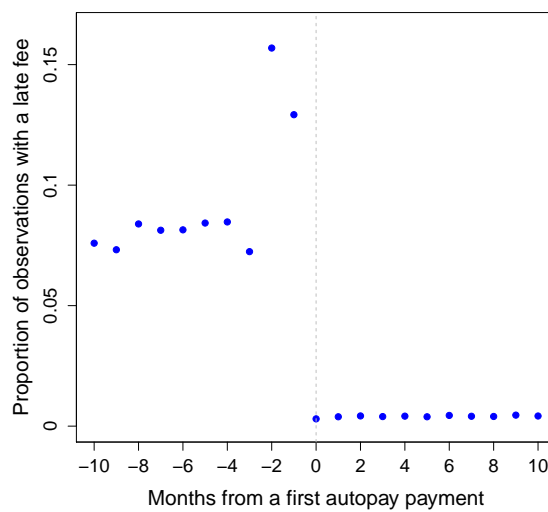
Note: Figures show the predicted probability of cards incurring a late payment fee in the next period by the age of the card in months. Predictions are from a linear probability model at covariate medians (Equation 1). The panels show three mutually exclusive groups of cards: cards which were subject 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



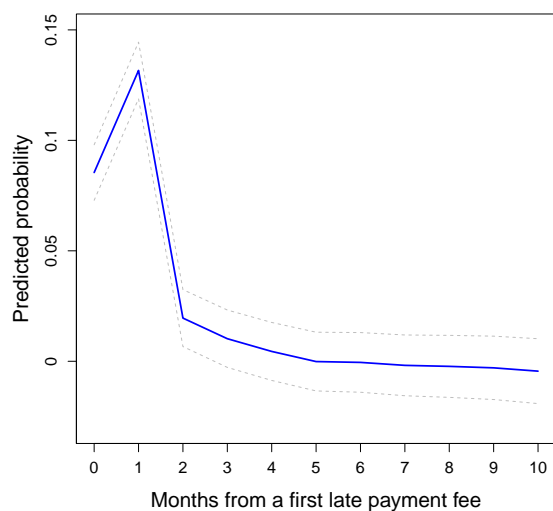
Note: Figures show the predicted probability of cards incurring a late payment fee in months after the first late payment fee is incurred (month zero). Predictions are from a linear probability model at covariate medians (Equation 2). The panels show two mutually exclusive groups: cards which were never 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



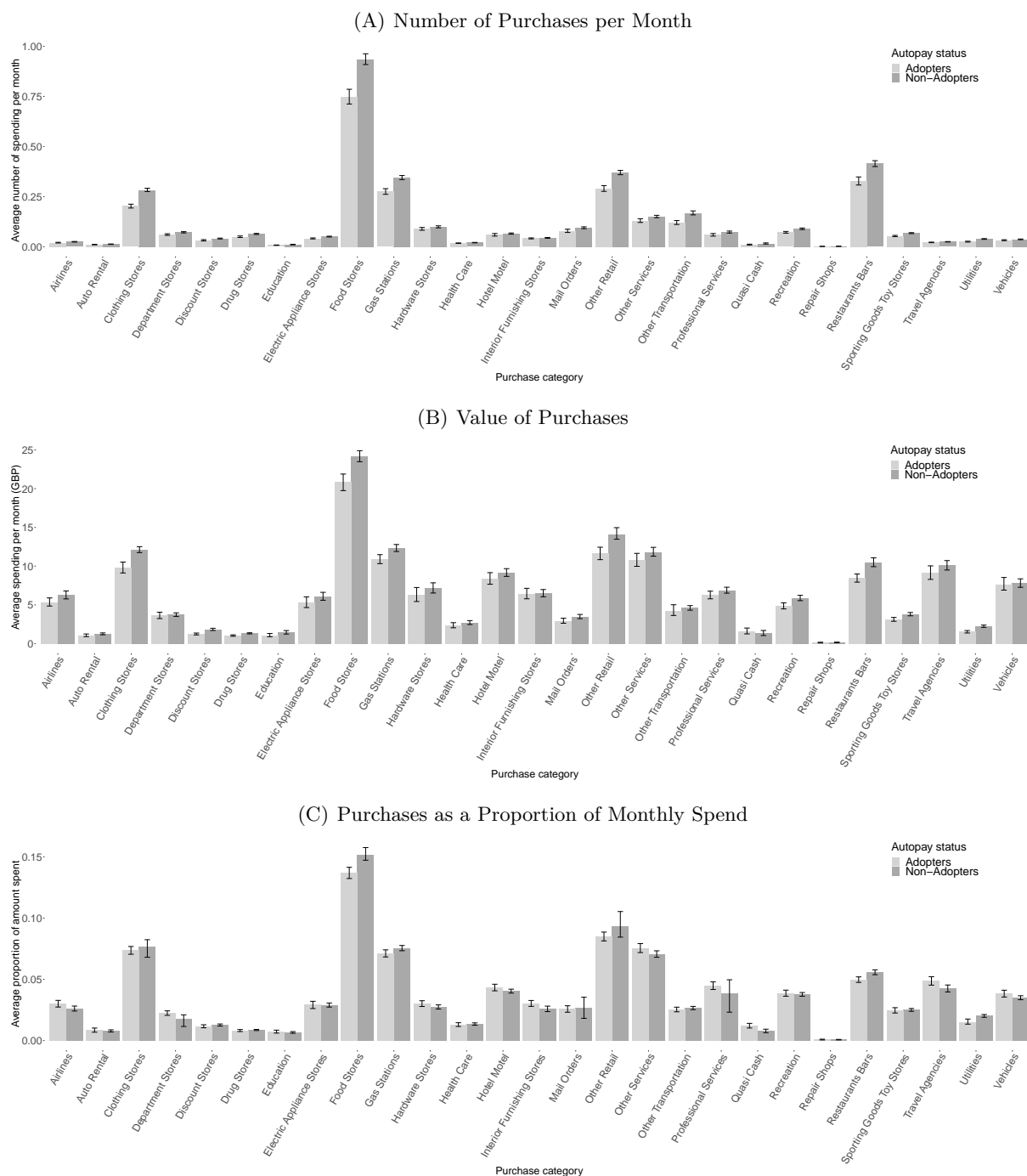
Note: Figure shows the proportion of cards incurring a late payment fee before and after adopting autopay. The sample comprises cards which adopt autopay within the sample period. Month zero on the x-axis denotes the month in which the card was first repaid using autopay.

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

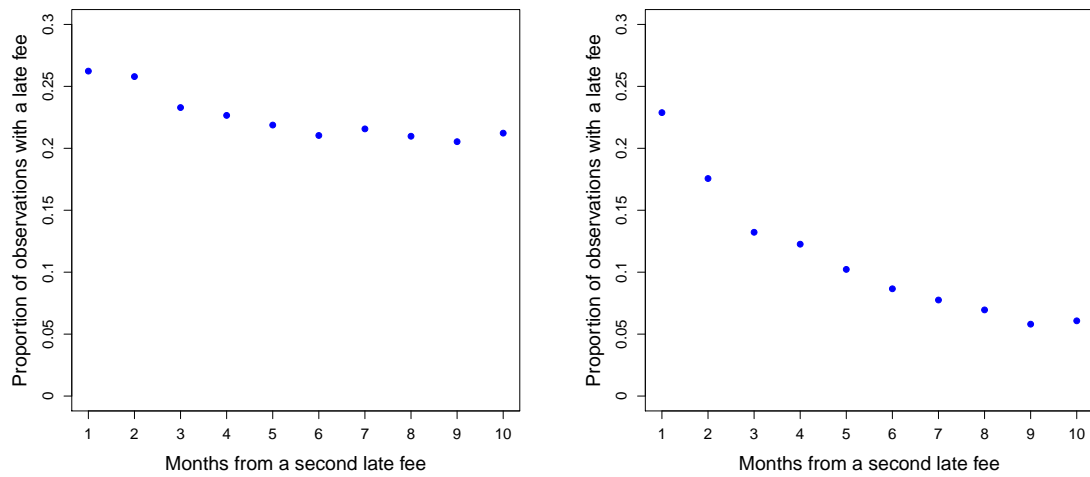


Note: Figures show spending patterns in card \times months following the first late payment fee for those who adopt autopay (light grey shading) compared with those who do not adopt autopay (dark grey shading). Categories on the x-axis represent merchant category codes created by Argus. Panel A shows 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

(A) Always non-autopay

(B) Adopt autopay



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 \times 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					
<i>Card Usage</i>					
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					
<i>Card Characteristics</i>					
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					
<i>Socio-Economic Characteristics (Postcode)</i>					
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 \times 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.