Risk-Based Quantity Limits in Credit Card Markets*

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Job market paper

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Abstract

Credit card lenders individualize contracts primarily through risk-based credit limits rather than interest rates. To understand lenders' credit limit choices, I use novel statement-level data on the near-universe of UK credit cards active between 2010–2015 to estimate a structural model of the credit card market. The model explains differences in lenders' credit limit distributions through a screening technology that provides lenders with a noisy signal of customers' risk. I identify model parameters using a novel cost shock that results from the April 2011 case in the England and Wales High Court concerning the mis-selling of payment protection insurance. I use the estimated model to evaluate a counterfactual scenario in which lenders can freely individualize interest rates and credit limits, which the existing environment precludes. As a result, interest rates and credit limits are individualized, and profits increase. Risk-based interest rate discrimination emerges, resulting in large reductions in consumer surplus for the riskiest individuals. I conclude with potential explanations for the puzzling absence of risk-based pricing in the UK credit card market.

Keywords: Risk-based pricing, risk-based credit limits, credit cards, adverse selection, credit scores

JEL Classification: D22, D82, E51, G21, G51, L13, L50

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1 Introduction

Asymmetric information is a pervasive feature of several markets considered essential for the functioning and development of the economy (Kiyotaki and Moore, 1997; Acemoglu, 2001). Two leading examples are insurance and credit markets. The presence of asymmetric information in these markets, specifically in the form of adverse selection, can lead to market inefficiencies and, in extreme cases, market unraveling (Akerlof, 1970; Rothschild and Stiglitz, 1976). The consequences of adverse selection can be severe, with the failure of credit markets described as "one of the major reasons for under-development" (Akerlof, 2001).

Accordingly, lenders in credit markets attempt to minimize the deleterious effects of adverse selection by tailoring contract characteristics to predictions of customers' default risk. Governments, however, want contracts to be simple and transparent so that consumers are not misled and can search effectively across lenders. As a result, regulation has limited the extent to which lenders can tailor certain features of credit contracts according to risk. In this paper, I investigate how lender heterogeneity and regulation affect the way UK credit card lenders individualize contracts according to risk.

The academic literature and policy discourse in this space generally focuses on risk-based pricing – the practice of interest rate discrimination based on customers' risk. However, in this paper, I provide evidence that UK credit card lenders adopt risk-based *credit limits* and not risk-based interest rates. My central contribution is to estimate a structural model of the credit card market to understand whether this empirical feature is a result of lenders' preference for risk-based credit limits over interest rates or the result of costs and constraints that affect lenders' willingness and ability to tailor interest rates according to risk.

Studying credit card lenders' credit limit and interest rate choices is important owing to its standalone economic interest and the credit card market's central role in the economy. It is the largest unsecured credit market, with most prime and superprime adults owning a credit card. UK cardholders borrowed a net £1.5bn on credit cards in February 2022 – the highest monthly amount since records began.[1] For this reason, lenders' credit limit and interest rate choices have material effects on individuals' financial well-being. This is especially true for subprime consumers, who are more likely to revolve a credit card balance and be credit

[1] Bank of England 2022, Bank of England website, https://www.bankofengland.co.uk/statistics/money-and-credit/2022/february-2022 last accessed 22 August 2022.

constrained.

To establish my findings, I use novel, statement-level administrative data on approximately 80% of all UK credit cards active between 2010 and 2015. I observe cardholder demographics and card characteristics for every card, along with monthly card use, borrowing, repayment, and default decisions. Among other advantages, the data contain lenders' proprietary risk scores for every credit card originated, hence, I can credibly check whether interest rates and credit limits are tailored to predictions of customers' risk.

Using the data, I document how credit limits vary substantially across individuals within lenders and credit card product, with the highest risk scores corresponding to the lowest credit limits. In contrast, interest rates are almost constant at the card-month level and are generally not risk-based. This fact is best understood in the context of UK credit card regulation, which requires that (i) lenders advertise one annual percentage rate (APR) for each credit card and (ii) at least 51% of customers on each card are granted the advertised APR or lower at origination. Nevertheless, 80 to 90% of customers are granted the advertised APR at origination, implying that the regulatory *constraint* cannot explain the minimal variation in interest rates. Finally, I report substantial heterogeneity in the shape and scale of credit limit distributions across lenders. This is a primary source of variation that I seek to explain with my economic model.

To this end, I construct and estimate a structural equilibrium model of the UK credit card market. My primary modeling novelty arises through the supply side. I endow each lender with a screening technology that generates a noisy signal for each individual's private type, which is their risk. Differences in the granularity of these signals across lenders explain differences in the shape of lenders' credit limit distributions. I offer the first quantitative model of credit card lenders' screening technologies and credit limit choices. I can estimate lender-specific screening technologies from lenders' optimizing equations because I have data on typically unobserved marginal costs of lending.

My supply-side estimates indicate that substantial variation exists in lenders' screening technologies, matching the variation in lenders' credit limit distributions. Further, I find that lenders with more precise screening technologies have a lower proportion of cases in which the customer repays their entire balance. This finding is consistent with a segmentation of credit card lenders in which lenders with the most precise screening technologies serve a riskier, but more profitable, market segment on average. Lenders with more precise screening technologies are more willing to serve customers will borrow but may default because they can more accurately set lower credit limits for customers they perceive to be riskier.

On the demand side, I model borrowers' credit card choices, level of borrowing, and default decisions, allowing for observed and unobserved heterogeneity in all endogenous demand-side variables. For credit card and borrowing choices, preferences over interest rates are heterogeneous, depending on individuals' incomes. I identify demand parameters using a novel source of quasi-experimental price variation. I create an instrument that exploits a cost shock resulting from the April 2011 case in the High Court concerning the mis-selling of payment protection insurance (PPI). Credit card lenders were forced to re-compensate thousands of consumers when the court deemed they had mis-sold PPI alongside credit cards. In my demand estimates, I find a positive correlation between unobservables driving the level of borrowing and default, implying adverse selection on the intensive borrowing margin.

The lack of interest rate variation, combined with the fact that the regulatory APR constraint does not bind, implies either that (i) alternative costs/constraints of setting individualized interest rates exist or (ii) lenders would optimally choose card-level interest rates even in the absence of such frictions. To investigate this further, I analyze a counterfactual scenario in which lenders have the option to use fully individualized interest rates and credit limits, subject to no costs or constraints. The distribution of interest rates moves from a small set of card-level interest rates to a more continuous, individual-level distribution, and interest rate discrimination emerges. The riskiest individuals experience large reductions in consumer surplus, and the safest individuals' consumer surplus increases. Further, credit limits remain individualized, borrowing increases, and lenders' profits increase.

The counterfactual findings suggest that lenders face frictions that limit their willingness to set individualized interest rates. Although I cannot identify the exact source of these frictions, I offer two possibilities. First, lenders may face reputational costs in advertising one APR while giving customers an alternative individualized APR.[2] Second, there are overhead and operational costs of tailoring prices optimally, specifically in the IT infrastructure required to operationalize individualized prices. Lenders are likely to focus their investments on tailoring credit limits if regulation limits their ability to tailor individuals' interest rates.

[2]In 2003, the UK House of Commons Treasury Committee described risk-based pricing as an "unacceptable practice", raising "serious transparency issues" (House of Commons Treasury Committee, 2003).

The paper proceeds as follows. Following a review of the literature in section 2, I describe my data and present my descriptive findings in section 3. My structural model follows in section 4. In section 5, I explain how I estimate the model parameters. Section 6 discusses my parameter estimates, and in section 7, I describe the results of the counterfactual analyses. Section 8 concludes the paper.

2 Related Literature

This paper relates to several bodies of literature, and I detail my contribution to the most closely related work in what follows. I describe this paper's relationship to the extensive credit card market literature more generally in Appendix A.

My paper contributes primarily to the literature on the role of credit limits in credit card markets. The most relevant article is that of Agarwal, Chomsisengphet, Mahoney, and Stroebel (2017), which shows that average credit limits increase along FICO scores in the US, and argues that credit limits are the main margin of adjustment for US credit card lenders. Further, the paper reveals that some lenders have FICO thresholds at which average credit limits increase discontinuously. For the authors, risk-based credit limits are a means rather than an end: Their paper focuses on banks' pass-through of credit expansions to customers. My contribution to this literature is to explain lender heterogeneity and discontinuities in credit limit schedules by estimating a model of lenders' credit limit choices. In the model, heterogeneous lender screening technologies that provide noisy signals on customers' levels of private risk justify differences in the shape and scale of lenders' credit limit distributions and can explain discontinuities in the credit limits.[3]

My work also relates to the literature on risk-based pricing. Existing research documents the presence of risk-based pricing in some financial markets (Edelberg, 2006; Magri and Pico, 2011; Magri, 2018; Bachas, 2019) and its absence in others (Benetton, 2021; Robles-Garcia, 2022). Notably, Adams, Einav, and Levin (2009) shows that risk-based pricing mitigates the effects of adverse selection in the US auto market. However, evidence of risk-based pricing in

[3] On a related theme, Agarwal, Chomsisengphet, Mahoney, and Stroebel (2017) and Gross and Souleles (2002b,a) estimate the causal effect of credit limits on borrowing and default. Aydin (2022) presents an interesting experiment randomizing credit limit shocks across credit card accounts in the United States. Fulford (2015) shows that US credit limits vary after origination, with more individuals obtaining credit limit increases than decreases. In the UK, credit limits are less volatile.

credit card markets is limited.[4] Hence, I contribute to the literature on risk-based pricing by documenting and justifying the lack of risk-based pricing in the UK credit card market.

Underpinning risk-based credit limits are lenders' use of statistical credit scoring models for measuring risk. Einav, Jenkins, and Levin (2012, 2013) and Paravisini and Schoar (2015) document significant profit increases for lenders following the adoption of risk-scoring methods. A large segment of the literature focuses on the predictive, *statistical* quality of credit scrores (Khandani, Kim, and Lo, 2010; Lessmann, Baesens, Seow, and Thomas, 2015; Butaru, Chen, Clark, Das, Lo, and Siddique, 2016; Albanesi and Vamossy, 2019; Fuster, Goldsmith-Pinkham, Ramadorai, and Walther, 2022). However, Einav, Finkelstein, Kluender, and Schrimpf (2016) takes a different approach, focusing on the *economic* content of risk scores. The paper notes that if risk scores determine contractual terms, then risk scores confound underlying default risk with endogenous responses to those terms. I contribute to this literature by estimating the underlying screening technologies of lenders, which provide a signal of the underlying unobservable risk on a harmonized scale. By estimating these harmonized scores off credit limits at origination, rather than ex-post default, my measure is not confounded with the potential endogeneity of origination contractual terms and lender-borrower relationship.

My final primary contribution is to the literature on price regulation in credit markets. Two contexts are particularly relevant. The first is Chilean credit markets, studied among others by Cuesta and Sepulveda (2021). The paper shows that tighter interest rate caps decrease surplus, with the welfare costs from loss of credit access outweighing the lower prices in equilibrium. Akin to my work, they show that risk-based interest rate caps cause less harm to welfare.

Nelson (2022) and Agarwal, Chomsisengphet, Mahoney, and Stroebel (2014) study the second relevant regulatory context: the 2009 US Credit Card Accountability, Responsibility, and Disclosure (CARD) Act. Agarwal, Chomsisengphet, Mahoney, and Stroebel (2014) documents substantial consumer savings as a result of the Act. Nelson (2022) focuses on how the Act limited lenders' abilities to reprice credit card customers after origination. The estimated economic model implies that consumer surplus rose at the expense of lender profits. In my

[4] Linares-Zegarra and Wilson (2012) argues that cards offered in riskier regions of the United States have lower APRs on average, though they do not look at the relationship between interest rates and risk within credit card.

paper, I focus entirely on ex-ante risk-based pricing. While I acknowledge the possible role of ex-post risk-based pricing, it has limited application in the United Kingdom, which is a feature I document in the next section. Instead, I show that price regulation limiting ex-ante risk-based pricing coincides with lenders adopting risk-based quantities through credit limits. Further, I consider counterfactual scenarios that allow lenders to freely base prices on risk in the context of endogenous risk-based credit limits, in which risk-based interest rates emerge.

3 Data and Descriptive Findings

I begin this section by summarizing the novel datasets I employ in my analysis. My primary data source is the Financial Conduct Authority (FCA) Credit Card Market Study (CCMS) Dataset.[5] The FCA used its legal authority as the regulator of UK financial markets to obtain data on all the credit cards active at 14 lenders between 2010 and 2015.[6] The data cover approximately 80% of the universe of cards active in 2010–2015, comprising around 74 million cards. The CCMS databases are only available to restricted staff and associated researchers at the FCA. In what follows, I summarize the three main databases in turn. In Appendix B, I describe the broader summary statistics of the data, for example, I provide evidence that rewards and annual fees are rare on UK credit cards.

Origination Data

The first dataset contains information on cardholders and their cards at origination, including the cardholder's demographics (age, income, etc.), their acquisition channel (whether in branch, online, by post, via telephone, etc.), and the interest rate and credit limit of their cards. The handiest feature of this dataset, however, is the inclusion of each customer's lender-specific risk score at origination.

Documenting that credit limits are based on risk rather than interest rates is the foundation of my analysis. As a result, I require observations of lenders' measures of customer risk. Furthermore, observations on publicly available risk scores are insufficient because UK lenders generally do not use them for credit decisions.[7] As such, it is critical that I have available

[5]See (FCA, 2015b) for a detailed summary of the data source.

[6]The FCA chose 11 firms (split into 14 separate lending entities) to be representative of the entire credit card market. For confidentiality reasons, I cannot reveal their identity. In the main analysis, I omit store cards and, where necessary, one other lender where there were data submission issues.

[7]For example, suppose a researcher only has access to public credit scores and that interest rates are based

observations of lenders' proprietary risk scores.

Lenders' proprietary risk scores are on different numerical scales and, as shown in Figure H.1, vary in how they are distributed over these scales. Further, public risk scores only explain a moderate proportion of the variation in each lender's proprietary risk scores. To provide evidence of this, I regress each lender's proprietary risk scores on percentile dummies of the main publicly available risk score. In these regressions, the proportion of variation in private risk scores explained is 21% on average.

The use of proprietary risk scores rather than public risk scores in the UK credit card market contrasts with the US, where FICO scores offer a measure of customer creditworthiness that many banks use as part of their lending decisions (Agarwal, Chomsisengphet, Mahoney, and Stroebel, 2017). Recent research has provided some justification for why lenders might create their own risk scores. For example, Albanesi and Vamossy (2019) shows that machine learning (specifically deep learning) methods consistently outperform standard credit scoring models, even when trained on the same data source. Further, lenders may have more granular customer data than credit reference agencies are able to access.[8]

<u>Statement Data</u>

The second dataset is a monthly panel of statement data for active credit cards. For the 61 months between January 2010 and January 2015, I observe opening and closing balances, repayment, the number and value of transactions, fees, interest, and the evolution of credit limits and interest rates. I also observe the account status, which records the months for which payment is overdue. In the event of repeated failures to repay the minimum repayment, the lender will typically charge off the account, which the dataset also details. Finally, these data contain observations on the lenders' costs of servicing the account, including typically-unobserved funding costs and provisions for non-repayment of debt at the *statement* level. Observations on lender's funding costs are essential to estimate screening technologies. Without these observations, I cannot separate differences in lenders' costs from differences in the precision of their screening technology.

Based on these data, I find substantial variation across lenders regarding the proportion of

solely on private risk scores. The researcher could find no relationship between public risk scores and interest rates, and it would be *incorrect* to interpret this as the absence of risk-based pricing.

[8]See FCA (2022) for a recent report on the UK credit information market and credit reference agencies.

statements in which the entire credit card balance is repaid. I present the proportions across lenders in Figure H.2. The proportion varies from approximately 20% at one lender to 80% at another.

Card Characteristics Panel

The third CCMS dataset is a monthly panel of card characteristics. For the months between January 2010 and January 2015, the panel collects card rewards (such as cashback and air miles) and income thresholds. Both income thresholds (for choice sets) and rewards (for observable card characteristics) make credible demand estimation feasible. Further, the dataset includes each card's monthly advertised APR. With this variable, I calculate the differences between the advertised and obtained APRs, which gives the intensive and extensive margins of risk-based pricing. At this point, a brief digression to explain the legal implications of advertised APRs is appropriate. I describe the UK and US APR regulations in more depth in Appendix C.

All promotional material and documentation for a credit card product must include a "representative" ("advertised") APR. Before February 2011, at least 66% of customers each month had to obtain the advertised APR or lower. The regulation changed in February 2011 when the UK harmonized with the EU to reduce the threshold to 51% and it has not changed since that time. US credit card lenders do not have to advertise one APR for each card, but instead have to provide a range of possible values in the "Schumer Box", which is a summary of the key credit card terms and conditions.

Other Sources

The CCMS data include a credit reference agency (CRA) dataset that matches cards to individuals. The CRA data confirm that, on average, UK adults hold fewer cards relative to the US population, with the majority holding only one card each (see Figure H.3 and FCA (2015a)). I estimate my model using those with one credit card, which circumvents complications arising from (i) balance transfers and (ii) balance-matching heuristics in repayment across multiple cards (Gathergood, Mahoney, Stewart, and Weber, 2019). Finally, I occasionally complement my analysis with an FCA survey of cardholders, detailed in FCA (2015d).

3.1 Central Descriptive Findings

The single aim of this subsection is to robustly show that the leading UK credit card lenders individualize credit card contracts through risk-based credit limits rather than interest rates. As such, most of the analysis is conducted within lender or within credit card product. Despite this, even when pooling across all lenders and months, credit limits are dispersed to a much greater extent than interest rates. Across all cards and lenders, the coefficient of variation (the ratio of standard deviation to mean) in credit limits is equal to 93%, compared to a value of 36% for interest rates.

3.1.1 Limited Variation in Lenders' Interest Rates

Limited Total Variation

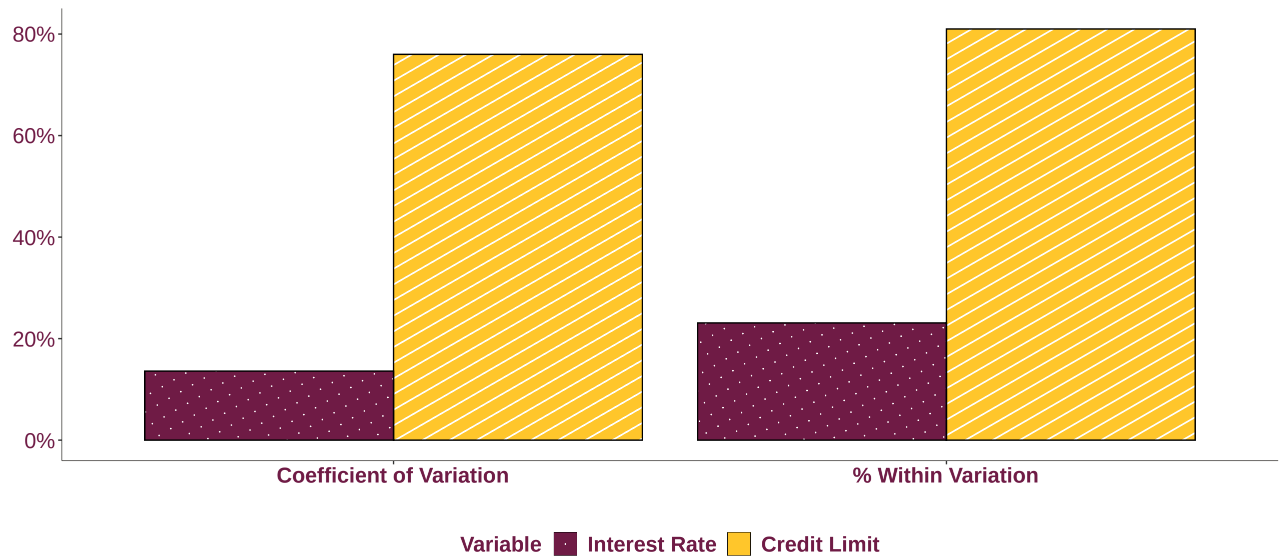
I begin by documenting limited variation in each lender's interest rates across originations within a month. Table H.1 column (1) reports the average (over months) of the lenders' interest rate coefficient of variation.[9] The values are below 23%, and, as shown in the left-hand dotted maroon bar in Figure 1, the average across prime and superprime lenders (weighted by originations) is 14%. This implies that the standard deviation in the interest rate is, on average, one-seventh of the mean at a lender in a given month. Additionally, as detailed in Table H.1 columns (2) and (3), the across-lender weighted average of the ratio of the 75^{th} to 25^{th} percentile (respectively 90^{th} to 10^{th}) for interest rates is 1.19 (respectively 1.38), further illustrating limited variation in interest rates within lenders.

Limited Within Variation

For the leading UK credit card lenders, a modest proportion of the already minimal total variation in interest rates is within credit cards rather than across them. To show this feature, I decompose the variation in lenders' interest rates into within-card and between-card terms. For each lender ℓ and month t, I split the total variation $V_{\ell t}^{TOT}$ in interest rates $r_{ij\ell t}$ for cards $j \in J_{\ell t}$ and originations $i \in I_{j\ell t}$ into within-card variation $V_{\ell t}^{W}$ and between-card variation

[9] For lender ℓ in month t, who offers cards $j \in J_{\ell t}$, creating originations $i \in I_{j\ell t}$, I calculate the grand average $\bar{r}_{\ell t}$ and standard deviations $sd_{r,\ell t}$ of interest rates, where $\bar{r}_{\ell t} = \frac{1}{I_{\ell t}} \sum_i \sum_j r_{ij\ell t}$ and $\text{sd}_{\ell t}^2 = \frac{1}{I_{\ell t}} \sum_j \sum_i (r_{ij\ell t} - \bar{r}_{\ell t})^2$, and $I_{\ell t}$ is the total number of originations. The value in column (1) of Table H.1, for lender ℓ is $cv_{r\ell} = \frac{1}{T_\ell} \sum_t \frac{sd_{r,\ell t}}{\bar{r}_{\ell t}}$, where $T_{\ell t}$ is the number of months of observations for each lender. The left-hand dotted maroon bar in Figure 1 shows the weighted average (weighted by market share) of $cv_{r\ell}$ over prime and superprime lenders.

Figure 1: Coefficient of variation and proportion of within-card variation in interest rates and credit limits for prime and superprime lenders



Notes: To construct each bar, I calculate the average of the statistic over the months within a lender to create a lender-specific value. Each bar in this plot is a weighted average (weighting by origination share) of the lender-specific averages for the prime and superprime lenders.

$V_{\ell t}^{B}$

$$\underbrace{\frac{1}{I_{\ell t}}\sum_{j=1}^{J_{\ell t}}\sum_{i=1}^{I_{j\ell t}}(r_{ij\ell t}-\bar{r}_{\ell t})^2}_{V_{\ell t}^{TOT}} = \underbrace{\frac{1}{I_{\ell t}}\sum_{j=1}^{J_{\ell t}}\sum_{i=1}^{I_{j\ell t}}(r_{ij\ell t}-\bar{r}_{j\ell t})^2}_{V_{\ell t}^{W}} + \underbrace{\sum_{j} s_{j\ell t}(\bar{r}_{j\ell t}-\bar{r}_{\ell t})^2}_{V_{\ell t}^{B}}, \tag{1}$$

where $I_{\ell t}$ is the total number of originations at lender ℓ in month t, $\bar{r}_{\ell t}$ is the grand mean of interest rates, $\bar{r}_{j\ell t}$ is the card-j-specific interest rate mean, and $s_{j\ell t} = \frac{I_{j\ell t}}{I_{\ell t}}$ is the share of originations on card j at lender ℓ in month t. Intuitively, the decomposition separates the grand variance into an average of within-card variances ($V_{\ell t}^{W}$) and a weighted variance of card averages ($V_{\ell t}^{B}$). As plotted in the right-hand dotted maroon bar in Figure 1, within variation for prime and superprime lenders is, on average, 23% of the total variation.[10] Table H.1 column (4) reports the values of the percentage of within-card variation for all lenders. In the extreme case, two lenders give over 99% of customers on a given credit card the same interest rate in *all* months, hence for these two lenders, practically all the variation in interest

[10] The weighted average including subprime lenders is 31%. I discuss subprime lenders separately in Appendix D.

rates at origination is at the card level.

Proportion of Customers Obtaining Advertised APR

To explain the lack of within-card variation in interest rates, I calculate the monthly percentage of customers obtaining the advertised APR and plot its value in Figure H.5. The value across all credit cards in the sample hovers around 80 to 90% and it does not change in February 2011 when regulation on advertised APRs was relaxed. Even though regulation required lenders to give the advertised APR to only 51% of their customers after February 2011, most lenders still gave almost all their customers the advertised APR.[11] Further, Figure H.6 plots the proportion of *cards* giving at least 70% (solid) and 90% (dashed) of customers the advertised APR at origination in each month. Each month, around 85% of cards give at least 70% of customers the advertised APR, and in 77% of card-months, over 90% of originations obtain the advertised APR. These statistics confirm that most *cards*, and not just *lenders*, give the majority of their consumers the advertised APR. I will embed this feature into my economic model by making borrowers' preferences for a credit card dependent on card-level APRs, abstracting from the minimal within-card variation in interest rates.

I summarize the descriptive facts presented thus far in Finding 1.

Finding 1 (Interest Rate Variation) *There is limited total variation in interest rates, of which an even smaller part is within-card variation. The fact that 80–90% of customers obtain the advertised APR at origination each month corroborates the limited within-card variation in interest rates.*

3.1.2 Substantial Variation in Credit Limits

Substantial Total Variation

Having confirmed the lack of variation (particularly within-card variation) in interest rates, I turn to credit limits. I provide the average of lenders' credit limit coefficients of variations (weighted by originations) in the left-hand striped gold bar in Figure 1. At 78%, it is over five times larger than the equivalent for the interest rate. As reported in columns (6) and (7) of Table H.1, the across-lender weighted average of the 75^{th} to 25^{th} (respectively 90^{th} to 10^{th}) credit limit percentile ratios is 3.34 (respectively 9.15), showing substantial variation in

[11] I pool over lenders here, but lender-by-lender and card-by-card plots are similar.

credit limits within each lender.

Substantial Within Variation

I perform the same within-card and between-card decomposition as in equation (1) for credit limits. Across lenders, as shown in the right-hand gold striped bar in Figure 1, the average percentage of total variation found within credit cards is 81%. The dominance of within variation suggests that lenders do not sort individuals onto cards with varying average credit limits. Rather, there is large variation in credit limits across individuals even within a given credit card product.

Shape and Scale of Credit Limit Distributions

The distribution of credit limits varies substantially across all lenders in both shape and scale.[12] I illustrate this fact in in Figure 2, where I plot the empirical cumulative distribution function (CDF) of credit limits for two contrasting lenders, labelled lender A and B. Two substantial differences are evident. The first relates to the *shape* of the credit limit distributions. Lender B's curve is step-like, implying a coarse process of assigning credit limits to individuals, where groups of consumers obtain the same credit limit. Lender A's smooth curve is consistent with a more finely tuned allocation mechanism for origination credit limits. The second difference relates to the *scale* of the credit limit distributions. Lender A has lower values of credit limits than lender B for the first 25 percentiles; all percentiles after the 25^{th}, however, are larger. The range of lender A's credit limit distribution is indeed much larger.

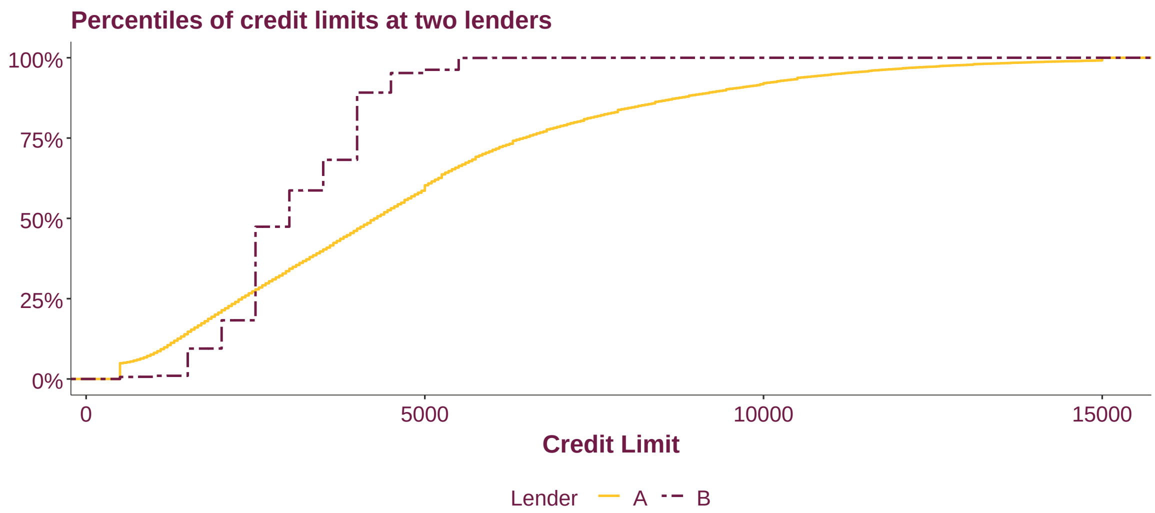
Other lenders' credit limit empirical CDF at origination, plotted in Figure H.7, lie between the two lenders in Figure 2. This range in the shape and scale of distributions is consistent with lenders who vary in the coarseness of their credit limit assignment.[13] Some lenders offer large groups of customers the same credit limit, while others with smoother CDFs adjust their credit limits more precisely to each customer. The model I build in the next section justifies differences in the shape and scale of lenders' credit limit distributions through differences in the coarseness of information they have on customers' risk.

I summarize my descriptive facts on the distributions of credit limits in Finding 2.

[12] To confirm differences between lenders' credit limit distributions formally, I conduct multiple distribution "Kolmogorov-Smirnov" hypothesis tests in Table H.2. I strongly reject the equality of empirical CDFs across lenders at lower than 0.5% significance levels in all tests.

[13] These findings are robust to splitting lenders into cards and splitting originations by year and by month.

Figure 2: Empirical CDFs of two particular lenders' credit limits



Finding 2 (Credit Limit Distributions) *There is substantial within-card variation in credit limits across lenders. The distributions of credit limits differ in shape and scale across lenders.*

3.1.3 Risk-Based Credit Limits, Not Risk-Based Prices

Since interest rates at a lender rarely vary within a credit card month, they are unlikely to relate strongly to lenders' predictions of customers' default risk. I confirm this in Figure H.8, in which most lenders' average interest rates are flat across the application risk score support. Exceptions exist for two subprime lenders, who, as described in Appendix D, engage in risk-based pricing.

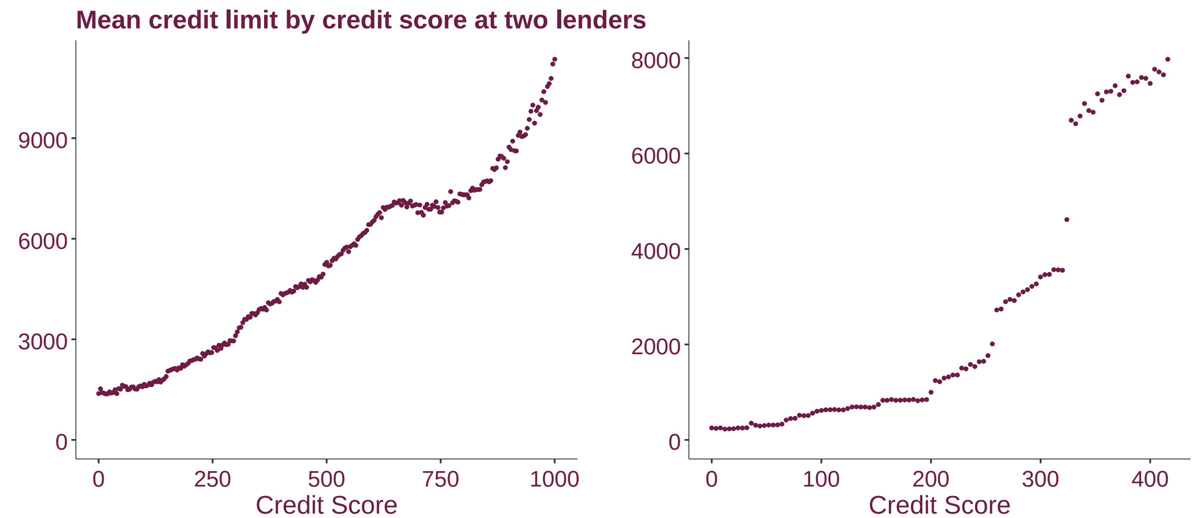
Lenders could employ risk-based pricing by adjusting interest rates after origination, *repricing* customers according to their evolving risk and behavior.[14] In the period I study, limited repricing occurred in the UK credit card markets. As detailed in Table H.3 and shown in Figure H.10, lenders reprice only 4% of cards within the first year after origination.

As expected, lenders link each individual's credit limit to an assessment of their risk. In Figure 3, I plot the mean of the origination credit limit along application credit scores for two contrasting lenders.[15] Both curves are upward sloping, consistent with risk-based credit limits.

[14]Nelson (2022) shows that repricing was a relatively common practice in the US credit card market until the (2009) CARD Act essentially outlawed the practice.

[15]In Figure H.9, I plot the mean of origination credit limit for each lender, along application credit scores.

Figure 3: Mean credit limits across lenders' risk scores for two particular lenders



Notes: Credit score scales differ across lenders so cannot be compared.

Further, the right-hand lender has discontinuities in credit scores at credit score thresholds. If risk is continuously distributed and lenders create finely tuned assessments of customers' risk, discontinuities in credit limits at points of their credit scores are difficult to rationalize. Accordingly, the overarching aim of my model is to rationalize discreteness and discontinuities in lenders' credit limit distributions through coarse (discrete) assessments of customers' risk. Separate and ongoing work exploits these discontinuities to measure the distribution of causal effects of credit limits on borrowing and default, similar to Agarwal, Chomsisengphet, Mahoney, and Stroebel (2017). Hundreds of discontinuities in credit limits exist over lenders' credit scores and time. Formally aggregating multiple regression discontinuity design estimates across cards, time, and proprietary risk scores is a detailed procedure and not the subject of this paper.

I summarize my descriptive facts on risk-based credit limits in Finding 3.

Finding 3 (Risk-based Credit Limits) *Credit limits vary with lender-specific application credit scores, while interest rates generally do not. Heterogeneity exists in how lenders map their credit scores into credit limits: Some, but not all, lenders exhibit discontinuities in their credit limits at certain credit score thresholds.*

In unreported plots, the same patterns emerge when produced by month.

3.2 Implications of Descriptive Findings

This section reveals that the leading UK credit card lenders individualize credit limits according to their assessments of the customer's risk but do not individualize interest rates. These empirical facts are best understood alongside UK credit card regulation, which demands a card-level advertised APR that most customers must obtain. The next step is to learn about how lender heterogeneity and the regulatory environment impact lenders' decision to individualise contract characteristics. For example, the empirical setting is not insightful on how lenders would set interest rates if they were not required to set and advertise a card-level APR. In the absence of meaningful exogenous variation in the regulatory environment or the makeup of lenders, the best—and perhaps only—way to achieve this aim is to build an economic model of the credit card market. This model follows in the next section.

4 A Model of the Credit Card Market

Here, I present a model of the UK credit card market. To help navigate the model, Tables H.4 and H.5 provide a glossary of notation and Figure H.11 depicts a timeline.

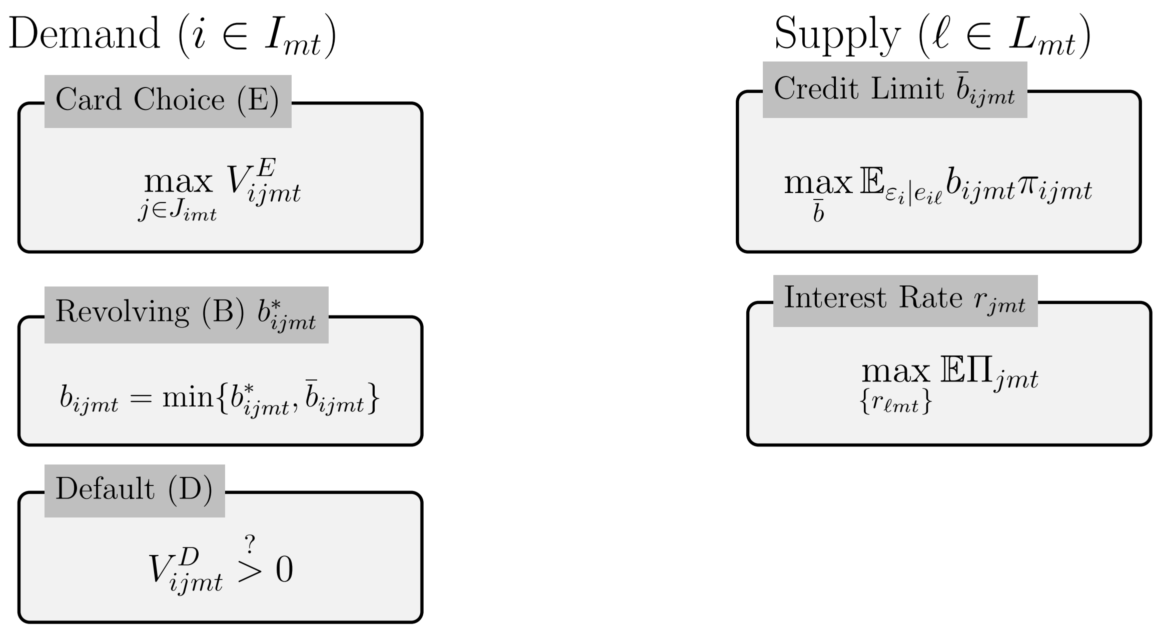
4.1 Preliminaries

The market is a pair (m, t). Here t represents an origination month between January 2010 and June 2013, and m represents the distribution channel, split between those occurring in the store and out of the store.[16] I describe the model through its three features: the credit card $j \in J_{mt}$, consumers $i \in I_{mt}$ currently without a credit card (who represent demand), and lenders $\ell \in L_{mt}$ (who represent supply). I focus on those currently without a credit card for two reasons. First, as discussed in section 3, most UK adults hold only one credit card. Second, estimating my model on the sample currently without a credit card circumvents complications arising from (i) balance transfers and (ii) balance-matching heuristics in repayment across multiple cards (Gathergood, Mahoney, Stewart, and Weber, 2019).

My demand model can be microfounded in a typical consumption-savings setup. However, I prefer to view my demand-side estimating equations as a set of linearized equations, agnostic to much of the behavior that generates them. This is similar to the approach of Einav, Jenkins, and Levin (2012), which focuses on a set of linearized estimating equations from

[16] I stop at June 2013 to ensure that I observe 18 months of borrowing and default data on each individual.

FIGURE 4: Model overview



their standard model of consumer choice. The benefit of this approach is that the econometric model becomes a valid approximation of several underlying models of consumer choice, not just the standard model of intertemporal optimization. Though this can limit the extent of welfare analysis, it is a worthwhile concession in modeling credit card borrowing, where standard assumptions about revealed preference, rational expectations, and consumer sophistication are subject to deserved scrutiny. I discuss the various departures from rational utility maximizing agents with standard intertemporal preferences in the in credit card market literature in Appendix A.

4.2 Credit Card

Following Lancaster (1966), I model a credit card as a bundle of features. There are four components. The first is the advertised interest rate r_{jmt}. The second component is the income threshold $\underline{Y}_{jmt}$, explained in section 4.3. The third and fourth are characteristics: those I observe, denoted X_{jmt} (e.g. cashback and air miles), and those I do not, ξ_{jmt} (e.g. prestige and brand loyalty).

4.3 Consumer

My demand model follows those in the credit market literature, sharing features with Crawford, Pavanini, and Schivardi (2018).[17] The left side of Figure 4 depicts the demand-side building blocks. Consumers potentially make three decisions (card choice, borrowing, and default), each of which I detail in turn.

4.3.1 Card Choice

In the first nest, consumers choose whether they will be transactors or revolvers. Transactors, denoted $j = 0$, do not use the borrowing facility and pay off their balance in full every month. Revolvers leave some of the balance unpaid, accruing interest.[18] The **revolving** consumer's utility from obtaining card j is

$$V^E_{ijmt} = \bar{V}^E(X^E_{jmt}, \xi^E_{jmt}, r_{jmt}, \eta^E_{mt}, y_i; \theta^E_{mt}) + \nu_{ijmt}.$$

Throughout, superscript E represents the ***E***xtensive margin. The term X^E_{jmt} represents the elements of observed card characteristics X_{jmt} that affect card choice; the same convention also applies to ξ. The term ν_{ijmt} represents a random taste shock . I model ν_{ijmt} as a *generalized* type-1 extreme value distributed taste shocks. These random taste shocks are independent and identically distributed (iid) across customers and correlated across choices for each consumer. The final components of revolvers' credit card utility currently undefined are η^E_{mt}, which is a card-utility market fixed effect, y_i, which denotes logged income, and θ^E_{mt}, which denotes market-specific parameters that govern the indirect utility function.

To justify my choice on the components of $\bar{V}^E$, I draw on the results of a question on my cardholder survey. Figure H.12 from the FCA Credit Card Market Study presents the results

[17] Grodzicki, Alexandrov, Bedre-Defoile, and Koulayev (2022) provides a more general setup of credit card demand.

[18] That consumers choose whether they will use the card for revolving or transacting is one of few substantive assumptions on behavior I require. Though not all consumers commit to transacting or revolving, consumers' use of direct debits (automatic transfers) suggests that many consumers have decided how they intend to use their credit card at origination. In the first three months of originating the card, 28% have set up a direct debit, rising to 34% by six months. Of those who set up a direct debit at origination, around 40% set up a direct debit to automatically pay off their entire balance each month, suggesting they intend to be a transactor. Of the remaining 60% who set up a direct debit for an amount less than the full balance, 77% set up a direct debit to pay the *minimum repayment*, which is usually the maximum of (i) 1-2.5% of the balance, and (ii) £5 (around \$6).

to the question "Which of the following applied when you took out your credit card?". The most common response is rewards, which 33% of respondents provide. For this reason, I include X^E_{jmt} in $\bar{V}^E$. Twelve percent of customers mention the card's interest rate, hence I include r_{jmt} in $\bar{V}^E$. Since I focus on individuals currently *without* a credit card, who by definition will not be making a balance transfer, I omit preferences over balance transfer characteristics. Finally, other non-price, non-reward, and non-promotional deal responses comprise some of the remaining survey responses, implying the importance of ξ^E_{jmt}. Such responses include "use abroad" (15%), "low fees (4%), and "good deal offered" (13%), all of which are examples of unobserved characteristics contained in ξ^E_{jmt}. Finally, there is little to no mention of credit limit, which I omit from $\bar{V}^E$ directly. However, through ξ^E_{jmt}, I do allow for individuals to prefer certain cards because they are aware that they have higher average credit limits.

I follow the literature (Berry, Levinsohn, and Pakes (1995), Nevo (2001) amongst numerous others) and linearize $\bar{V}^E$ to imply

$$V^E_{ijmt} = \beta^{E\prime} X^E_{jmt} + \xi^E_{jmt} + \nu_{ijmt} + \alpha^E_{imt} r_{jmt} + \eta^E_{mt}. \tag{2}$$

The random coefficient α^E_{imt} represents individual-specific preferences over interest rates. Heterogeneous preferences over interest rates read

$$\alpha^E_{imt} = \alpha^E + \Omega^{E,r}_{mt} \tilde{y}_{imt}. \tag{3}$$

The term $\tilde{y}_{imt} = y_i - \bar{y}_{mt}$ denotes log income recentered around the market-average, where the market average is given by $\bar{y}_{mt} = I^{-1}_{mt} \sum_{i \in I_{mt}} y_i$. Logged income is centered around the market average so that α^E represents the mean interest rate sensitivity in the card choice equation.

In this version of the model, preferences over rewards, β^E, are constant across individuals. I use random coefficients on interest rates because on the supply side, I take rewards as exogenous and model lenders' choices of interest rates. Since my counterfactual scenarios explore how lenders would choose individualized interest rates, it is important that I allow preferences over interest rates to differ across individuals.

I generate choice sets for individuals by comapring individuals' income at origination to the card's income threshold. Individuals qualify for a card if their income Y_i exceeds the income threshold $\underline{Y}_{jmt}$. Resultantly, the set of cards available to customer i is

$$J_{imt} = \{j \in J_{mt} | Y_i > \underline{Y}_{jmt}\}.$$

I discuss the rationale for lenders' use of income thresholds in section 4.4.

The utility from **transacting**, also linearized, is $V^E_{i0mt} = \delta_{0mt} + \nu_{i0mt} + \Omega^{E,cons}_{mt}\tilde{y}_{imt}$, where δ_{0mt} is a market-level constant of transacting utility. If the individual chooses to borrow, they choose the card j^* in their choice set corresponding to the maximal value of V^E_{ijmt}. The individual chooses to transact if V^E_{i0mt} exceeds $V^E_{ij^*mt}$.

4.3.2 Revolving

Next, **revolvers** choose their level of borrowing. Denote by b^*_{ijmt} the *desired* level of borrowing, which represents the individual's level of borrowing in the absence of any credit limit. The word desired reflects that individuals may wish to revolve a larger balance than their credit limit $\bar{b}_{ijmt}$ allows. The value of b^*_{ijmt} satisfies

$$b^*_{ijmt} = b(X^B_{jmt}, \xi^B_{jmt}, r_{jmt}, \eta^B_{mt}, y_i, \varepsilon^B_{imt}; \theta^B_{mt}).$$

Like in card choice utility, the log of borrowing is *linear* in parameters:

$$\log(b^*_{ijmt}) = \beta^{B'} X^B_{jmt} + \xi^B_{jmt} + \alpha^B_{imt} r_{jmt} + \eta^B_{mt} + \Omega^{B,cons}_{mt}\tilde{y}_{imt} + \varepsilon^B_{imt}. \tag{4}$$

The terms X^B_{jmt}, ξ^B_{jmt}, α^B_{imt}, and η^B_{mt} in (4) have analogous definitions to those in (2) and (3), swapping E for ***B***orrowing. The random variable ε^B_{imt} reflects a revolver's unobserved demand for borrowing. Both the lender and I do not perfectly observe ε^B_{imt}. I define its distribution in section 4.3.4.

Revolvers make different choices on borrowing each month, such as those implied by the solution to an inter-temporal consumption-savings problem. However, this paper concerns lenders' choices of origination credit limits. What matters to lenders when choosing origination credit limits are consumers' overall borrowing over the immediate period that they use the card, and less so the dynamics of borrowing within that period. As such, "borrowing" can be interpreted either as the result of a borrowing choice in a two-period consumption-savings model, or as a summary statistic (such as an average) of multiple choices of borrowing.[19] In either case, my setup does not require a model of multiple values of borrowing across periods

[19]When I take the model to data, I take the average of individuals' borrowing over 18 months. Since many individuals have only a few spells of borrowing over 18 months, an alternative choice such as the choice of borrowing at 18 months will not be representative of all 18 monthly borrowing choices made by individuals over the period.

as implied by a consumption-savings problem. Modeling a summary statistic of borrowing is a clear profitable abstraction for my context.[20]

4.3.3 Default

Finally, **revolvers** choose whether or not to default on their balance. The net utility from defaulting reads

$$V_{imt}^D = V^D(\eta_{mt}^D, y_i, \varepsilon_{imt}^D; \theta_{mt}^D),$$

where, again, all terms are analogous to those defined in (2) and (4), swapping E for ***D***efault. The individual defaults if $V_{imt}^D > 0$. Once again, I linearize V_{imt}^D, implying

$$V_{imt}^D = \eta_{mt}^D + \Omega_{mt}^D \tilde{y}_{imt} + \varepsilon_{imt}^D. \tag{5}$$

I follow Nelson (2022) by not including interest rate in default utility. Nelson (2022) and Castellanos, Jiménez Hernández, Mahajan, and Seira (2018) provide empirical evidence of an insignificant effect of price on default in credit markets. Assuming price-invariance of default also follows other structural models of selection markets without moral hazard, for example Cohen and Einav (2007); Einav, Finkelstein, and Schrimpf (2010b). These findings support research in consumer finance suggesting limited channels through which prices can affect default. Much of the research on default implies that short-run liquidity drives default, rather than the long-run value of a loan contract, especially for the relatively small credit lines found on credit cards (Bhutta, Dokko, and Shan, 2017; Guiso, Sapienza, and Zingales, 2013; Ganong and Noel, 2020; Indarte, 2021).

I also follow Nelson (2022) in assuming that default is not a direct function of credit limit. If credit limit does affect default, then, insofar as market fixed effects, income, and the lenders' signal on risk explain individuals' credit limits, my default model in part accounts for the effect of credit limits on default, and my estimates are lower, rather than upper, bounds.

4.3.4 Private Information Structure

I decompose private characteristics $(\varepsilon_{imt}^B, \varepsilon_{imt}^D)$ into a common component $\tilde{\varepsilon}_i$ and an idiosyncratic component $\tilde{\varepsilon}_i^h$ so that

$$\varepsilon_{imt}^h = \sigma_{mt}^h \tilde{\varepsilon}_i + \tilde{\varepsilon}_i^h$$

[20] Further evidence supporting an abstraction from the dynamics of borrowing choice is the lack of ex-post repricing, as I discuss in Section 3.1.3.

for $h \in \{B, D\}$. The common component simplifies the lender signal structure (following in section 4.4) and generates correlation among unobserved private characteristics for each individual. The distribution of unobserved preferences varies over markets through σ^B_{mt} and σ^D_{mt}. Finally, I simplify further by setting $\tilde{\varepsilon}^B_i$ to zero and letting $(\tilde{\varepsilon}_i, \tilde{\varepsilon}^D_i)$ be independently standard normal distributed. Henceforth, I simplify the notation, writing ε_i instead of $\tilde{\varepsilon}_i$.

4.4 Lender

My model of supply—lenders' screening technologies and the credit limit optimization problem—contains my central novelty, though it shares a few similarities with the model of credit limit categories sketched in Agarwal, Chomsisengphet, Mahoney, and Stroebel (2017) and the model in Livshits, Mac Gee, and Tertilt (2016). The right side of Figure 4 depicts the supply-side building blocks. Lenders observe individuals' incomes Y_i and take X_{jmt}, ξ_{jmt}, and $\underline{Y}_{jmt}$ as given. I take lenders' choices of card characteristics as given for three reasons. First, in the data, lenders do not individualize rewards and rewards are sticky, rarely changing over the entire five-year period on which I have data. Second, many unobserved characteristics such as brand prestige and loyalty are not something that a lender can adjust in a given month. Third, contract pricing introduces issues in equilibrium existence and uniqueness that are profitable to abstract from, where justified.

The sorting of individuals onto cards based on their income happens through income thresholds. Lenders use income thresholds because UK lenders must be able to inform consumers of the information used to reject them if they source data from a credit reference agency (Department for Business Innovation and Skills, 2010). Resultantly, lenders base decisions on *eligibility* at least in part on income.

To match the institutional environment and my empirical findings in section 3.1, lenders choose credit limits for individuals non-competitively *after they have originated a card*. The regulatory environment requires that, at the beginning of each month, lenders set advertised APRs r_{jmt} at the card-month-market level. This institutional feature handily circumvents issues of equilibrium existence and uniqueness that are pervasive in the empirical literature on contract pricing in credit markets. I estimate the supply side entirely off lenders' credit limit choices and therefore do not need to take a stance on how lenders set interest rates in the baseline. This avoids the need to model how lenders optimize interest rates around the fiddly regulatory requirements of (i) an advertised APR and (ii) a minimum of 51% of customers obtaining the advertised APR.[21] By not requiring a model of how lenders set interest rates, I also avoid making a specific assumption about the nature of conduct.

Before presenting the lenders' two optimization problems in detail, I describe the main exogenous characteristic of the lender – their screening technology.

4.4.1 Screening Technology

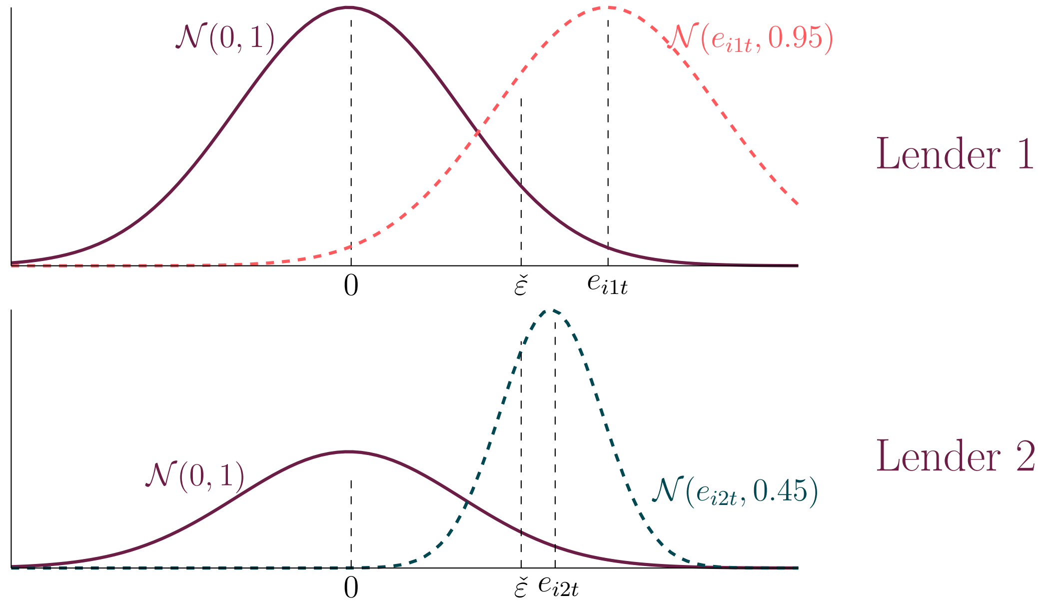
Each lender has their own screening technology. The screening technology takes in data available to the lender on a customer, and provides the lender with a tailored prediction of possible values of the customer's common risk component ε_i. Without a screening technology, for each customer, the lender would take expectation over a standard normal, which is the population distribution of ε_i. The screening technology intends to provide a distribution with a mean closer to each individual's realization of ε_i and a variance less than 1.

Indeed, the lender-specific, tailored, distributions that the screening technology delivers are characterized by two features. The first is the set of signals, or central points around which the tailored distributions are based. I denote these as $e_{i\ell t}$, which can take a finite number of values $\{e_{\ell t1}, \dots, e_{\ell t L_{\ell t}}\}$. The second feature is the precision of the distribution it generates. The distribution generated by the screening technology accounts for the fact that the signal may not be a correct prediction of a customer's risk, so allows for error. I assume that, for an individual who generated the signal $e_{i\ell t}$, the distribution provided by the screening technology is normal with mean $e_{i\ell t}$ and variance $\sigma^2_{\ell t} \leq 1$, and I call $\sigma_{\ell t}$ the precision parameter. Given the value of $e_{i\ell t}$, the screening technology approximates ε_i as $\hat{\varepsilon}_i = e_{i\ell t} + w_{i\ell t}$, where $w_{i\ell t} \sim \mathcal{N}(0, \sigma^2_{\ell t})$. When setting profits, the lender takes expectation using the distribution $\mathcal{N}(e_{i\ell t}, \sigma^2_{\ell t})$, as provided by the screening technology.

Figure 5 depicts distributions of ε_i and $\hat{\varepsilon}_i$ for two fictitious lenders. The distribution of risk provided by lender 1's screening technology for customer i is $\mathcal{N}(e_{i1t}, 0.95)$. The mean of the conditional distribution is relatively far from the customer i's true realization of $\varepsilon_i = \check{\varepsilon}$. Lender 2 has a better screening technology. The screening technology distribution given the signal e_{i2t} is much closer to $\check{\varepsilon}$. Furthermore, since σ_2 is smaller than σ_1, the signal errors at lender 2 are less dispersed around the signal than at lender 1. When setting credit limits for

[21] Appendix E.2 presents one model—the standard Nash-Bertrand pricing model—of how lenders may set advertised APRs competitively for the yearning reader.

Figure 5: Distribution of ε (solid) and $\hat{\varepsilon}_i$ (dashed) across two lenders for a customer with unknown value $\varepsilon_i = \check{\varepsilon}$



Notes: The bottom lender's screening technology, which delivers the signal e_{i2t}, outperforms the top lender's signal of e_{i1t} for this individual.

customer i, lender 2 will put more weight (relative to lender 1) on potential values close to $\check{\varepsilon}$ and less weight on incorrect values, such as those close to zero.

4.4.2 Credit Limit

To model lenders' credit limit choices requires an expression for their profits, that is, their costs and revenues. Regarding costs, lenders incur some fixed costs such as overheads and operational costs, but the majority of their costs vary with the number of cards they issue and how consumers use the cards they issue. I focus on charge-off (default) costs, and cost of funds, denoted c. According to statistics from US credit card lenders, these account for over two-thirds of lenders' total from issuing credit cards (Evans and Schmalensee, 2005). The remaining third comprises in most part of fixed costs, which I am free to ignore since they do not affect lenders' margins in choosing credit limits or interest rates. As such, the decision to model cost of funds and charge-off costs is a reasonable match to lenders' decisions that I see in the data.

Regarding revenue, I focus entirely on finance charges coming from interest, For US lenders in 2001, this accounts for 70% of their card revenue (Evans and Schmalensee, 2005). The remaining 30% comes from three main factors: interchange, fees, and cash-advances. Each of these three factors are likely to account for a smaller percent of revenue for UK lenders, motivating their abstraction. Appendix E.1 describes each of the three factors in more detail and explains why they are less relevant in the UK credit card market relative to the US.

Each lender's profit from a transacting customer is Π_{i0mt}, unrelated to the credit limit and interest rate.[22] Therefore, the credit limit decision is unaffected by whether the individual originating card j is a transactor or a borrower. Let Δ_{imt} denote the probability that borrower i defaults and c_{jmt} denote funding rate. Then the profit per unit of credit borrowed from individual i is the interest rate minus the funding cost if the customer does not default, and $-(1-\psi) - c_{jmt}$ if they do, where ψ is the proportion of the balance that debt collectors are able to recover, which I set to zero in my empirical specification.[23]

Hence, the expected profit per unit credit for individual i on card j is

$$\pi_{ijmt} = (1 - \Delta_{imt})(r_{ijmt} - c_{jmt}) + \Delta_{imt}(-1 - c_{jmt}).$$

Given the signal $e_{i\ell t}$ and the implied screening technology distribution, the lender chooses the credit limit $\bar{b}_{ijmt}$ to maximize the expected profit from the individual:

$$\begin{aligned} \Pi_{ijmt} &= \max_{\bar{b}_{ijmt}} \mathbb{E}\left[\min\{b^*_{ijmt}, \bar{b}_{ijmt}\}\pi_{ijmt}\right] \\ &= \max_{\bar{b}_{ijmt}} \int \min\{b^*_{ijmt}(e_{i\ell t}, w), \bar{b}_{ijmt}\}\pi_{ijmt}(e_{i\ell t}, w) f_w(w) dw. \end{aligned} \tag{6}$$

As derived in Appendix E.3, the first order condition for credit limit is

$$\mathbb{E}\left[\pi_{ijmt} | b^*_{ijmt} \geq \bar{b}_{ijmt}\right] = \int_{\omega(\bar{b}_{ijmt})}^{\infty} \pi_{ijmt}(e_{i\ell t}, w_{i\ell t}) \phi\left(\frac{w_{i\ell t}}{\sigma_{\ell t}}\right) dw_{i\ell t} = 0, \tag{7}$$

[22] The revenue and costs from transactors do not relate to the interest rate, since they do not revolve a balance on which interest accrues. I assume that lenders' variable cost from non-defaulting customers is per-unit credit, and therefore lenders' costs from transactors are unrelated to the credit limit. The credit limit may affect interchange revenue, but I abstract from interchange revenue for revolvers and do so for transactors for the same reason. Resultantly, profits from transactors are not related to credit limit and interest rate choices

[23] When cardholders default, payment card issuers start collection procedures. These cardholders will often have other debts, which may be collected before credit card debt. Debt collection procedures are very costly relative to the size of the loan for credit card lenders. Further, in the US in 2002, 50% of all charge-offs resulted from bankruptcy, where debt collection is often futile (Evans and Schmalensee, 2005). These factors considered together, $\psi = 0$ is a reasonable abstraction.

where

$$\omega_{i\ell t}(\bar{b}_{ijmt}, e_{i\ell t}) = \frac{\log(\bar{b}_{ijmt}) - \delta^B_{jmt} - u^B_{ijmt}}{\sigma^B_{mt}} - e_{i\ell t} \tag{8}$$

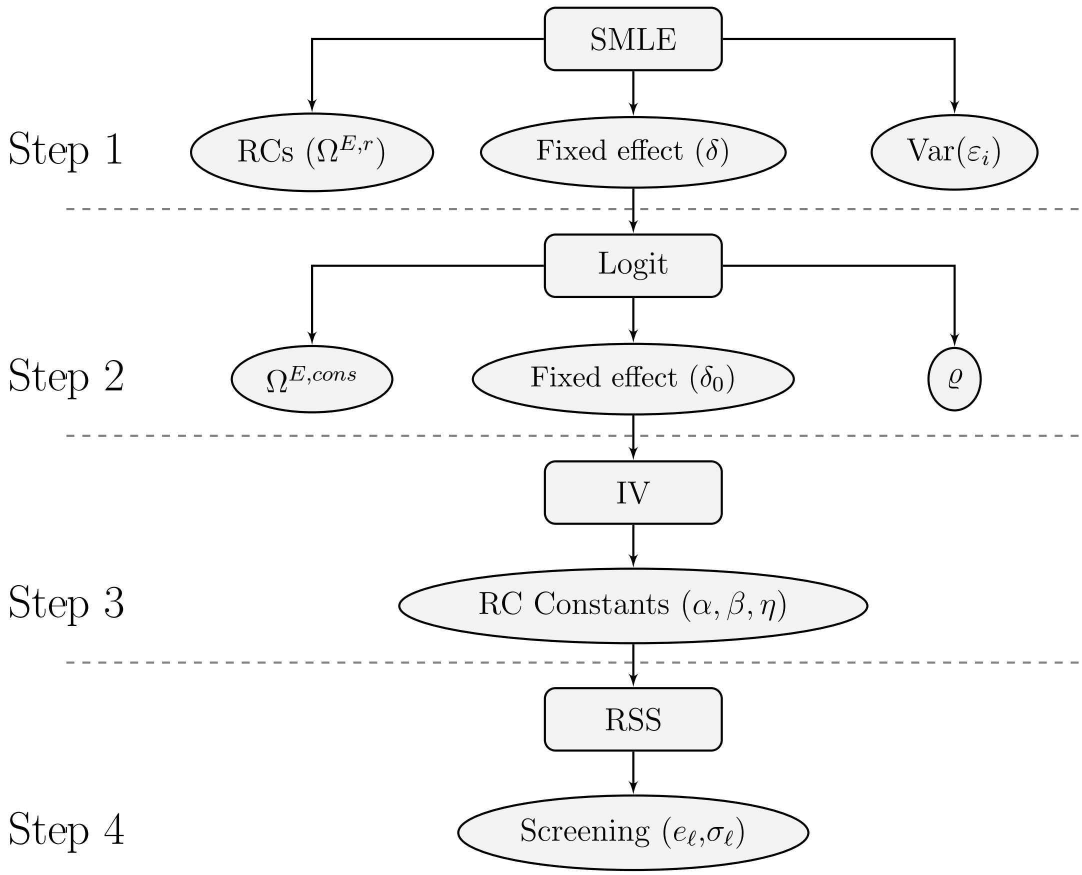
is the risk signal uncertainty at which the individual wants to borrow exactly their credit limit, that is, the value of $w_{i\ell t}$ which makes $\log(b^*_{ijmt})$ equal to $\log(\bar{b}_{ijmt})$. The intuition of the first order condition is that at the optimal credit limit, the expected profit per unit credit, over those with unobservables that drive them to use their full credit line, is zero. If the expected profit per unit credit were positive, the lender should raise the credit limit, because the expected benefit of safer types using the full credit limit exceeds the expected costs of riskier types using the full credit limit. On the other hand, if the expected profit per unit credit over those with unobservables that drive them to use the full balance were negative, the types exploiting the full credit line are too risky, and therefore the lender should lower their credit limit choice in this case, to make the marginal individual using their entire credit line less risky.

My descriptive findings in section 3.1.2 on the differences in lenders' credit limit distributions motivate the tight relationship between lenders' screening technologies and the shape of the distribution of credit limits. Each unique signal implies a different choice of credit limit for the lender, and therefore, given income, there is an mapping between the number of unique credit limits at each lender and the number of unique signals provided by their screening technology. Lenders who give observably identical consumers (to the econometrician) a wide range of credit limits must have a wide range of different signals of these consumers' unobserved risk. On the other hand, lenders who give consumers identical on observables a coarse set of credit limits appear not to have a sophisticated screening technology. I use this link between credit limits and signals to estimate the distribution of signals from each of the unique values of credit limits. Consumers who obtain the maximum credit limit for their income category obtained the lowest signal on their underlying risk ε_i and those obtaining the lowest credit limit for their income category obtained the highest signal on their underlying risk scale.

5 Estimation

In this section, I outline how the model parameters are estimated. I start with demand estimation, since the demand estimates serve as inputs into supply estimation. My approach to demand estimation shares features with Benetton (2021), Robles-Garcia (2022) and Benetton, Gavazza, and Surico (2022). Figure 6 displays the four steps of the estimation procedure.

FIGURE 6: Four steps of model estimation



Notes: Step 1 refers to simulated maximum likelihood estimation of the demand parameters, for those who borrow. Step 2 refers to the choice between transacting and borrowing and the maximum likelihood estimation of the parameters governing the transaction utility. Step 3 refers to instrumental variables estimation of the parameters inside of the fixed effects δ_{jmt}. Step 4 refers to supply estimation.

5.1 Demand

5.1.1 Log-likelihood Conditional on Borrowing

I start with Step 1 in Figure 6. My demand model for those who borrow consists of equations for consumer card choice (equation 2), borrowing (equation 4), and default (equation 5). The equations map cardholders' characteristics and lenders' interest rates, credit limits, and card characteristics into card choice, borrowing level, and default choice. Together with stochastic assumptions on unobservables, the three equations imply a log-likelihood function for observed decisions, enabling MLE estimation. Appendix F.1 provides detailed expressions for its terms; in the text below I provide its basic structure and give intuition for the main components. I focus on how the estimation approach overcomes two primary challenges and discuss exogenous variation I exploit to identify the parameters.

The conditional log-likelihood is the sum of a log-likelihood for card choice $\log \mathcal{L}_{mt,E}$ and a joint log-likelihood for borrowing and default choices $\log \mathcal{L}_{mt,BD}$, hence is equal to

$$\log \mathcal{L}_{mt} = \log \mathcal{L}_{mt,E} + \log \mathcal{L}_{mt,BD}. \tag{9}$$

This feature comes from the fact that unobservables for card choice are uninformative about the the unobservables driving borrowing and default. I start by discussing the components relating to borrowing and default and then move to the components relating to card choice.

The first challenge in forming the log-likelihood components relating to borrowing and default is the truncation in borrowing. Specifically, I observe the *constrained* level of borrowing $b_{ijmt} = \min\{b^*_{ijmt}, \bar{b}_{ijmt}\}$, rather than the *desired* level b^*_{ijmt}. As a result, I do not observe desired borrowing for the revolvers who borrow their entire credit limit. Revolvers either borrow their entire credit line (full utilization) or not (interior utilization), and also default or not. This creates four possible outcomes for revolver i:

1. $i \in I_1$: Interior utilization and default
2. $i \in I_2$: Interior utilization and no default
3. $i \in I_3$: Full utilization and default
4. $i \in I_4$: Full utilization and no default

Let $s^{(g)}_{ijmt}$ denote the likelihood of $i \in I_g$. Then the expression for $\log \mathcal{L}_{mt,BD}$ is

$$\log \mathcal{L}_{mt,BD} = \sum_{i \in I_{mt}} \sum_{j \in J_{imt}} \sum_{g=1}^{4} 1^{(g)}_{ijmt} \log(s^{(g)}_{ijmt}), \tag{10}$$

where $1^{(g)}_{ijmt}$ is a dummy equal to one if individual i chooses card j and is in group I_g. I provide the expressions for $s^{(g)}_{ijmt}$ in Appendix F.1.

Individuals borrowing their entire credit line create most complication. Their contribution to the log-likelihood is an integral with no closed form and as a result, I use simulated maximum likelihood (Pakes and Pollard, 1989; Gouriéroux and Monfort, 1993, 1996; Hajivassiliou and Ruud, 1994; Lee, 1992, 1995) with Halton (1960) draws (Bhat, 2003; Train, 2003).

The second challenge is the endogeneity of interest rates in the card choice and borrowing level equations. Interest rates r_{jmt} are likely to correlate with unobserved card characteristics

ξ_{jmt}. For example, interest rates may be high on a given card because its unobserved card characteristics imply high demand for the card. To deal with this first, I estimate a full set of product-channel-month fixed effects in the card choice and borrowing equations. Formally, I rewrite equations (2) and (4) respectively as

$$\begin{aligned} V^E_{ijmt} &= \delta^E_{jmt} + \nu_{ijmt} + u^E_{ijmt}, \qquad (11) \\ \delta^E_{jmt} &= \beta^{E'} X^E_{jmt} + \xi^E_{jmt} + \eta^E_{mt} + \alpha^E r_{jmt}, \qquad (12) \\ u^E_{ijmt} &= \Omega^{E,r}_{mt} \tilde{y}_{imt} r_{jmt}, \end{aligned}$$

and

$$\begin{aligned} \log(b^*_{ijmt}) &= \delta^B_{jmt} + \varepsilon^B_{imt} + u^B_{ijmt}, \\ \delta^B_{jmt} &= \beta^{B'} X^B_{jmt} + \xi^B_{jmt} + \alpha^B r_{jmt} + \eta^B_{mt}, \qquad (13) \\ u^B_{ijmt} &= \Omega^{B,cons}_{mt} \tilde{y}_{imt} + \Omega^{B,r}_{mt} \tilde{y}_{imt} r_{jmt}, \end{aligned}$$

where δ^E_{jmt} and δ^B_{jmt} are the card-channel-month fixed effects. Because of the typical identification issue in discrete choice models, I normalize $\delta^E_{0mt} = 0$ and take interest rates and card characteristics in (12) and (13) as differences from the outside option.

The term in the log-likelihood containing the card choice parameters is

$$\log \mathcal{L}_{mt,E} = \sum_{i \in I_{mt}} \sum_{j \in J_{imt}} 1^E_{ijmt} \log(s^E_{ijmt|j \in J_{imt}}), \qquad (14)$$

where $1^E_{ijmt} = 1(j^*_{imt} = j)$ is a dummy equal to one if individual i chooses card j in their choice set J_{imt} and $s^E_{ijmt|j\in J_{imt}}$ are logit shares, derived in Appendix F.1. The term $s^E_{ijmt|j\in J_{imt}}$ reflects the probability that individual i chooses card j in channel m and origination month t, *conditional* on individual i choosing to revolve a credit card balance.

To summarize, in the first step of demand estimation, I use market-by-market simulated maximum likelihood estimation on the log likelihood for card choice, borrowing, and default, *conditional on borrowing*, to estimate scaled versions of the product-market fixed effects (δ^E_{jmt} and δ^B_{jmt}), thereby sidestepping the endogeneity problem for the moment. This step also estimates the variance-covariance matrix of private characteristics ($\varepsilon^B_{imt}, \varepsilon^D_{imt}$) (specifically σ^B_{mt} and σ^D_{mt}) and the demographic coefficients ($\Omega^{E,r}_{mt}$, $\Omega^{B,r}_{mt}$, and $\Omega^{B,cons}_{mt}$).

5.1.2 Log-likelihood for Borrowing and Transacting

In the second step of demand estimation (Step 2 in Figure 6) I maximize a log-likelihood for the choice between transacting and borrowing, which estimates δ_{0mt} and outside option utility term $\Omega_{mt}^{E,cons}$, along with the correlation coefficient for the generalized extreme value shocks, ϱ_{mt}. I provide more detail and an expression for the log-likelihood of borrowing/transacting in Appendix subsection F.2 .

5.1.3 Constant Demand Parameters

In the third and final step of demand estimation (Step 3 in Figure 6), I estimate the constant parameters of the card-choice and borrowing equations by projecting the estimates of card-channel-month fixed effects ($\delta_{jmt}^{E}, \delta_{jmt}^{B}$) onto distribution channel-month fixed effects, interest rates, and observed characteristics as in (12) and (13). The endogeneity problem still exists, so I use instrumental variables, the choice of which I now detail.

As an instrument for interest rates, I exploit a cost shock to lenders in mid-2011 relating to the mis-selling of payment protection insurance (PPI). PPI is a form of insurance designed to cover loan repayments in the event that an individual cannot make credit repayments due to adverse events such as unemployment, illness, or disability. In the late 20^{th} Century, UK lenders started bundling PPI with loans and other credit products such as credit cards. In the mid-2000s, it was claimed that PPI was being mis-sold to borrowers. For example, lenders were selling PPI to self-employed individuals who would not be able to use it because of their employment status. In 2006, the Financial Services Authority started imposing fines on financial institutions for the mis-selling of PPI. An important development came in January 2011 when the British Bankers' Association (BBA) took the FSA to court over its decision to *retrospectively* impose standards on the correct selling of PPI.[24] The British Bankers' Association suffered a defeat at the High Court, and in May 2011, banks informed the BBA they were withdrawing their support for an appeal of the decision. The ruling forced banks to reopen thousands of claims for PPI mis-selling. In total, around 64 million policies were mis-sold between the 1970s and late 2000s, with over £33bn repaid to individuals who complained about the sale of PPI.[25]

The court case loss in April 2011 and the reopening of PPI claims led to cost increases, which were spread unevenly amongst banks according to how frequently they mis-sold PPI. Shortly after, some credit card lenders increased interest rates for all individuals at origination

[24]See *R (on the application of the British Bankers' Association) v Financial Services Authority and another [2011] EWHC 999*.

[25]See `https://www.fca.org.uk/ppi/ppi-explained`, last accessed 8 October 2022.

for some of the cards in their portfolios. From this cost shock, I create an instrument for interest rates by interacting lender fixed effects with a "post" treatment dummy.[26] Validity of the instrument requires that the only channel through which the court case ruling affects individuals' card choice and subsequent borrowing is through the impact of cost increases on cards' interest rates. I know of no other events in the same period that affected credit card lenders' unobservable card characteristics, and I find no significant changes in observable characteristics or credit limits in the same period.

5.2 Supply

The final step of estimation (Step 4 in Figure 6) concerns the supply parameters. The parameters to estimate in the supply model are the screening technology signals $e_{i\ell t}$ and the standard deviation of the signal noise, $\sigma_{\ell t}$. I estimate these by minimizing the residual sum of squares from the first order condition of the credit limit optimization problem in (6). As derived in Appendix E.3, for each unique observed credit limit $\bar{b}_{ijmt}$ on card j at lender ℓ in month t, the corresponding signal $e_{i\ell t}$ satisfies

$$\int_{\omega_{i\ell t}(\bar{b}_{ijmt}, e_{i\ell t})}^{\infty} \pi_{ijmt}(e_{i\ell t}, w_{i\ell t}) \phi\left(\frac{w_{i\ell t}}{\sigma_{\ell t}}\right) dw_{i\ell t} = 0, \tag{15}$$

Towards an estimation strategy, note that under the distributional assumptions on private characteristics,

$$\Delta_{imt} = \Phi\left(\eta^D_{mt} + \Omega^D_{mt}\tilde{y}_{imt} + \sigma^D_{mt}(e_{i\ell t} + w_{i\ell t})\right).$$

From this expression I can calculate Δ_{imt}—and therefore the integrand—as a function of the model parameters and the signal error.

For each observed credit limit and income, equation (15) provides an equation where the only unknowns are the screening technology $e_{i\ell t}$ and $\sigma_{\ell t}$. The basis of the estimation strategy is to estimate the screening technologies as the values that minimize the sum of squared deviations (over individuals) from the integral in (15). As in parts of the demand estimation, the integral in (15) has no closed form. Therefore, for each lender-month, I simulate the integral using

[26]Unfortunately, I do not have data on the proportion of PPI repayments made by each lender over time. If this were available, I could construct the instrument by constructing a measure of lenders' exposure to the court case decision.

Halton draws $\omega^h_{i\ell t}$, and solve

$$\min_{\{e_{i\ell t}\},\sigma_{\ell t}} \sum_{i\in I_{\ell t}} \left(\frac{1}{H} \sum_{h=1}^{H} 1\left(\sigma_{\ell t}\omega^h_{i\ell t} > \omega_{i\ell t}(\bar{b}_{ijmt}, e_{i\ell t})\right) \pi_{ijmt}(e_{i\ell t}, \sigma_{\ell t}\omega^h_{i\ell t}) \right)^2,$$

where $1(A)$ denotes the indicator function, equal to 1 if A is true and 0 otherwise. Though I can estimate the model at the lender-month level, I prefer more parsimonious models that pool months within a year (estimating at the lender-year level) and pooling over all months (estimating at the lender level).

6 Model Estimates

Now I discuss parameter estimates. I start with demand model parameters and then move to my estimates of lenders' screening technologies.

6.1 Demand Estimates

6.1.1 First and Second Stage Estimates

Table 1 presents the demand estimates from the first stage (log-likelihood of card choice, borrowing, and default) and the second stage (log-likelihood for transacting/revolving) of demand estimation. I report means and standard deviations of estimates over markets.

The signs of the parameters are largely as expected, and some particular parameter estimates warrant discussion. I start with the default equation parameters. The negative value for Ω^D implies that higher-income revolvers are less likely to default. The mean value of 0.532 for σ^D indicates unobserved heterogeneity in default, justifying the role of lenders' screening technology.

Moving to the borrowing equation, the estimate of 0.250 for $\Omega^{B,cons}$ means that, conditional on revolving, higher-income individuals revolve more. The negative value of $\Omega^{B,r}$ implies that, on average, higher-income borrowers are more sensitive to interest rates. The correlation between unobserved preferences for borrowing and default is 0.466, implying that revolvers with a positive unobserved preference to borrow have a positive unobserved preference to default. I refer to this as evidence of adverse selection along the intensive borrowing margin.[27] This

[27] Lacking data on those without a credit card, I cannot at this point assess correlation between take-up of a credit card and default, which would be the more traditional form of (extensive margin) adverse selection.

Table 1: First and second step demand estimates

Variable	Mean	SD
η^D	-1.804	0.125
Ω^D	-0.092	0.088
σ^D	0.532	0.100
$\Omega^{B,cons}$	0.250	0.523
$\Omega^{B,r}$	-0.196	1.515
σ^B	2.909	0.213
$\text{Corr}(\varepsilon^B, \varepsilon^D)$	0.466	0.069
$\Omega^{E,r}$	-0.468	0.717
$\Omega^{E,cons}$	-0.513	2.079
ϱ	0.328	0.182

estimate is larger than the estimate of 0.16 obtained by Crawford, Pavanini, and Schivardi (2018), whose context is the Italian market for small business loans between 1988 and 1998.

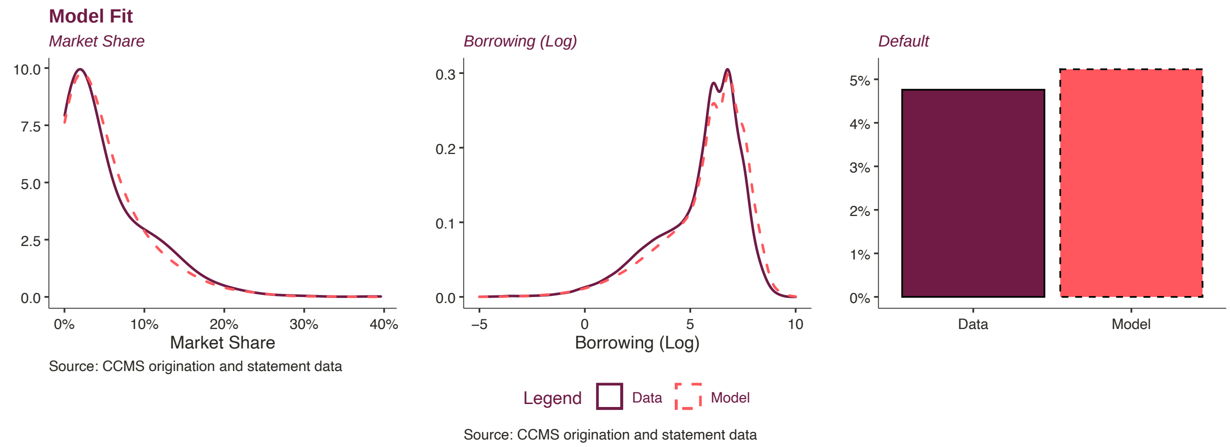
Third, I discuss my parameter estimates for the card choice equation and the utility for transacting. I estimate a negative mean value for $\Omega^{E,r}$, implying that higher-income individuals who decide to revolve are more sensitive to interest rates when they choose their card. The negative value for $\Omega^{E,cons}$ in the transaction utility implies that higher-income individuals are less likely to transact. Finally, the parameter ϱ, estimated at 0.328, indicates a reasonable substitution between transacting and borrowing choices.

Figure 7 displays three plots that illustrate how the demand model fits the data on card choice, borrowing, and default. The fit is good, indicating that the model captures the heterogeneity of the data well.

6.1.2 Third Stage Estimates and Elasticities

Table H.6 reports estimates and bootstrapped standard errors of the demand parameters recovered in the third stage of demand estimation. OLS coefficients on interest rates in both card choice and borrowing equation are positive, whereas IV estimates are negative, indicating the severity of interest rate endogeneity. Coefficients on dummies for most rewards in the card choice equation are positive across specifications, though the effect of cashback

FIGURE 7: Model fit



cannot be estimated precisely. Cashback rewards are rare in the UK and the rate of cashback tends to be low compared to the US, owing to lower interchange fees in the UK. Finally, Figures H.13 and H.14 plot the distribution of random coefficients α_i^E and α_i^B, which are negative almost everywhere and indicate substantial variation in preferences over interest rates.

Next, I turn to interest rate elasticities, where equations (19) and (21) provide the formulas for borrowing and card choice price elasticity respectively. Figures H.15 and H.16 plot the distribution of elasticities over individuals. Three noteworthy features emerge. First, revolvers are much more elastic to the interest rate in their card choice relative to their borrowing choice. Second, there is a very large degree of dispersion in both elasticities: The coefficient of variation of both card choice and borrowing elasticity is approximately one. This implies substantial heterogeneity in responsiveness to changes to interest rates across individuals. Third, both distributions are skewed. The distribution of card choice elasticities has a long left tail and the distribution of borrowing elasticities has a large mass close to zero. Finally, the elasticities are similar, though slightly larger in magnitude to other experimental estimates of interest rate elasticities in credit markets (Alan and Loranth, 2013; Karlan and Zinman, 2018). Estimates of borrowing elasticity are very similar to those in Nelson (2022).

Table 2: Summary statistics for variation in signal mismeasurement across lenders

Variable	Mean	SD	10%	25%	50%	75%	90%
σ_ℓ	0.196	0.333	0.002	0.004	0.004	0.198	0.704

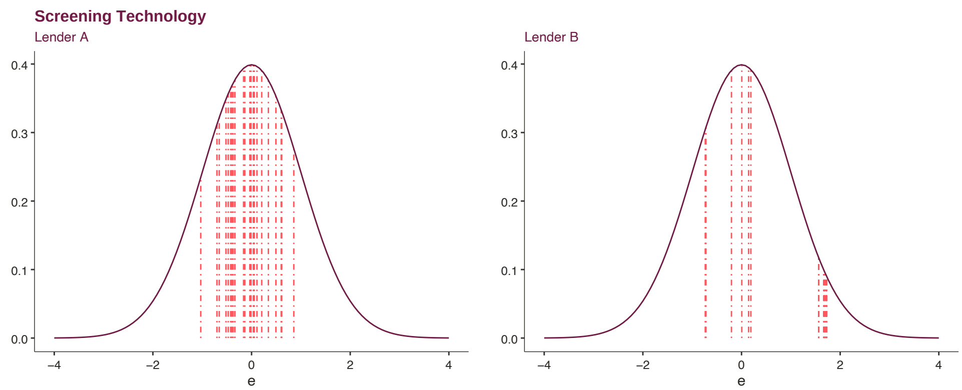
6.2 Supply Estimates

My supply estimation delivers two sets of parameter estimates. The first is the variation in signal mismeasurement across lenders, denoted σ_ℓ. For simplicity, first I present estimates from the model pooling over years and consider the nine prime or superprime lenders in the data. Table 2 reports summary statistics in the values of σ_ℓ across lenders. The coefficient of variation is 1.699, showing that lenders' screening technologies differ substantially in their precision.

The second set of parameter estimates from supply estimation are the lenders' screening technology signals, denoted e_ℓ. Figure 8 shows the estimated screening technologies for two contrasting lenders superimposed onto a standard normal distribution. Each vertical line represents one of the lender's possible signals. I superimpose the values onto a standard normal distribution since the signals partition the standard normally distributed signal, ε_i. The left lenders' screening technology contains many values, and represents a sophisticated screening technology, providing sharp signals on borrowers' type. The right lenders' screening technology offers only a few values, implying less precise signals on borrowers' unobservables. Figure H.17 shows the screening partitions for other lenders. Like with the values of σ_ℓ, there is substantial variation in the values and the coarseness of the screening technology across lenders.

The variation in screening technologies supports the descriptive evidence in section 3.1.2, showing that different lenders have available screening technologies of varying sophistication. Finally, across lenders, the correlation between σ_ℓ and the proportion of periods in which individuals repay the full balance is 0.17. This estimate is consistent with a segmentation of credit card lenders in which lenders with the most precise screening technologies serve a riskier, but more profitable, market segment on average. Lenders with more precise screening technologies are more willing to serve customers will borrow but may default because they can more accurately set lower credit limits for customers they perceive to be riskier.

FIGURE 8: Screening technology at two lenders



7 Counterfactual Analysis

7.1 Individualizing Interest Rates

The central empirical finding I present in this paper is that lenders only individualize credit limits, with minimal within-card variation in interest rates. Related to this empirical fact is the regulatory environment, which requires lenders to set an interest rate for each credit card product offered. Despite the requirement to *advertise* a card-level interest rate, lenders could still individualize interest rates to some extent. Under the assumption of profit maximization, my empirical findings imply that either (i) it is optimal for lenders only to individualize credit limits, or (ii) there exist costs/constraints restricting lenders' willingness or ability to individualize interest rates. To shed light on this, I use my estimated model to run counterfactual scenarios changing lenders' optimization problem. In my main counterfactual, I allow lenders to set individualized interest rates subject to no costs or constraints in doing so, and analyze the resulting distribution of interest rates and credit limits. It is not obvious whether lenders will individualize interest rates, credit limits, or both, in equilibrium. Indeed, elementary economic theory suggests that in a perfect information, monopolistic environment where interest rates and credit limits can be used as screening instruments, credit limits are redundant.

7.2 Implementation

I simulate the final market of my previous analysis (June 2013 out of branch) under the new regime, with lenders setting interest rates and credit limits, keeping income thresholds and card characteristics fixed. Then, cardholders make decisions on card choice, borrowing, and default. In the counterfactual I present, I follow the baseline model by assuming that individuals know their potential interest rate at each lender when choosing their card.[28]

For customer i, lender ℓ now solves simultaneously for all interest rates and credit limits across their cards $J_{i\ell}$ that consumer i is eligible for. This is because the whole vector of interest rate choices affects the probability that the individual chooses each one of the cards that they offer. Formally, given other lenders' optimal interest rate choices $\boldsymbol{r}^*_{-i\ell mt}$, for customer i, lender ℓ solves

$$\max_{\boldsymbol{r}_{i\ell},\bar{\boldsymbol{b}}_{i\ell}} \sum_{j\in J_{i\ell}} s^E_{ij}(\boldsymbol{r}_{i\ell}, \boldsymbol{r}^*_{-i\ell})\mathbb{E}_{\varepsilon_i|e_{i\ell}}\left[\min\{b^*_{ij}, \bar{b}_{ij}\}\pi_{ij}\right] \tag{16}$$

Similar to supply estimation, I minimize the residual from the first order conditions to equation (16) to calculate $\boldsymbol{r}_{i\ell}$ and $\bar{\boldsymbol{b}}_{i\ell}$ for all individuals i.[29] Appendix G provides the first order conditions that I use for the calculation of the counterfactual interest rates and credit limits.

In the counterfactual, I measure changes to the distributions of several endogenous variables of interest. The first set I describe is interest rates and credit limits. Then I consider changes to consumers' card choices, level of borrowing, and consumer surplus. I calculate individuals' card choice and borrowing using indirect card utility (2) and borrowing equation (4) respectively, replacing r_{jmt} with r_{ijmt}. Consumer surplus is defined

$$CS_i = \frac{1}{\alpha_i}\log\left(\sum_{j\in J_i}\exp\left(\bar{U}^E_{ij}\right)\right),$$

where $\bar{U}^E_{ij}$ is equal to $\bar{V}^E_{ij}/\varrho$, a scaled version of indirect utility. Ex-post profit from borrower i is given by

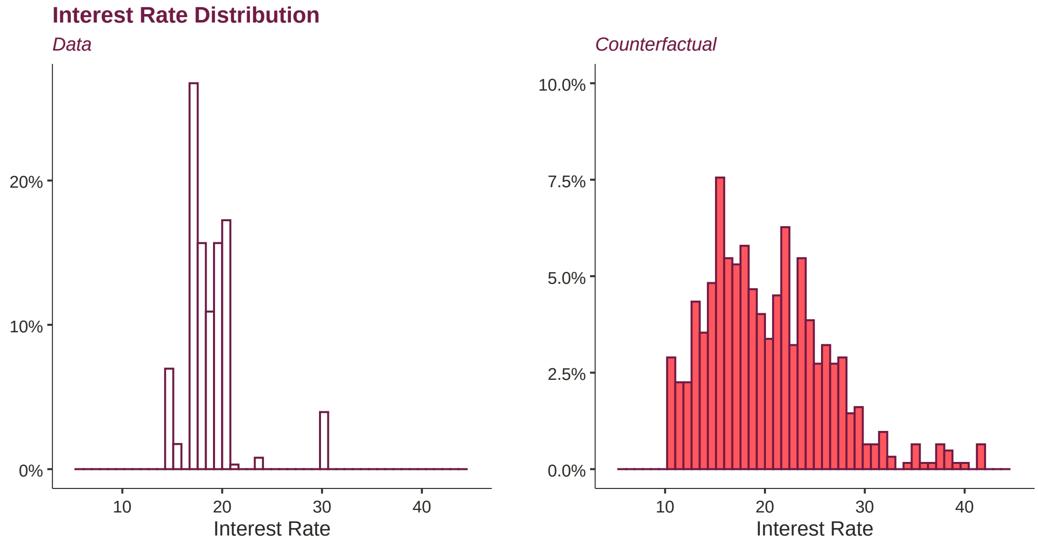
$$\pi^{\text{post}}_{ij} = b_{ij}\left[\mathcal{D}_i(r_j - c_j) + (1-\mathcal{D}_i)(-1-c_j)\right],$$

where $\mathcal{D}_i$ is equal to 1 if borrower i defaults. Finally, I measure concentration using the combined market share of the largest three, four, and five lenders.

[28]I maintain the assumption that consumers do not know their credit limit to ensure that I am only changing one object at a time and also due to the absence of any credible source of way to measure what individuals' preferences over credit limits would be, were they known to the consumer.

[29]This is a computationally intensive procedure because I have to solve the optimization problem for each consumer separately. Consequently, I use a random sample of 1000 consumers.

FIGURE 9: Changes to the distribution of interest rates



7.3 Counterfactual Results

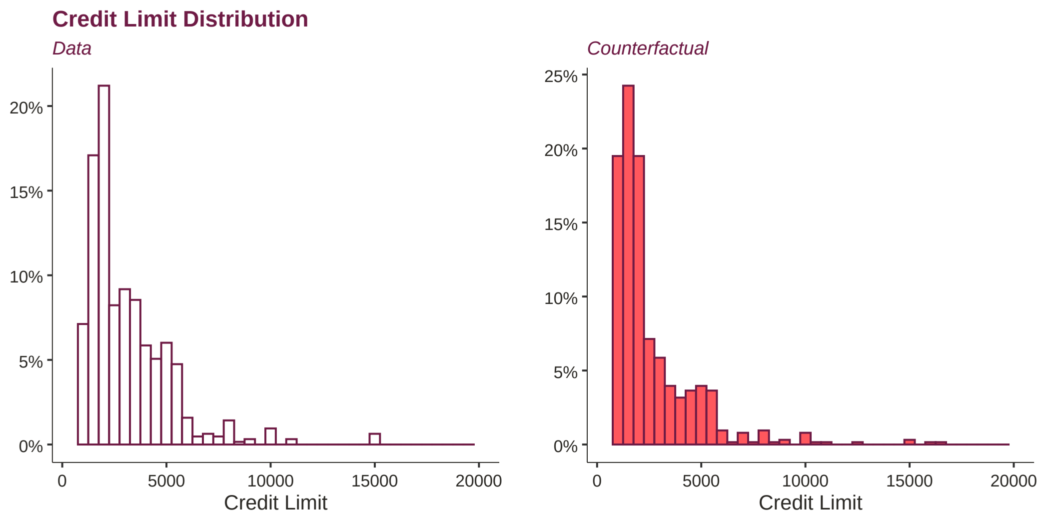
7.3.1 Interest Rates and Credit Limits

The two variables driving all changes in the counterfactual are lenders' new choices of interest rates and credit limits. Figure 9 displays the distribution of interest rates in the data and separately in the counterfactual. The distribution of interest rates becomes individualized in the counterfactual, where there are over 500 unique values of interest rates. This contrasts with the observed data, which features 21 distinct interest rate values across 22 cards. The coefficient of variation in interest rates increases from 15.0% in the data to 32.9% in the counterfactual, and the standard deviation increases from 0.028 to 0.068. These together imply a large increase in the dispersion of interest rates.

The net directional effect of the counterfactual on the values of interest rates is ambiguous. Interest rates may increase because lenders can now price discriminate, but interest rates may decrease because lenders need not pool interest rates across risk types. The former slightly dominates in the counterfactual, with interest rates increasing by 1.9 percentage points, equivalent to a 10.0% increase.

The net increase in interest rates in the counterfactual masks vast heterogeneity in interest rate changes across borrowers. In the counterfactual, lenders practice traditional third-degree price discrimination. Individuals with the most inelastic demand receive an average interest rate increase of 7.5 percentage points, equivalent to a 39.4% increase. On the contrary, interest rates fall by 2.5 percentage points for the most elastic individuals. Further, interest rates become risk-based. I create two groups of consumers representing high-risk (income below the 25^{th} percentile and risk above the 75^{th} percentile) and low-risk (income above the 75^{th} percentile and risk below the 25^{th} percentile) borrowers. The proportion of borrowers defaulting in the high-risk group is 5.3%, compared to 2.6% in the low-risk group. Interest rates rise by 12.3 percentage points for the high-risk group and fall by 4.7 percentage points for the low-risk group.

FIGURE 10: Distributions of credit limit in baseline and counterfactual



The second screening instrument available to the lender is the credit limit. Figure 10 displays the distribution of credit limits in the data and the counterfactual scenario. Credit limits remain individualized and become more dispersed, with the coefficient of variation in credit limits increasing by 11.8% and standard deviation increasing by 7.8%. Credit limits fall by 15.9% on average in the counterfactual. The coincidence of rising interest rates and falling credit limits follows the intuition of downward sloping cost curves in Einav, Finkelstein, and Cullen (2010a) and Einav and Finkelstein (2011). The set of individuals receiving an increase in interest rates reduce their borrowing, and therefore the set of individuals using their entire credit limit becomes riskier. To rebalance this and make the marginal profit over those using the entire credit limit zero, credit limits must fall.

The intuition for why lenders combine individualized interest rates and credit limits is that interest rates also affect an individual's choice of card through the term s_{ij}^E in the profit function for individual i. Individualized prices are also a device for standard third-degree price discrimination, along with their role as a tool for competition among lenders. Credit limits do not affect individuals' card choices and therefore serve as a tool for managing downside risk from default only. This intuition explains why lenders use a combination of individualized interest rates and credit limits in the counterfactual scenario.

7.3.2 Demand-Side Variables

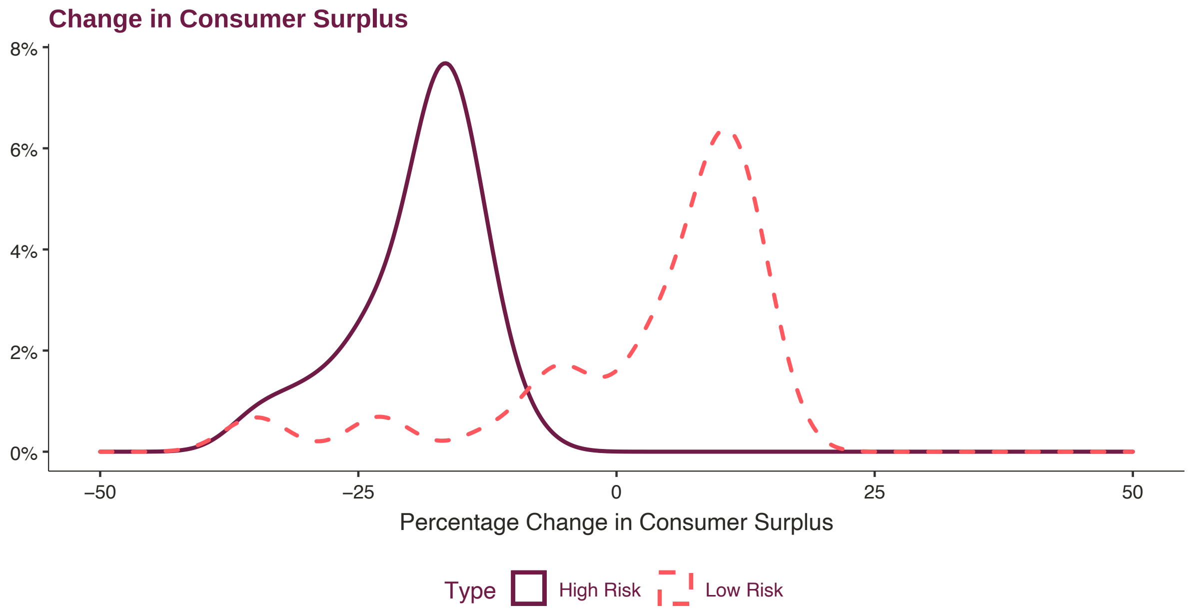
Next, I explore changes to borrowers' outcomes. In the counterfactual, borrowing increases for revolvers by 13.8% on average. The increase occurs because the most elastic borrowers obtain reductions in interest rates, which they respond to with significant increases in borrowing. This contrasts the least elastic borrowers, who react to interest rate increases with smaller borrowing reductions. The net effect is, therefore, an increase in borrowing on average.

Relative to the baseline, consumer surplus falls by 6.6% on average in the counterfactual. It is intuitive that on net, consumers are disadvantaged once lenders obtain the freedom to individualize interest rates costlessly. However, as with interest rates, this decrease in the average masks vast heterogeneity across borrowers. In Figure 11, I plot the distribution of percentage changes in consumer surplus for high-risk and low-risk individuals. Consumer surplus generally *increases* in the counterfactual for the low-risk group—a 2.6% increase on average—because they benefit from lower interest rates. Consumer surplus falls by 19% on average for the high-risk group. In sum, the counterfactual induces discrimination in interest rates and credit limits, which benefits individuals with the lowest probability of default.

7.3.3 Supply-Side Variables

Finally, I explore changes to lenders' outcomes. The lender with the largest market share captures even more of the market in the counterfactual. The market share of the largest three, four, and five firms all increase by approximately eight percentage points, implying an increase in concentration in the counterfactual relative to the baseline. With the ability to individualize interest rates, the largest lender captures a set of consumers that were not profitable to obtain at the optimal card-level interest rate. Finally, lenders' ex-post profits increase by 25.3%, equivalent to approximately £45.65 per borrower over the 18 month period for which interest rates are set. These significant changes to profit imply that the gains from tailoring interest rates alongside credit limits are substantial.

FIGURE 11: Distributions of consumer surplus in baseline and counterfactual



7.4 Implications

The results of the previous subsection suggest that in the absence of any costs/constraints on lenders' optimization problems, lenders tailor interest rates and credit limits. However, in the data, interest rates are set at the card level and not individualized. These findings, together with the substantial increases in profits available from individualizing interest rates, imply that some friction restricts lenders' willingness to adopt individualized prices. Identifying the exact sources of these frictions is beyond the scope of this project. Nevertheless, in what follows, I discuss two potential contributing factors.

First, as described in section 3, UK regulation requires that at least 51% of customers originating a card must obtain the advertised APR. This constraint directly stops lenders from in fully individualized pricing. If there is a sufficiently large fixed cost in individualizing *any* interest rate, which can only be recovered if over 51% of interest rates are individualized, it may be optimal not to individualize any interest rates, even if the regulatory constraint allows 49% to be tailored individually. These fixed costs may include administrative costs in setting up infrastructure and software to set individualized prices optimally. Given that there were already restrictions in place on the ability to individualize interest rates, lenders may have focused their investments on optimal individualized credit limits instead.

Second, lenders may face potential reputational costs if they advertise a particular APR yet give customers an alternative individualized APR, especially if the individualized rate is determined after the individual signs the contract. Members of the UK Government have expressed their disapproval of this practice (House of Commons Treasury Committee, 2003). In April 2022, the UK Chancellor of the Exchequer stated that it was "important that advertised APRs reflect the rate the consumer is likely to receive".[30] The chancellor's comments came in response to a report on advertised APRs by the largest UK consumer website, MoneySavingExpert.com.[31] As part of their report, they conducted two nationally representative surveys of over 2000 British adults. In their results, 35% of customers offered a higher rate than advertised said that it had a negative effect on their financial well-being, and 35% said that it had a negative effect on their emotional well-being. Lenders understand that negative attention resulting from unpopular business practices generates reputational risk, and a large body of literature has discussed the importance of reputational risk in the banking sector (Fiordelisi, Soana, and Schwizer, 2013; Scandizzo, 2011; Xifra and Ordeix, 2009). Furthermore, my dataset covers the years immediately following the global financial crisis – an event that led to a substantial deterioration in the favorability of public attitudes towards the banking industry (Bennett and Rita, 2012). Avoiding further reputational damage was likely to a primary short-run objective of credit card lenders as a result. Hence, though hard to quantify, the long-run reputational cost resulting from routinely deviating from the interest rate advertised may exceed the profit increases it enables.

8 Concluding Remarks

This paper explains how credit card lenders in the UK manage customers' unobserved default risk by individualizing contracts through risk-based credit limits. I use novel microdata to estimate a structural model of the UK credit market. The critical innovation in the model is the lender screening technology that provides noisy signals on borrowers' unobserved types. Lenders make credit limits contingent on these signals, and the coarseness of the set of potential signals offered by the screening technology corresponds to the coarseness of their equilibrium credit limit distribution. I use the estimated model to evaluate a counterfactual scenario in which lenders can freely individualize interest rates and credit limits, which the existing regulatory environment precludes. As a result, individualized, risk-based interest

[30] https://on.ft.com/3uKGZ92 last accessed 8 December 2022.

[31] https://www.moneysavingexpert.com/news/2022/03/chancellor-ask-regulator-credit-card-loan-aprs-martin-lewis/ last accessed 8 December 2022.

rates and credit limits emerge. The induced interest rate discrimination results in consumer surplus gains for low-risk individuals and losses for high-risk individuals. Lenders' profits increase on average. My findings imply that the current environment imposes meaningful restrictions on lenders' willingness to adopt risk-based pricing, hence, motivating lenders' use of risk-based credit limits instead.

There are several important extensions of this paper. For example, my model considers screening technologies as exogenous. Endogenizing screening technologies is a natural and interesting extension that may provide additional insights into lenders' interest rates and credit limit choices and their investments into financial technologies. In future work, I also intend to analyze counterfactuals that change lenders' screening technologies. One example would be a scenario in which lenders share their screening technologies. This would create a setting closer to the US environment, where many lenders use FICO scores to make decisions about consumers. Furthermore, building on the empirical work of Panetta, Schivardi, and Shum (2009) I can analyze the welfare effects of mergers in which the merging lenders combine their screening technologies. Along with the typical trade-off between cost synergies and increased concentration, mergers would have an advantage from shared and improved screening technologies. The profit increases resulting from improved screening technologies gauge the private benefits of screening technologies. The model can also *measure* an element of the cost synergies from the merger, which is typically challenging.

There are two other avenues for extensions of this research. The first is the role of consumer search and inattention. Throughout this study, I assume that consumers are fully aware of the interest rates at all lenders and are aware of all the cards for which qualify, implying that their consideration set (Abaluck and Adams-Prassl, 2021) is equal to their choice set. The role of consumer search in this context is nuanced by the fact that lenders currently impose heterogeneous costs on consumers learning their interest rates and credit limits. Some lenders allow consumers to learn their contractual terms before origination. In contrast, other lenders will not divulge them until after the credit card is originated. A second extension relates to behavioral biases. Consumers may have incorrect expectations or be overly optimistic about their interest rate at each lender. These biases may affect lenders' optimal use of risk-based credit limits and interest rates. These extensions warrant particular attention in work that quantifies consumer welfare in this context.

Regarding the external validity of my findings, financial products in developed economies use a variety of risk-based prices and quantities. For example, mortgages and credit cards across

UK and US markets all feature different combinations of risk-based contractual characteristics. No general theory exists to explain how product features and regulatory environments interact to influence lenders' choices among multiple screening instruments. Understanding the product characteristics and regulatory conditions that result in risk-based prices or quantities (or both) is a natural sequel to this work.

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Online Appendix

A Broader Literature on Credit Card Markets

Through this paper, I contribute to the vast literature in economics and finance studying credit card markets. Several research articles, books, and reports on credit card markets are noteworthy. Agarwal and Zhang (2015) surveys the literature, and Knight (2010) extensively summarizes the UK credit card market. The Financial Conduct Authority produced a UK credit card market study in 2015 (FCA, 2015a), and the Consumer Finance Protection Bureau (CFPB) produce a biennial report on the US credit card market, most recently in 2021 (CFPB, 2021). Evans and Schmalensee (2005) offers a comprehensive account of the history of credit cards in the US.

Many papers explore the impact of behavioral biases on the credit card market. The biases include **time inconsistency and present bias** (Ausubel and Shui, 2005; Ausubel, 1991, 1999; Laibson, Repetto, and Tobacman, 2000; Meier and Sprenger, 2010; Kuchler and Pagel, 2021), **self-control and naivete** (Heidhues and Kőszegi, 2010), **anchoring** (Keys and Wang, 2019; Stewart, 2009), **exponential growth bias** (Stango and Zinman, 2009; Adams, Guttman-Kenney, Hayes, Hunt, Laibson, and Stewart, 2022), **over-optimism** (Exler, Livshits, MacGee, and Tertilt, 2021; Yang, Markoczy, and Qi, 2007), **shrouding** (Ru and Schoar, 2016), and **repayment heuristics** (Gathergood, Mahoney, Stewart, and Weber, 2019). Though my model does not explicitly account for these features, I base my estimation on a set of linearized equations that are not inconsistent with behavioral biases. Future research can explore the interaction between consumer behavioral biases and lenders' risk-based credit limits and interest rates.

Other papers stress the importance of **search** (Galenianos and Gavazza, 2022; Stango, 2002; Stango and Zinman, 2015; Drozd and Nosal, 2011; Calem and Mester, 1995), **promotional deals** (Drozd and Kowalik, 2019), **learning** (Agarwal, Driscoll, Gabaix, and Laibson, 2008), **minimum repayments** (Druedahl and Jørgensen, 2018), and **information frictions** (Ausubel, 1999; Karlan and Zinman, 2009) in credit card markets. These topics are relevant features of credit card markets, and, like behavioral biases, further work can explore how they interact with risk-based prices and credit limits. In particular, when lenders have to advertise an APR, search becomes less costly for consumers, so the role of consumer search is particularly important.

B Summary Statistics

B.1 Demographics

Table H.7 provides summary statistics on individuals at origination. The mean age is 43 years. Net monthly income is £2099 at the mean, though the distribution is right-skewed, and the median income is £1604. Around 18% of individuals set up a direct debit at origination, approximately 52% of cardholders report being female, 57% are homeowners, and 76% are employed (not including self-employed). Finally, most customers (53%) originate online, 32% originate in a store, 12% originate via post, and 4% do so by telephone.

B.2 Cards

Table H.8 provides summary statistics on card features at origination. The mean credit limit is £3390, and the mean purchase APR at origination is 21.5%. The coefficient of variation in credit limits across all lenders and months is almost 1. The variation in interest rates (purchase and balance transfer) is much smaller. This matches the within-lender and within-card analysis of variation in credit limits and interest rates discussed in section 3.1. Promotional deal lengths for purchases are short, typically around three or six months where they exist, and over 25% of cards have no purchase promotional deal. Across all cards, 83% of customers obtain the advertised APR, a fact I describe in depth in section 3.1.1. Finally, 28% of customers transfer a balance from a previous card at origination.

Second, Table H.9 provides summary statistics on cards, where the unit of observation is the card-month. The most important conclusion from this table is that rewards are scant in the UK, with only 9% of card-months offering cashback and 7% offering air miles. This differs from the US, where rewards are generally more readily available. The table also shows the following facts. First, over 75% of cards have no annual fees. Annual fees are also more common in the US. Second, there is significant dispersion across card-months in minimum and maximum credit limits. Third, individuals usually receive around 30 days to repay their bill before interest is added. Fourth, most cards are available to all customers, with only 5% reserved for students and 7% exclusive to those who are employed.

B.3 Statement Variables

Table H.10 provides summary statistics for statement-level variables. Credit limits are slightly larger, and interest rates are marginally lower relative to origination as riskier individuals are repriced or eventually close their card. Over 25% of balances are zero, and the distribution of account balances is heavily right-skewed, with the mean account balance approximately £830 larger than the median. Repayments are much lower than balances, which is unsurprising as many individuals make the minimum monthly repayment. Interest is also highly skewed: over half the statement-months carry no interest, but the right tail is sizeable, with a 90^{th} percentile of £26.58. Finally, only 2% of statement months have an overdue payment, and 2% of statement months involve a charge off of the account.

C Summary of UK and US APR Regulation

This section provides a brief and non-technical overview of regulations relating to Annual Percentage Rates (APR) in the UK and the US. For precise details, the interested researcher can consult the Consumer Credit Sourcebook (CONC) section 3.5 for the UK case and the Code of Federal Regulations (CFR) §1022.70 for the US case.[32] FCA (2015c) offers a more general summary of UK credit card regulation.

C.1 Definitions and UK Advertised APR Regulation

A credit card's *purchase balance* is the total amount spent on the card relating to non-cash transactions currently not repaid.[33] A *purchase interest rate* for a credit card is the percentage rate at which interest is added to a credit card purchase balance.

As a prelude to defining the annual percentage rate (APR), I first describe the daily interest compounding method, which many lenders use to add interest to credit cards. At the end of a statement cycle, lenders may give individuals a grace period of interest-free days to pay their balance. This period is typically between 20 to 40 days. Lenders charge interest for the statement cycle if the total balance is not paid within the grace period. Lenders compound interest on unpaid balances daily by taking each day's average balance and multiplying it by the daily periodic purchase rate. The *daily periodic purchase rate* is the percentage rate at

[32] `https://www.handbook.fca.org.uk/handbook/CONC/3/5.html` and `https://www.consumerfinance.gov/rules-policy/regulations/1022/70/`, last accessed 29 September 2022.

[33] The withdrawal of cash counts towards the cash advance balance and cash advance interest rates are typically higher than purchase interest rates. Transfers of balances from a previous credit card counts towards the balance transfer balance, which also can have a different interest rate to the purchase rate and cash advance rate.

which interest is added to an unpaid balance daily. The consumer is notified of the interest charged on their monthly statement, where the monthly interest charge is the sum of daily interest across all the days in the month.

The *annual purchase rate* is the daily periodic rate multiplied by 365. For example, if the daily periodic rate is 0.0005, the annual purchase rate is 0.1825, or 18.25%. An *annual percentage rate* is similar to the annual purchase rate, except it also accounts for all mandatory fees that an individual must pay each year on the card so that it represents the total cost of revolving a balance on a credit card each year. If a card has no compulsory fees or charges, its APR equals the annual purchase rate.

Accounting for fees when calculating a total cost of borrowing on a card requires a representative credit limit. The calculation of APR assumes that the individual pays the fees, spends the entire representative credit limit on the first day of the year, and then pays it back in equal, regular installments over a year without spending anything else. The sum of the charges and interest accruing over a year (as a percentage) when an individual follows this spending pattern and pays the fees defines the APR.

The *representative* or *advertised APR* is defined as “an APR at or below which the firm communicating or approving the financial promotion reasonably expects, at the date on which the promotion is communicated or approved, that credit would be provided under at least 51% of the credit agreements which will be entered into as a result of the promotion”. Credit card lenders must include a representative APR on all promotional materials for a credit card, and by definition, most consumers each month must obtain the representative APR. Before February 2011, the proportion of customers on a given credit card required to obtain the advertised APR was 66%. After February 2011, the UK harmonized regulation with the EU and the proportion changed from 66% to 51%.

C.2 US Regulation

US credit card lenders do not have to provide one representative APR for each credit card, but they are still subject to regulation should they use risk-based pricing. Since the Truth in Lending Act in 1998, credit card agreements must include a “Schumer” Box: a table showing basic information about the card’s rates and fees. The box on purchase APR must contain either a list of values or a range of values for APR that the lender will use. The APR values must be in at least an 18-point font size.

Further, lenders must provide a consumer with a "risk-based pricing notice" if they (i) use a consumer credit report in connection with a credit application and (ii) grant or extend credit to that consumer on "material terms that are materially less favorable than the most favorable material terms available to a substantial proportion of consumers from or through the lender." The risk-based pricing notice must inform the consumer that a consumer report includes information about their credit history, that the terms offered have been set based on information from the consumer report, and that the terms offered may be less favorable than the terms offered to consumers with better credit histories, among other information.

Another major piece of recent US credit card regulation is the 2009 Credit Card Accountability Responsibility and Disclosure Act of 2009. This Act limited lenders' ability to change interest rates after origination and is the subject of Nelson (2022) and Agarwal, Chomsisengphet, Mahoney, and Stroebel (2014).

D Pricing by Subprime Lenders

I identify two particular subprime lenders in the sample. These lenders (removed from the solid line to create the higher dashed line in Figure H.5) price differently, giving many customers a rate different from the advertised APR. As Table H.1 reveals, in contrast to prime and superprime lenders, most variation in interest rates for these two lenders is within rather than between cards. I investigate these two lenders' pricing strategies in Figure H.18 by plotting the distribution of percentage point differences (rounded to the nearest integer) between advertised APRs and those customers actually received. The differences are minor and often favorable to consumers. In the most commonly occurring case, 42% of customers received an interest rate six percentage points *lower* than that advertised. Very few customers (around 2.6%) received interest rates more than eight percentage points above the APR advertised.

E Additional Modeling Details

E.1 Focus on Interest Revenue

I focus on interest revenue because it comprises the vast majority of revenue for US lenders (around 70%) (Evans and Schmalensee, 2005). Further, the remaining 30% contains revenue sources that are likely to be smaller proportions in the UK relative to the US. I detail the three largest alternative revenue sources below.

The first is interchange revenue, which accounts for 15% of US lenders' revenues on average. Interchange revenues are the funds lenders receive from merchants and their banks when individuals use their cards for purchases. Interchange fees were much lower in the UK than in the US between 2010-2013, making it likely that interchange accounted for a lower proportion of UK lenders' revenue than in the US.[34]

The second part of the remaining 30% of non-interest revenue comes from cash-advance fees. Cash-advance fees are the charges consumer pay for using a credit card to withdraw cash or conduct other non-standard card uses such as gambling. Cash-advance revenues became a negligible part of UK lenders' revenue in April 2011, when new credit card regulation forced lenders to use customers' repayments towards high-interest cash advance balances first rather than last, as most lenders did before the regulation.

The final source of revenue is fee revenue. Over 75% of cards have no annual fee in the UK, so I focus on fees other than annual fees. In 2003 the Office of Fair Trading (OFT) began an inquiry into the 'default charges' levied by credit card companies when, for example, a cardholder exceeded their credit limit or was late to make the minimum monthly payment.[35] In 2006, the OFT stated that many of the charges were "unlawful," saying that it would act upon receiving notice of any fee over £12 (Office of Fair Trading, 2006). In 2010-2015, all fees apart from annual fees (including late, dormancy, over-limit, and foreign transaction) were at most £12, around 50% lower than in 2003 (House of Commons Treasury Committee, 2003). Fees are generally more common and are usually larger than £12 in the US, once more suggesting that fees accounted for a smaller proportion of UK lenders' revenues. These arguments imply that interest revenue accounts for the main part of UK credit card lenders' revenue, suggesting that this should be the sole source of lenders' revenue in my model.

E.2 Interest Rates

The following subsection offers one possible model of how lenders set advertised APRs. I provide it merely to give one such example of how these rates may be set, rather than

[34] In 2015, the European Parliament and the Council of the European Union adopted the Interchange Fee Regulation (IFR), which set the default interchange fee cap at 0.3% of the transaction for credit cards. The UK adopted these changes in late 2015.

[35] https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/284445/oft842.pdf, last accessed 2nd Septemer 2022.

prescribing that it accurately represents the method used by lenders.

In this model, lenders choose rates strategically so that interest rates form a Nash-Bertrand equilibrium. Let $\boldsymbol{r}^*_{-\ell mt}$ denote the equilibrium interest rates on cards at lenders other than ℓ. Then for every lender ℓ, the vector of interest rate $\boldsymbol{r}^*_{\ell mt}$ solves

$$\max_{\boldsymbol{r}_{\ell mt}} \sum_{i \in I_{mt}} \sum_{j \in J_{i\ell mt}} s^E_{ijmt}(\boldsymbol{r}_{\ell mt}, \boldsymbol{r}^*_{-\ell mt}) \Pi_{ijmt}(r_{jmt}). \tag{17}$$

The term s^E_{ijmt} denotes the probability of individual i originating card j as a borrower. The term $J_{i\ell mt} = J_{imt} \cap J_{\ell mt}$ is the set of cards offered by lender ℓ with income thresholds lower than Y_i. I define the term Π_{ijmt} in equation (6).

E.3 First Order Condition Derivation

Now I derive equation (7) from the first order condition of the lender's profit maximization problem. The first step is to replace ε_i with $e_{i\ell t} + w_{i\ell t}$. The second—and main—step is to note that for every $\bar{b}$, there exists a threshold signal error $\omega_{i\ell t}(\bar{b})$ such that if the signal error is larger (respectively smaller) than $\omega_{i\ell t}$, the individual's desired borrowing will be larger (respectively smaller) than $\bar{b}$.[36] The value of $\omega_{i\ell t}$ sets $\log(b^*_{ijmt})$ equal to $\log(\bar{b}_{ijmt})$ and is therefore

$$\omega_{i\ell t}(\bar{b}_{ijmt}, e_{i\ell t}) = \frac{\log(\bar{b}_{ijmt}) - \delta^B_{jmt} - u^B_{ijmt}}{\sigma^B_{mt}} - e_{i\ell t}.$$

From this, I split the objective function into

$$\int_{-\infty}^{\omega_{i\ell t}} b^*_{ijmt} \pi_{ijmt}(e_{i\ell t}, w_{i\ell t}) \phi\left(\frac{w_{i\ell t}}{\sigma_{\ell t}}\right) dw_{i\ell t} + \bar{b}_{ijmt} \int_{\omega_{i\ell t}}^{\infty} \pi_{ijmt}(e_{i\ell t}, w_{i\ell t}) \phi\left(\frac{w_{i\ell t}}{\sigma_{\ell t}}\right) dw_{i\ell t}.$$

By L'Hopital's rule, the first derivative is equal to

$$\int_{\omega_{i\ell t}}^{\infty} \pi_{ijmt}(e_{i\ell t}, w_{i\ell t}) \phi\left(\frac{w_{i\ell t}}{\sigma_{\ell t}}\right) dw_{i\ell t} \tag{18}$$

and the second derivative

$$-\frac{d\omega_{i\ell t}}{d\bar{b}_{ijmt}} \pi(e_{i\ell t}, \omega_{i\ell t}) \phi\left(\frac{\omega_{i\ell t}}{\sigma_{\ell t}}\right),$$

which is negative provided that $\pi(e_{i\ell t}, \omega_{i\ell t}) > 0$. In this region, the objective is concave and the first order condition is necessary and sufficient for a maximum.

[36]This version assumes that σ^B_{mt} is positive, a condition I impose in estimation without loss of generality. The sign of σ^B_{mt} is not identified so I normalize it as positive. The sign of σ^D_{mt} then determines the sign of the correlation between ε^B_{imt} and ε^D_{imt}. If I normalize σ^B_{mt} as negative, the first order condition bounds would swap to $(-\infty, \omega_{i\ell t}]$ but the equation is otherwise unchanged.

E.4 Elasticities

I derive exact formulas of the demand elasticities, both for the intensive borrowing quantity b_{ijmt} and extensive product choice s^E_{ijmt}. I start with the intensive borrowing quantity. The elasticity for individual i is

$$\frac{\partial \log(b_{ijmt})}{\partial \log(r_{jmt})} = r_{jmt} \frac{\partial \log(b_{ijmt})}{\partial r_{jmt}}.$$

The right-hand side derivative is the marginal effect from a Tobit model with top censoring at $\log(\bar{b}_{ijmt})$. The marginal effect in this model is (Greene, 2017)

$$\frac{\partial \log(b_{ijmt})}{\partial r_{jmt}} = \alpha^B_{ijmt} \Phi \left(\frac{\bar{\mathcal{Q}}^B_{ijmt}}{\sigma^B_{mt}} \right),$$

where

$$\bar{\mathcal{Q}}^B_{ijmt} = \log(\bar{b}_{ijmt}) - \delta^B_{jmt} - u^B_{ijmt}.$$

Hence the elasticity of intensive borrowing is

$$\frac{\partial \log(b_{ijmt})}{\partial \log(r_{jmt})} = r_{jmt} \alpha^B_{ijmt} \Phi \left(\frac{\bar{\mathcal{Q}}^B_{ijmt}}{\sigma^B_{mt}} \right). \tag{19}$$

The elasticity for the extensive product choice is more involved. By definition, the probability that an individual chooses card j as a borrower is

$$s^E_{ijmt} = (1 - s^E_{i0mt}) s^E_{ijmt|j \in J_{imt}},$$

where $s^E_{ijmt|j \in J_{imt}}$ is the probability of individual i choosing card j, conditional on revolving, and s^E_{i0mt} is the probability that individual i chooses to transact. From this,

$$\frac{\partial s^E_{ijmt}}{\partial r_{jmt}} = (1 - s^E_{i0mt}) \frac{\partial s^E_{ijmt|j \in J_{imt}}}{\partial r_{jmt}} - s^E_{ijmt|j \in J_{imt}} \frac{\partial s^E_{i0mt}}{\partial r_{jmt}}.$$

The standard logit derivative for the inside options is

$$\frac{\partial s^E_{ijmt|j \in J_{imt}}}{\partial r_{jmt}} = s_{ijmt|j \in J_{imt}} (1 - s_{ijmt|j \in J_{imt}}) \frac{\alpha^E_{ijmt}}{\varrho_{mt}}$$

and derivative of the outside option probability is

$$\frac{\partial s^E_{i0mt}}{\partial r_{jmt}} = -\alpha^E_{imt} s^E_{ijmt|j \in J_{imt}} s^E_{i0mt} (1 - s^E_{i0mt}) = -\alpha^E_{imt} s^E_{i0mt} s_{ijmt}.$$

Putting these together yields

$$\frac{\partial s^E_{ijmt}}{\partial r_{jmt}} = \alpha^E_{ijmt} s^E_{ijmt} \left[\frac{1 - s^E_{ijmt|j\in J_{imt}}}{\varrho_{mt}} + s^E_{ijmt|j\in J_{imt}} s^E_{i0mt} \right]. \tag{20}$$

Multiplying (20) by $\frac{r_{jmt}}{s^E_{ijmt}}$ provides the product choice price elasticity of demand for individual i, given by

$$\frac{\partial \log(s^E_{ijmt})}{\partial \log(r_{jmt})} = r_{jmt} \alpha^E_{ijmt} \left[\frac{1 - s^E_{ijmt|j\in J_{imt}}}{\varrho_{mt}} + s^E_{ijmt|j\in J_{imt}} s^E_{i0mt} \right]. \tag{21}$$

F Details on Estimation

F.1 Conditional Log Likelihood

Recall that the demand model (conditional on revolving) is a system of three equations: (i) a logit equation for card choice, (ii) a Tobit equation for borrowing choice (with censoring at the credit limit), and (iii) a Probit equation for default. The estimating equations for individual i, card j, in channel m, and origination month t are

$$\begin{aligned} V^E_{ijmt} &= \delta^E_{jmt} + \nu_{ijmt} + u^E_{ijmt} \\ \log(b^*_{ijmt}) &= \delta^B_{jmt} + \varepsilon^B_{imt} + u^B_{ijmt} \\ V^D_{imt} &= \eta^D_{mt} + \Omega^D_{mt} \tilde{y}_{imt} + \varepsilon^D_{imt}, \end{aligned}$$

where

$$\begin{aligned} \delta^E_{jmt} &= \beta^{E\prime} X^E_{jmt} + \xi^E_{jmt} + \eta^E_{mt} + \alpha^E r_{jmt} \\ u^E_{ijmt} &= \Omega^{E,r}_{mt} \tilde{y}_{imt} r_{jmt}, \\ \delta^B_{jmt} &= \beta^{B\prime} X^B_{jmt} + \xi^B_{jmt} + \eta^B_{mt} + \alpha^B r_{jmt} \\ u^B_{ijmt} &= \Omega^{B,cons}_{mt} \tilde{y}_{imt} + \Omega^{B,r}_{mt} \tilde{y}_{imt} r_{jmt}, \end{aligned}$$

with all terms defined as in the main text and in the notation tables H.4 and H.5.[37] The system's endogenous variables are borrowing utility V^E_{ijmt}, desired borrowing b^*_{ijmt}, and default net utility V^D_{imt}. Interest rates r_{jmt} correlate with unobserved card characteristics ξ_{jmt}, creating additional endogeneity along with the simultaneity. The exogenous variables are

[37]As described in text, because of the typical identification issue in discrete choice models, I normalize $\delta^E_{0mt} = 0$ and take interest rates and card characteristics in the card choice equation as differences from the outside option.

card characteristics X_{jmt} and individual logged income y_i. I never observe utilities V^E_{ijmt} and V^D_{ijmt}. I observe card choice j^*_{imt}, constrained borrowing b_{ijmt}, and default choice for revolvers. Constrained borrowing b_{ijmt} is equal to $\min\{b^*_{ijmt}, \bar{b}_{ijmt}\}$, implying that I only observe desired borrowing b^*_{ijmt} for those who borrow less than their credit limit $\bar{b}_{ijmt}$. Unobservables ε^B_{imt} and ε^D_{imt} satisfy

$$\begin{aligned}
\varepsilon^B_{imt} &= \sigma^B_{mt}\varepsilon_i \\
\varepsilon^D_{imt} &= \sigma^D_{mt}\varepsilon_i + \tilde{\varepsilon}^D_i,
\end{aligned}$$

where $(\varepsilon_i, \tilde{\varepsilon}^D_i) \sim \mathcal{N}(0, I_2)$. I require no distributional assumption on ξ^E_{jmt} and ξ^B_{jmt}.

F.1.1 Expressions for $s^{(g)}_{ijmt}$

I derive the expressions $s^{(g)}_{ijmt}$ in equation (10) for $g = 1, \ldots, 4$. The first term $s^{(1)}_{ijmt}$ for an individual who borrows $b < \bar{b}_{ijmt}$ and defaults is

$$\begin{aligned}
s^{(1)}_{ijmt} &= \mathbb{P}(\text{Default}|\log(b^*_{ijmt}) = \log(b)) \cdot f_{\log(b^*_{ijmt})}(\log(b)) \\
&= \frac{1}{\sigma^B_{mt}}\mathbb{P}(\varepsilon^D_{imt} > -\mathcal{Q}^D_{imt}|\varepsilon^B_{imt} = \mathcal{Q}^B_{ijmt}(b))\phi\left(\frac{\mathcal{Q}^B_{ijmt}(b)}{\sigma^B_{mt}}\right) \\
&= \frac{1}{\sigma^B_{mt}}\Phi^{BD,1}_{ijmt}\phi\left(\frac{\mathcal{Q}^B_{ijmt}(b)}{\sigma^B_{mt}}\right),
\end{aligned}$$

where

$$\begin{aligned}
\Phi^{BD,1}_{ijmt} &= \Phi\left(\mathcal{Q}^D_{imt} + \frac{\sigma^D_{mt}}{\sigma^B_{mt}}\mathcal{Q}^B_{ijmt}(b)\right) \\
\mathcal{Q}^B_{ijmt}(b) &= \log(b) - \delta^B_{jmt} - u^B_{ijmt}, \\
\mathcal{Q}^D_{imt} &= \eta^D_{mt} + \Omega^D_{mt}\tilde{y}_{imt},
\end{aligned}$$

By a similar derivation,

$$s^{(2)}_{ijmt} = \frac{1}{\sigma^B_{mt}}\left[1 - \Phi^{BD,1}_{ijmt}\right]\phi\left(\frac{\mathcal{Q}^B_{ijmt}(b)}{\sigma^B_{mt}}\right).$$

The third and fourth terms are slightly more complicated, because of the full utilization of credit limit. The third term $s^{(3)}_{ijmt}$ is

$$
\begin{aligned}
s^{(3)}_{ijmt} &= \mathbb{P}\left(\log(b^*_{ijmt}) > \log(\bar{b}_{ijmt})\right) \mathbb{P}\left(V^D_{imt} > 0 | \log(b^*_{ijmt}) > \log(\bar{b}_{ijmt})\right) \\
&= \mathbb{P}\left(\varepsilon^B_{imt} > \bar{\mathcal{Q}}^B_{ijmt}\right) \mathbb{P}(\varepsilon^D_{imt} > -\mathcal{Q}^D_{imt} | \varepsilon^B_{imt} > \bar{\mathcal{Q}}^B_{ijmt}) \\
&= \mathbb{P}\left(\varepsilon^B_{imt} > \bar{\mathcal{Q}}^B_{ijmt}\right) \int_{\bar{\mathcal{Q}}^B_{ijmt}}^{\infty} \mathbb{P}(\varepsilon^D_{imt} > -\mathcal{Q}^D_{imt} | \varepsilon^B_{imt} = a) f_{\varepsilon^B_{imt}|\varepsilon^B_{imt} > \bar{\mathcal{Q}}^B_{ijmt}}(a | \varepsilon^B_{imt} > \mathcal{Q}^B_{ijmt}) da \\
&= \frac{1}{\sigma^B_{mt}} \int_{\bar{\mathcal{Q}}^B_{ijmt}}^{\infty} \Phi\left(\mathcal{Q}^D_{imt} + \frac{\sigma^D_{mt}}{\sigma^B_{mt}} a\right) \phi\left(\frac{a}{\sigma^B_{mt}}\right) da \\
&= \int_{\bar{\mathcal{Q}}^B_{ijmt}/\sigma^B_{mt}}^{\infty} \Phi\left(\mathcal{Q}^D_{imt} + \sigma^D_{mt}\tilde{a}\right) \phi\left(\tilde{a}\right) d\tilde{a},
\end{aligned}
$$

where

$$
\bar{\mathcal{Q}}^B_{ijmt} = \mathcal{Q}^B_{ijmt}(\bar{b}_{ijmt}).
$$

Similarly,

$$
s^{(4)}_{ijmt} = \int_{\bar{\mathcal{Q}}^B_{ijmt}/\sigma^B_{mt}}^{\infty} \left[1 - \Phi\left(\mathcal{Q}^D_{imt} + \sigma^D_{mt}\tilde{a}\right)\right] \phi\left(\tilde{a}\right) d\tilde{a}.
$$

F.1.2 Expressions for $s^E_{ijmt|j\in J_{imt}}$

Now I write out the expression for $s^E_{ijmt|j\in J_{imt}}$ in equation (14). It is

$$
s^E_{ijmt|j\in J_{imt}} = \frac{\exp\left(\bar{U}^E_{ijmt}\right)}{\sum_{k\in J_{imt}} \exp\left(\bar{U}^E_{ikmt}\right)},
$$

where

$$
\bar{U}^E_{ijmt} = \frac{\bar{V}^E_{ijmt}}{\varrho_{mt}},
$$

ϱ_{mt} is the parameter of the generalized type-1 distributed terms ν_{ijmt}, and the indirect utility term $\bar{V}^E_{ijmt}$ is

$$
\bar{V}^E_{ijmt} = \delta^E_{jmt} + u^E_{ijmt}.
$$

The first step yields estimates of the following parameters

$$
\frac{\delta^E_{jmt}}{\varrho_{mt}},\ \frac{\Omega^{E,r}_{mt}}{\varrho_{mt}},\ \delta^B_{jmt},\ \Omega^{B,r}_{mt},\ \Omega^{B,cons}_{mt},\ \Omega^D_{mt}, \eta^D_{mt},\ \sigma^B_{mt},\ \sigma^D_{mt}.
$$

The next subsection derives the log likelihood of borrowing/transacting, which delivers estimates of δ_{0mt}, ϱ_{mt} and $\Omega^{E,cons}_{mt}$.

F.2 Log Likelihood For Transacting

An individual transacts if the utility from transacting V_{i0mt}^{E} exceeds the maximal utility from borrowing. The probability that this occurs for individual i is

$$s_{i0mt}^{E} = \frac{1}{1 + \exp\left(\varrho_{mt} F_{imt} - \bar{V}_{i0mt}\right)},$$

where

$$F_{imt} = \log \sum_{k \in J_{imt}} \exp\left(\bar{U}_{ikmt}^{E}\right)$$

is the inclusive value and $\bar{V}_{i0mt} = \delta_{0mt} + \Omega_{mt}^{E,cons} \tilde{y}_{imt}$. Let ζ_{imt} be a dummy equal to one if the individual chooses to transact. Then the log likelihood for transacting is

$$\log \mathcal{L}_{mt}^{tr} = \sum_{i \in I_{mt}} \zeta_{imt} \log(s_{i0mt}^{E}) + (1 - \zeta_{imt}) \log(1 - s_{i0mt}^{E}).$$

Maximizing $\log \mathcal{L}_{mt}^{tr}$ market-by-market provides estimates of δ_{0mt}, ϱ_{mt} and $\Omega_{mt}^{E,cons}$, from which I recover $\Omega_{mt}^{E,r}$ and δ_{jmt}^{E}.

G Additional Counterfactuals Details

I derive the first order conditions to the optimization problem in equation (16). First, I define

$$\mathcal{E}_{ij} = \mathbb{E}_{\varepsilon_i | e_{i\ell}} \left[\min\{b_{ij}^{*}, \bar{b}_{ij}\} \pi_{ij}\right]$$

and rewrite the objective function by separating out card j as

$$s_{ij}^{E}(\boldsymbol{r}_{i\ell}, \boldsymbol{r}_{-i\ell}^{*}) \mathcal{E}_{ij} + \sum_{k \neq j} s_{ik}^{E}(\boldsymbol{r}_{i\ell}, \boldsymbol{r}_{-i\ell}^{*}) \mathcal{E}_{ik}. \tag{22}$$

Since $\bar{b}_{ij}$ only affects the lenders' profit for card j, the first order condition with respect to $\bar{b}_{ij}$, after cancelling $s_{ij}^{E}(\boldsymbol{r}_{i\ell}, \boldsymbol{r}_{-i\ell}^{*}) > 0$, is

$$\frac{\partial}{\partial \bar{b}_{ij}} \mathbb{E}_{\varepsilon_i | e_{i\ell}} \left[\min\{b_{ij}^{*}, \bar{b}_{ij}\} \pi_{ij}\right] = \frac{\partial \mathcal{E}_{ij}}{\partial \bar{b}_{ij}} = 0.$$

The equation is exactly the same first order condition for credit limits as in the baseline model. However, because interest rates change in equilibrium, even if the individual stays on the same card, their credit limit may change.

The first order condition with respect to r_{ij} is

$$\frac{\partial s_{ij}^{E}}{\partial r_{ij}} \mathcal{E}_{ij} + s_{ij}^{E} \frac{\partial \mathcal{E}_{ij}}{\partial r_{ij}} + \sum_{k \neq j} \frac{\partial s_{ik}^{E}}{\partial r_{ij}} \mathcal{E}_{ik} = 0.$$

Equation (20) provides an expression for $\dfrac{\partial s_{ij}^E}{\partial r_{ij}}$. To finish this section, I provide expressions for $\dfrac{\partial \mathcal{E}_{ij}}{\partial r_{ij}}$ and $\dfrac{\partial s_{ik}^E}{\partial r_{ij}}$ when $k \neq j$. The former of these two terms is

$$\frac{\partial \mathcal{E}_{ij}}{\partial r_{ij}} \quad = \quad \int_{-\infty}^{\omega_{i\ell}} \left[b_{ij}^*(1-\Delta_i) + \alpha_i^B b_{ij}^* \pi_{ij}\right] \phi\left(\frac{w_{i\ell}}{\sigma_\ell}\right) dw_{i\ell} \; + \; \bar{b}_{ij} \int_{\omega_{i\ell}}^{\infty} (1 \; - \; \Delta_i) \phi\left(\frac{w_{i\ell}}{\sigma_{\ell t}}\right) dw_{i\ell}.$$

The expression for $\dfrac{\partial s_{ik}^E}{\partial r_{ij}}$ is more involved. To start,

$$\frac{\partial s_{ik}^E}{\partial r_{ij}} = (1 - s_{i0}) \frac{\partial s_{ik|k\in J_i}^E}{\partial r_{ij}} - \frac{\partial s_{i0}^E}{\partial r_{ij}} s_{ik|k\in J_i}^E.$$

Then

$$\frac{\partial s_{ik|k\in J_i}^E}{\partial r_{ij}} = -s_{ij|j\in J_i}^E s_{ik|k\in J_i}^E \frac{\alpha_i^E}{\varrho}$$

and

$$\frac{\partial s_{i0}^E}{\partial r_{ij}} = -\alpha_i^E s_{i0}^E s_{ij}^E.$$

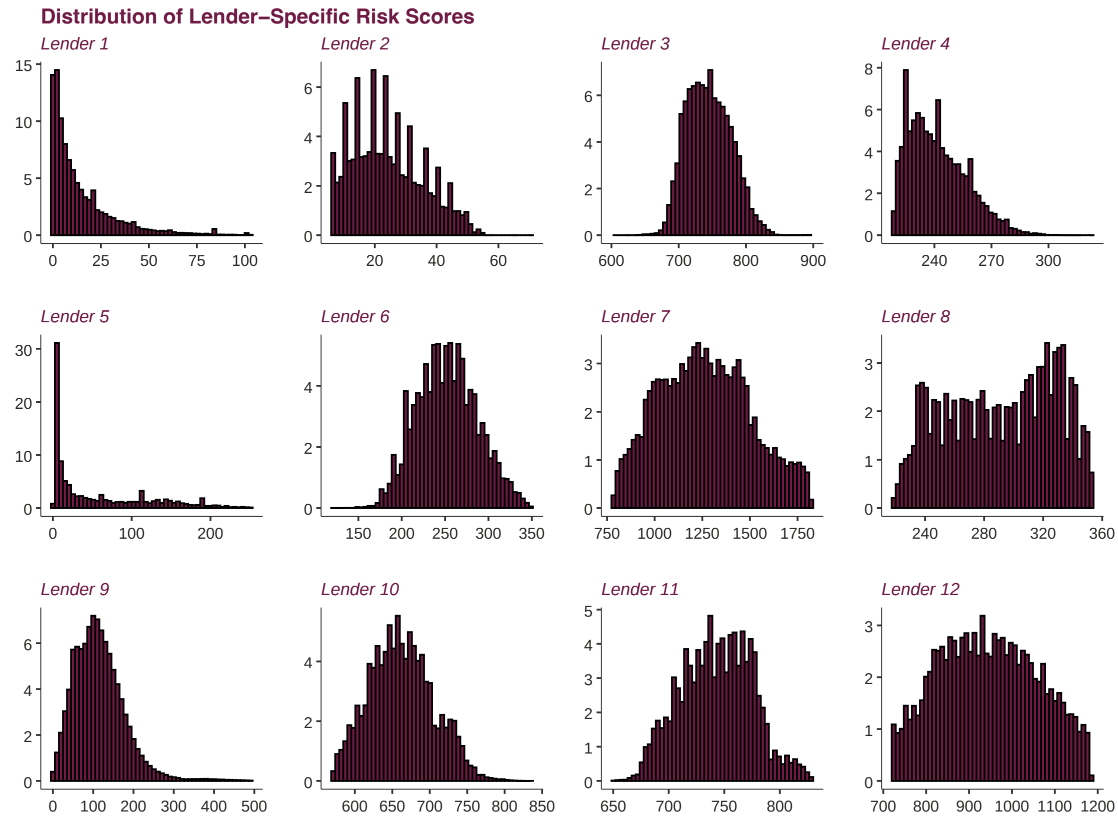
Putting these together yields

$$\frac{\partial s_{ik}^E}{\partial r_{ij}} = s_{ij}^E s_{ik|k\in J_i}^E \alpha_i^E \left[s_{i0}^E - \frac{1}{\varrho}\right].$$

H Additional Figures and Tables

H.1 Figures

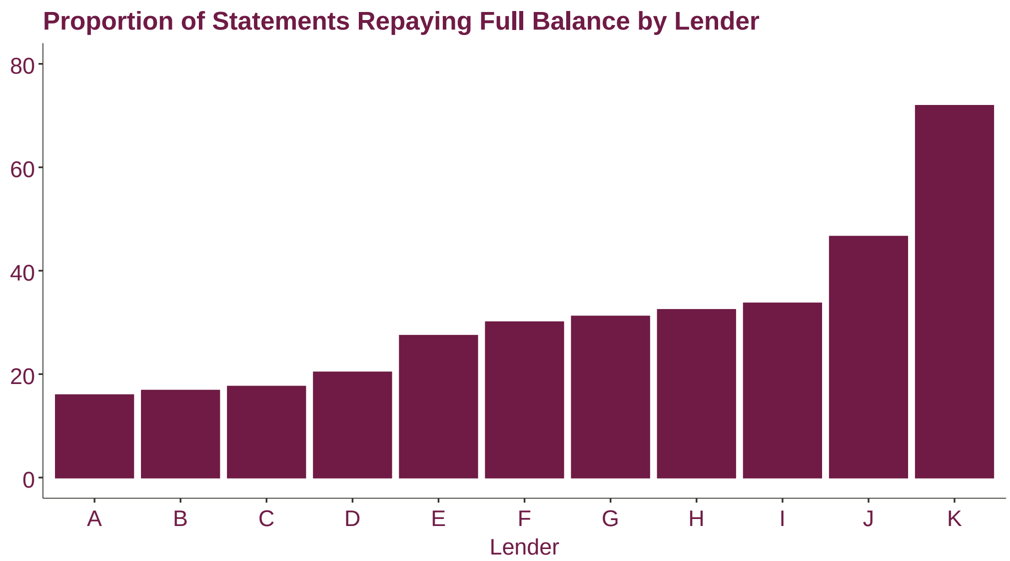
Figure H.1: Distribution of proprietary credit scores across lenders



Notes: I scramble lenders' identities to preserve anonymity, so labels do not necessarily match the identities in other tables and figures.

Link back to data section

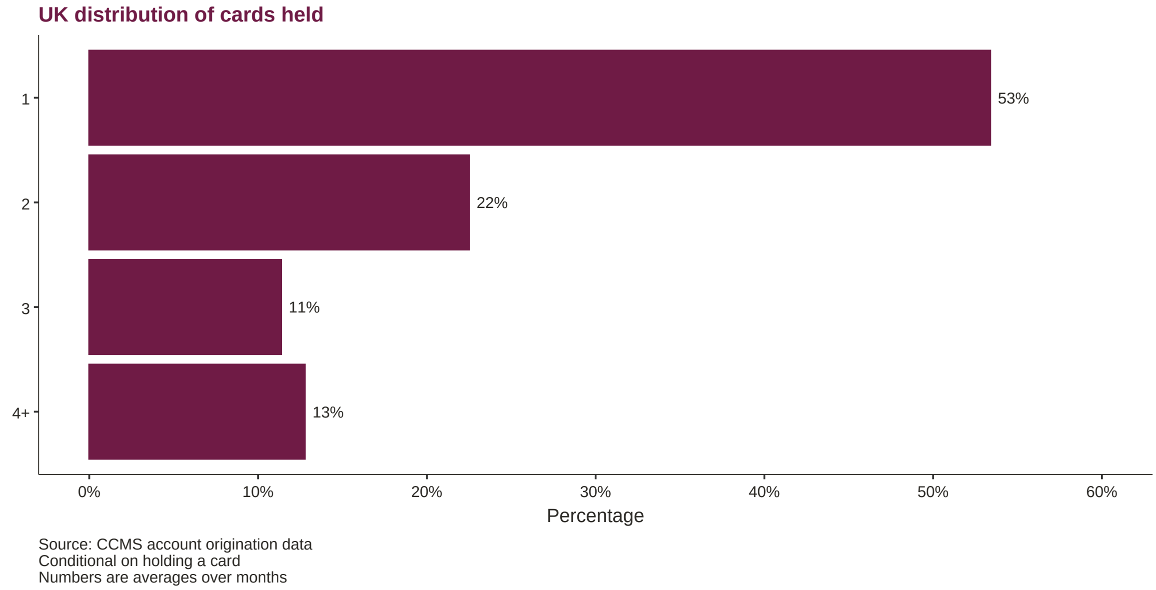
Figure H.2: Proportion of statements where full balance is repaid



Notes: I scramble lenders' identities to preserve anonymity, so labels do not necessarily match the identities in other tables and figures.

Link back to data section

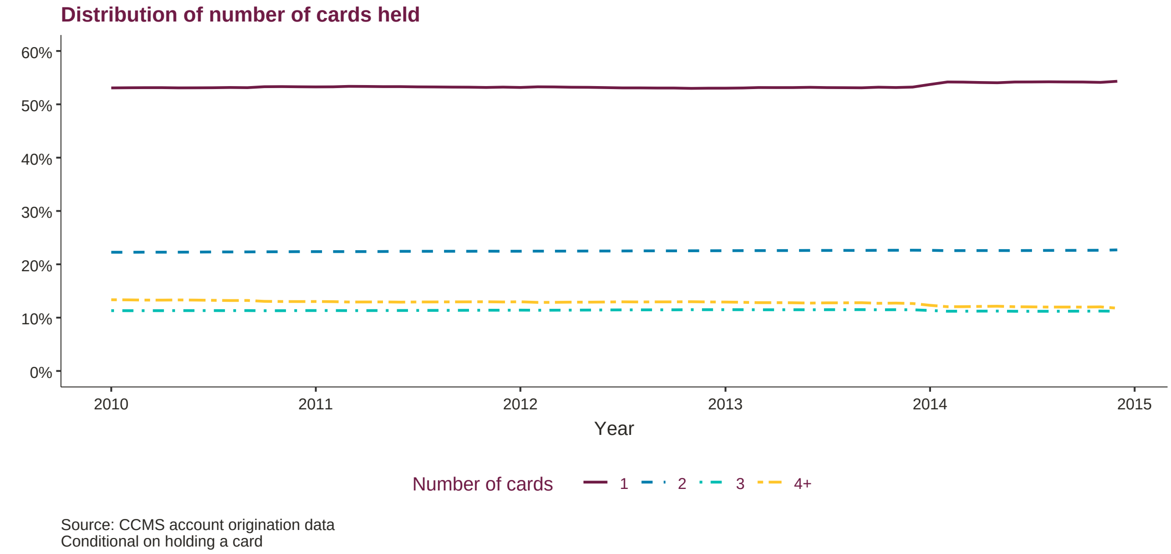
FIGURE H.3: Distribution of the number of cards



Notes: Distribution of the number of cards held by individuals with at least one credit card in the UK. I calculate the distribution using the CRA dataset described in text. I calculate the distribution of cards held, conditional on holding a card, in each month, and then average over months. Figure H.4 below shows the time series of the distribution, and its stability over time justifies averaging the distribution over months.

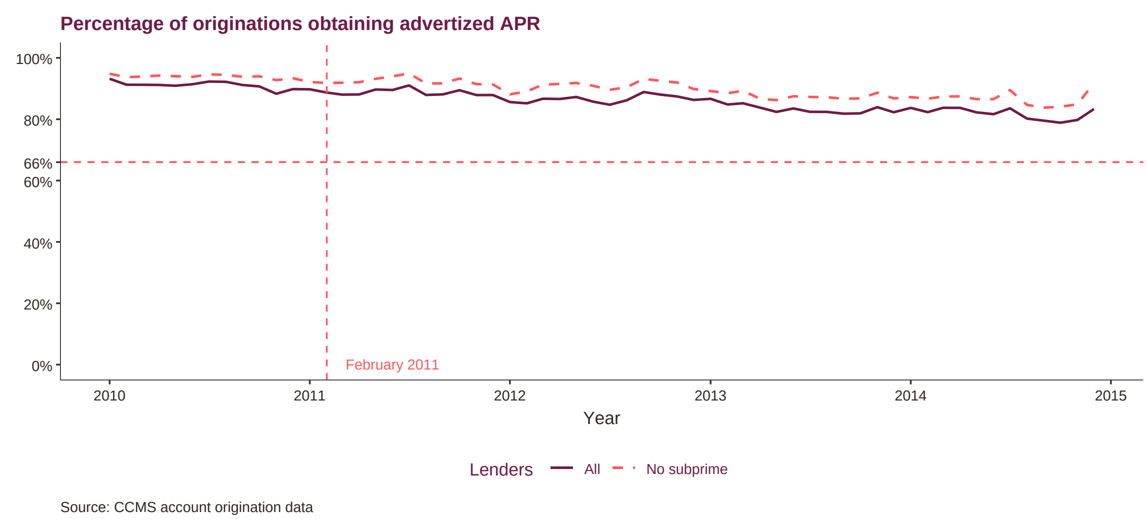
Link back to data section

Figure H.4: Distribution of the number of cards held by individuals over time



Notes: Time series of the UK distribution of number of cards, conditional on holding a card.

Figure H.5: Proportion of originations each month that obtain the advertised APR

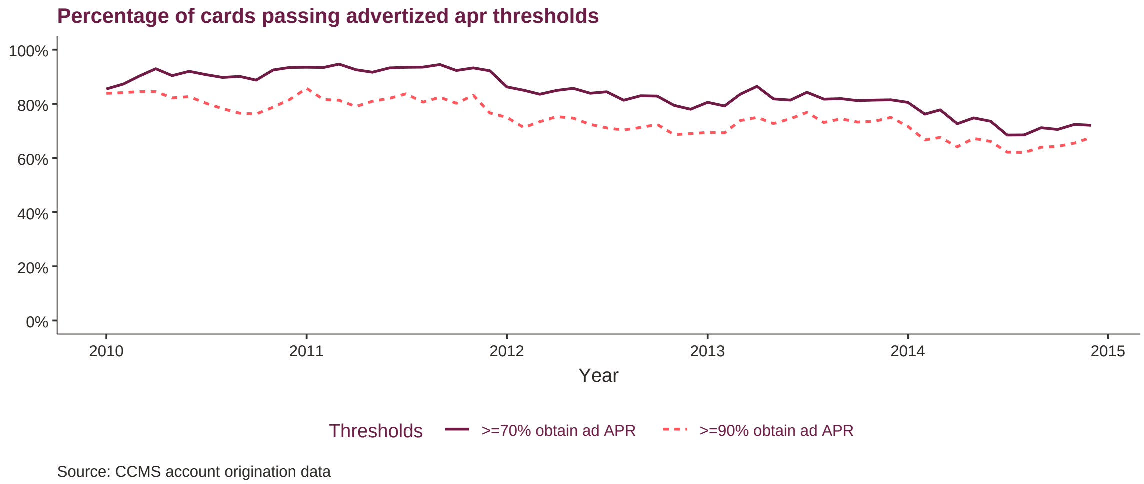


Notes: The solid line includes all lenders; the dashed line removes the two subprime lenders discussed in text. The proportion did not change in February 2011 when regulation on the proportion required to obtain the advertised APR or below fell from 66% to 51%.

Link back to descriptive findings

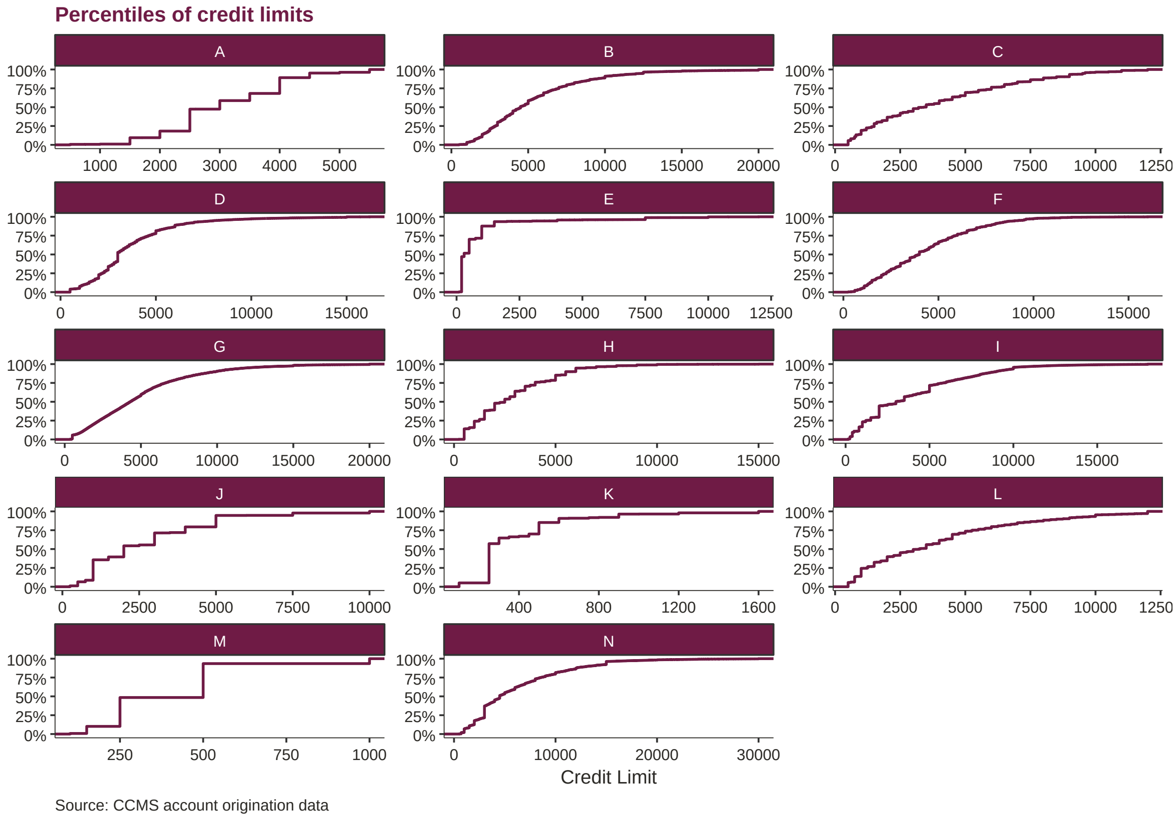
Link back to subprime discussion

FIGURE H.6: Proportion of cards each month that give at least 70% (solid) and 90% (dashed) the advertised APR



Link back to descriptive findings

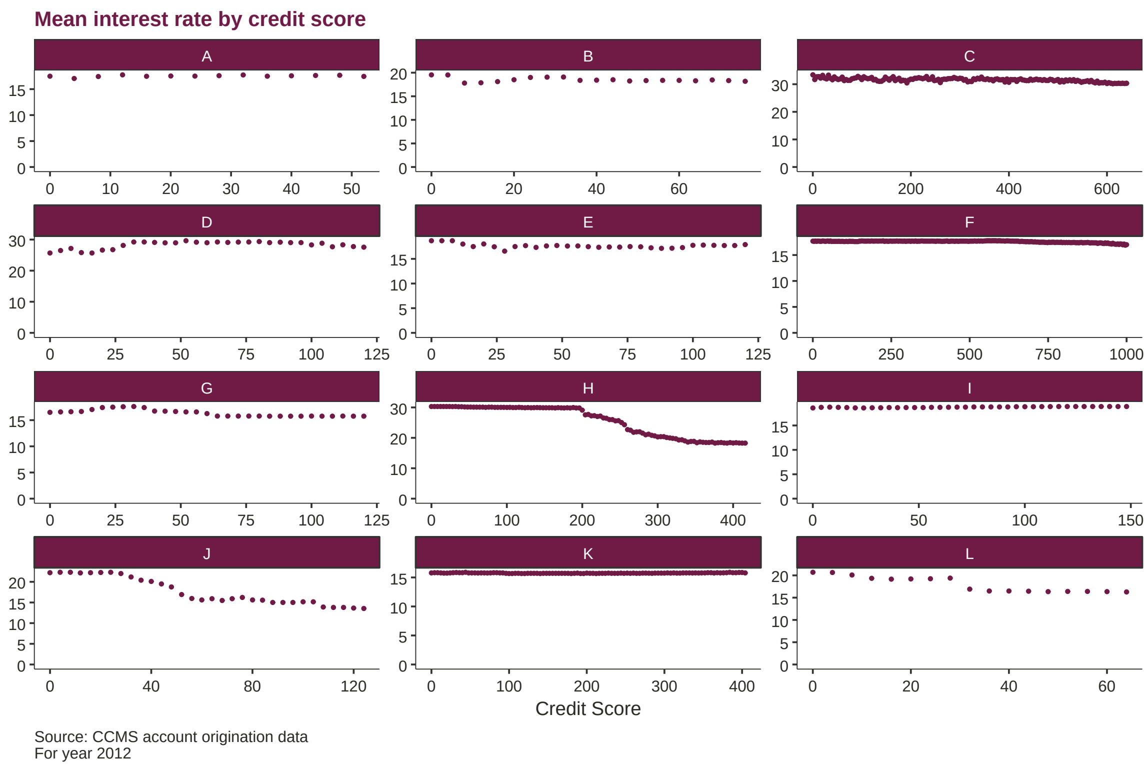
Figure H.7: Empirical CDFs of credit limits at all lenders, pooled over time



Notes: I scramble lenders' identities to preserve anonymity, so labels do not necessarily match the identities in other tables and figures.

Link back to descriptive findings

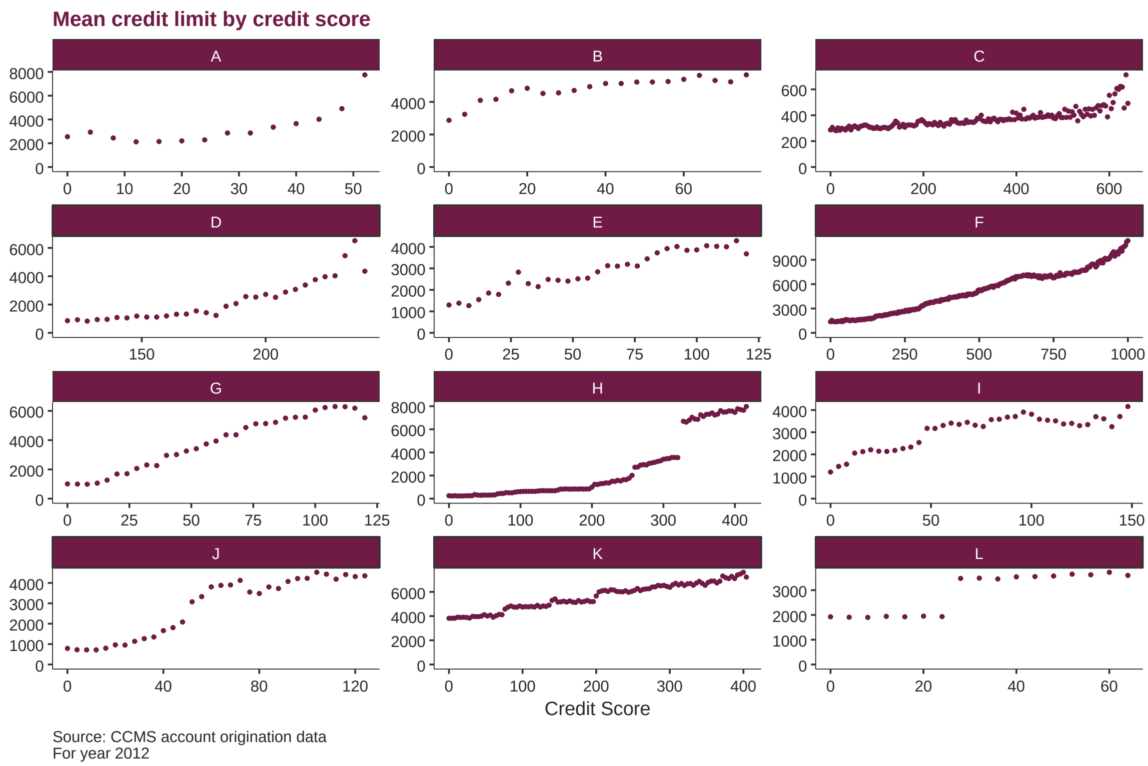
FIGURE H.8: Mean interest rates across lenders' risk scores



Notes: I scramble lenders' identities to preserve anonymity, so labels do not necessarily match the identities in other tables and figures. Credit score scales differ across lenders so cannot be compared. Credit scores are not available at two lenders.

Link back to descriptive findings

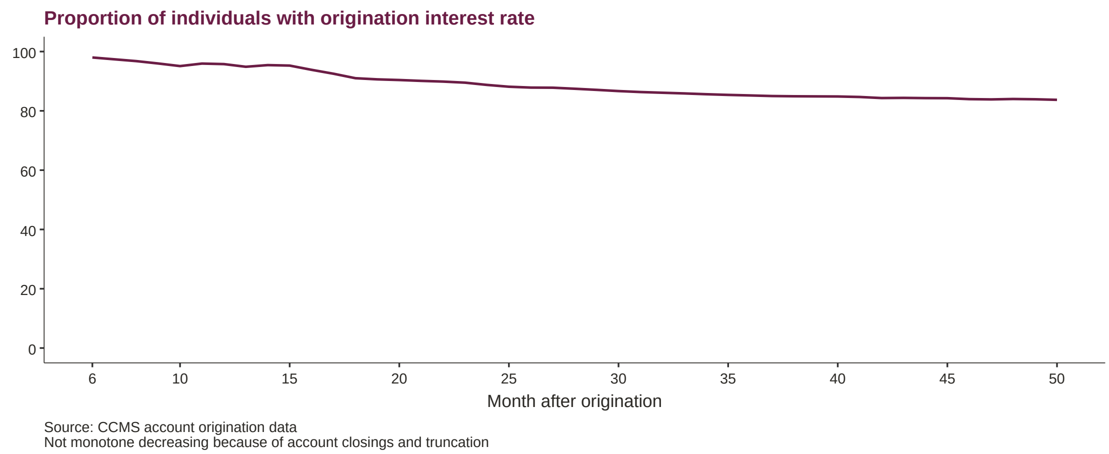
Figure H.9: Mean credit limits across lenders' risk scores



Notes: I scramble lenders' identities to preserve anonymity, so labels do not necessarily match the identities in other tables and figures. Credit score scales differ across lenders so cannot be compared. Credit scores are not available at two lenders.

Link back to descriptive findings

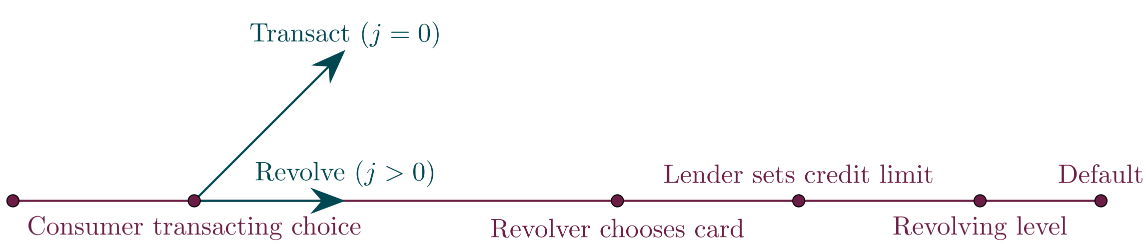
Figure H.10: Percentage of cards with origination interest rate by month after origination



Notes: The line is marginally updward sloping at points because of account closings and the truncation caused by statement data ending in January 2015.

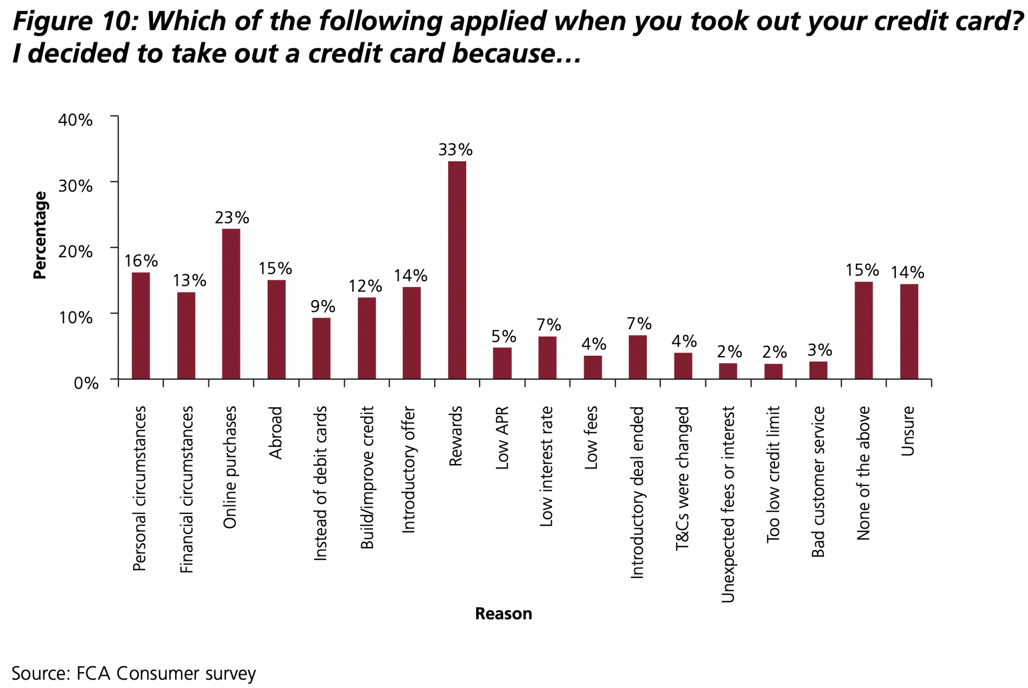
Link back to repricing discussion

Figure H.11: Model timeline within a market



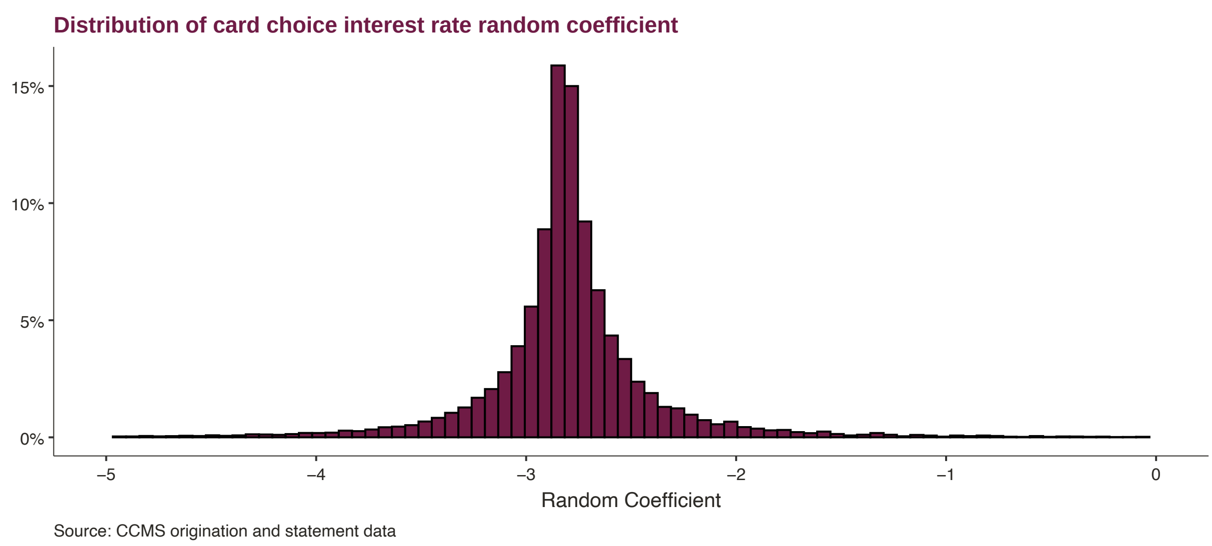
Link back to model section

Figure H.12: Answers to question on reasons for taking out a credit card



Link back to card utility discussion

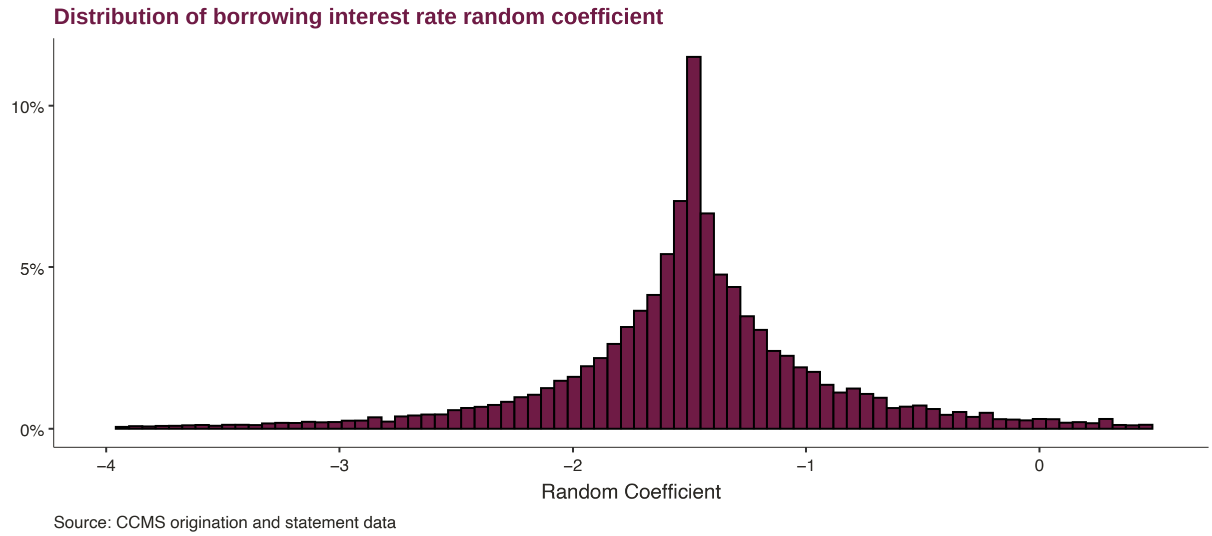
Figure H.13: Histogram of card choice interest rate random coefficient



Notes: I plot the estimated distribution of α_{imt}^{E}, defined in equation (3).

Link back to demand estimates discussion

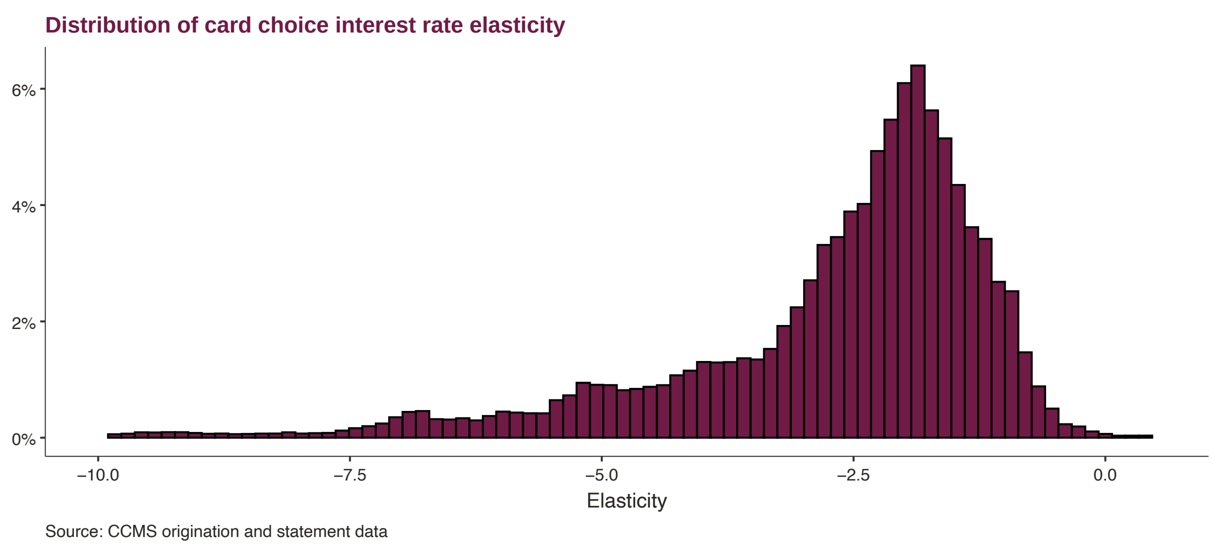
Figure H.14: Histogram of borrowing interest rate random coefficient



Notes: I plot the estimated distribution of α^B_{imt}.

Link back to demand estimates discussion

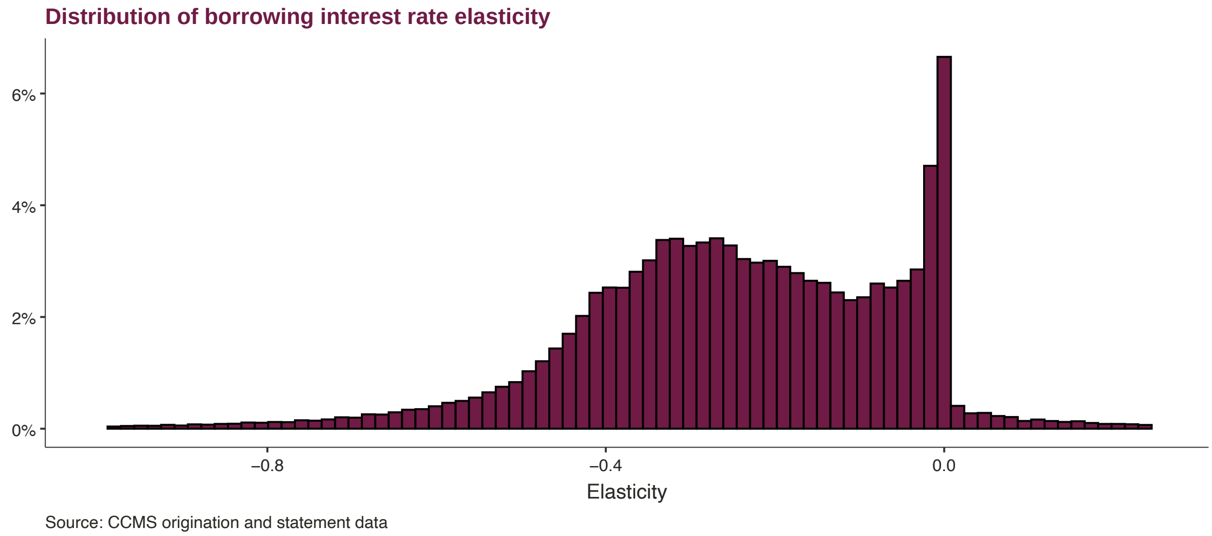
Figure H.15: Histogram of revolvers' interest rate elasticity for card choice



Notes: Equation (21) defines card choice elasticity.

Link back to demand estimates discussion

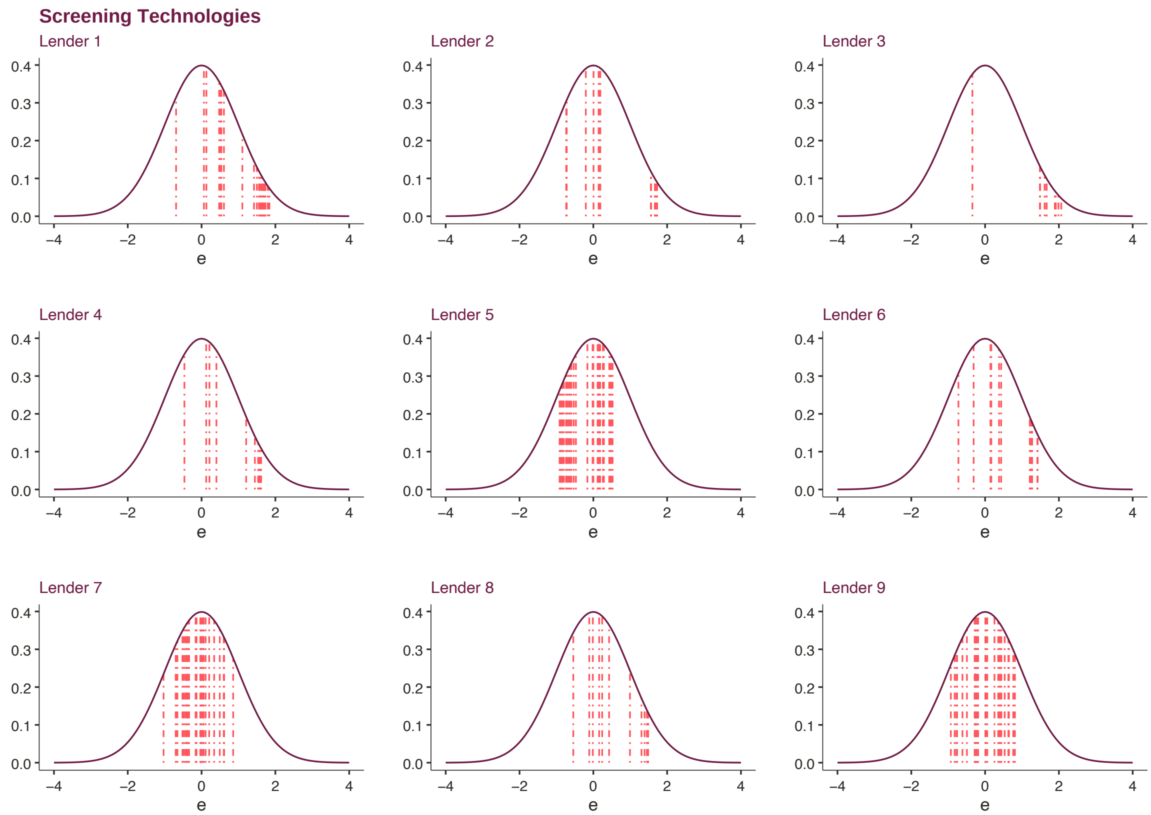
Figure H.16: Histogram of revolvers' interest rate elasticity for borrowing levels



Notes: Equation (19) defines borrowing elasticity.

Link back to demand estimates discussion

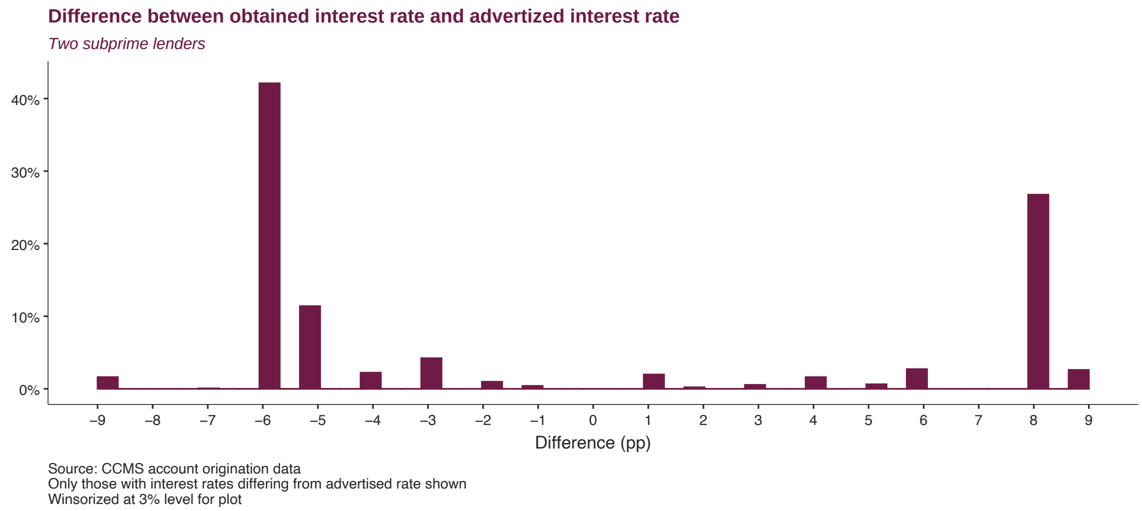
FIGURE H.17: Screening technologies at prime and superprime lenders



Notes: I scramble lenders' identities to preserve anonymity, so labels do not necessarily match the identities in other tables and figures.

Link back to supply estimates

Figure H.18: Histogram of differences between obtained APR and advertised APR at two subprime lenders (conditional on not obtaining advertised APR)



Link back to subprime discussion

H.2 Tables

Link back to descriptive findings section

Table H.1: Interest rate and credit limit variation by lender

	Interest Rate				Credit Limit				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Bank	**C. of V.**	**75/25**	**90/10**	**Within**	**C. of V.**	**75/25**	**90/10**	**Within**	**Share**
A	0.11	1.19	1.32	20.45	0.78	3.28	8.98	88.53	2.2
B	0.15	1.25	1.39	45.62	0.79	4.57	11.74	77.89	8.27
C	0.22	1.29	1.59	18.63	0.84	4.45	16.18	71.11	21.79
D	0.14	1.02	1.66	23.13	0.74	3.87	9.76	73.92	3.16
E	0.11	1.09	1.27	44.72	0.76	3.12	10.36	82.38	8.36
F	0.12	1.11	1.21		0.59	2.65	6.08		5.98
G	0.12	1.06	1.32	0.00	1.64	4.71	9.99	24.97	8.48
H	0.06	1.11	1.15	0.99	0.66	2.07	5.18	98.57	11.35
I	0.23	1.53	1.77	66.07	0.76	4.44	10.83	92.51	5.11
J	0.08	1.03	1.15	19.15	0.66	2.42	5.37	91.31	9.49
K	0.08	1.01	1.17		0.32	1.51	2.39		4.36
Subprime 1	0.19	1.41	1.42	83.68	0.51	2.00	2.68	88.62	8.78
Subprime 2	0.15	1.31	1.49	96.48	0.70	1.77	2.97	97.38	2.66
Mean	0.14	1.19	1.38	38.08	0.75	3.14	7.88	80.65	-
Weight Mean	0.14	1.19	1.38	31.22	0.78	3.34	9.15	78.28	-
NS Mean	0.13	1.15	1.36	26.53	0.78	3.37	8.81	77.91	-
NS Weight Mean	0.14	1.17	1.37	23.09	0.81	3.52	9.98	76.47	-

Notes: "Share" column reports share of originations; "C. of V." columns report coefficients of variation; "75/25" and "90/10" columns report 75^{th} to 25^{th} and 90^{th} to 10^{th} percentile ratios respectively; "within" columns report the ratio of within to total variation, in percentage terms. All values are averages over months. Weighted mean is weighted by number of originations. NS stands for "no subprime", and NS means calculate the mean omitting the subprime lenders. Missing values of within correspond to lenders who only offer one card. Lenders' identities are scrambled for confidentiality reasons and do not necessarily match the identities in other tables and figures. Shares may not add up to 100 because of rounding.

Table H.2: Tests for equality of lenders' credit limit distributions

Test	p-value
Anderson-Darling Version 1	0.00
Anderson-Darling Version 2	0.00
Rank Score Version 1	0.00
Rank Score Version 2	0.00

Notes: p-values from a collection of tests for the equality of lenders' credit limit distributions. p-values are averages over months of the test statistic calculated on the month-by-month credit limit distributions using a random sample of size 1 million. The Anderson-Darling version 1 (respectively 2) test statistic is A^2_{kN} (respectively $A^2_{\alpha kN}$) in Scholz and Stephens (1987). The Rank Score test statistic is QN in Lehmann (2006) and Sidak, Sen, and Hajek (1999), where versions 1 and 2 use integer scores and van der Waerden scores respectively. See Scholz and Zhu (2019) for more details.

Link back to descriptive findings section

Table H.3: Percentage of cards retaining origination interest rate by month after origination

Month after origination	Cards not repriced (%)
6	98.00
9	95.98
12	95.77
15	95.27
18	91.01
21	90.11
24	88.75
27	87.81
30	86.67

Notes: I calculate the proportion of cards that have the same interest rate as they received at origination, for $t = 6, 9, 12, \ldots, 30$ months after origination.

Link back to descriptive findings section

Table H.4: Variable glossary: Latin

Letter	Meaning
b	Observed borrowing
b^*	Desired borrowing
$\bar{b}$	Credit limit
B	Borrowing symbol
c	Funding rate (marginal cost)
D	Default symbol
e	lender signal
E	Extensive margin symbol
F	Inclusive value
h	Halton draw dummy
H	Number of Halton draws
i	Credit card origination
I	Number of originations
j	Card
J	Number of cards
ℓ	Lender
L	Number of lenders
m	Distribution channel
M	Number of channels
r	Interest rate
s	Market share
t	Origination month
T	Number of origination months
u	Individual-specific terms in indirect utility
$\bar{U}$	Scaled indirect utility
$\bar{V}$	Indirect utility
V	Utility
w	Signaling error
X	Card characteristics
y	Logged income
$\tilde{y}$	Centered logged income
$\underline{Y}$	Minimum income threshold

Link back to model section

Table H.5: Variable glossary: Greek

Letter	Meaning
α	Interest rate sensitivity
β	Rewards sensitivity
δ	Card-market fixed effect
Δ	Default probability
ε	Individual unobserved characteristics
ζ	Transactor dummy
η	Market fixed effect
ν	Generalized Type-1 EV shocks
ξ	Unobserved card characteristics
π	Profit per unit credit
Π	Total profit
ρ	Correlation
ϱ	ν substitution parameter
σ	Standard deviations
ϕ	Standard normal PDF
Φ	Standard normal CDF
ψ	Proportion of default debt recovered
Ω	Demographic random coefficient

Link back to model section

Table H.6: Third step demand estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variable	δ^B	δ^B	δ^E	δ^E	δ^E	δ^E	δ^E	δ^E	δ^E
Price Sensitivity (α)	2.626	-1.489	1.083	-1.277	-0.934	-1.238	-3.264	-0.901	-2.825
	(0.369)	(1.71)	(0.269)	(0.804)	(0.831)	(0.793)	(0.904)	(0.815)	(0.834)
Airmiles (β_{airmiles})					0.121			0.124	0.266
					(0.048)			(0.049)	(0.042)
Cashback (β_{cashback})						0.059		0.072	-0.026
						(0.069)		(0.070)	(0.056)
Contactless ($\beta_{\text{contactless}}$)							0.178		0.270
							(0.035)		(0.075)
Estimation	OLS	IV	OLS	IV	IV	IV	IV	IV	IV
First-stage F	-	22.870	-	21.912	20.562	22.416	19.540	21.508	20.007
Wu-Hausman	-	30.120	-	13.410	4.653	9.196	32.177	4.699	22.316

Notes: This table provides the estimates and bootstrapped standard errors of the demand parameters recovered in the third stage of demand estimation. In IV specifications I use a cost shifter as excluded instrument for interest rate. I include distribution-month, and network fixed effects in all regressions.

Link back to parameter estimates section

Table H.7: Summary statistics on credit card originators

Variable	Mean	SD	10%	25%	50%	75%	90%
Age	42.88	14.83	25.00	31.00	41.00	53.00	64.00
Net Monthly Income (£)	2099.26	5185.72	630.00	1058.56	1604.14	2335.00	3393.00
Existing Customer	0.40	0.49					
Female	0.52	0.50					
Homeowner	0.57	0.50					
Direct Debit	0.18	0.38					
Employment							
Employed	0.76	0.43					
Self-Employed	0.09	0.29					
Unemployed	0.01	0.10					
Retired	0.12	0.33					
Student	0.01	0.12					
Channel							
Branch	0.32	0.46					
Online	0.53	0.50					
Post	0.12	0.32					
Telephone	0.04	0.20					

Notes: Monthly income is net of tax. Homeownership is equal to one if the individual owns a house (with a mortgage or without) at origination. Categorical variables' means may not add to 1 because of rounding.

Link back to summary statistics description

Table H.8: Summary statistics of card features at origination

Variable	**Mean**	**SD**	**10%**	**25%**	**50%**	**75%**	**90%**
Credit Limit (£)	3390.33	3144.37	300.00	1000.00	2500.00	5000.00	7700.00
Purchase APR (%)	21.52	7.64	15.76	16.90	18.90	23.95	31.11
BT APR (%)	20.24	5.28	15.90	17.50	18.90	20.90	30.33
Purch Promo Length	3.57	4.71	0.00	0.00	3.00	6.00	13.00
BT Promo Length	9.21	8.71	0.00	0.00	9.00	15.00	21.00
Balance Transfer	0.28	0.45					
Get Advertised APR	0.83	0.37					

Notes: Unit of observation is the credit card origination (i). "Balance Transfer" is equal to one if the originator transferred a balance from another card onto this newly originated card at origination. Promotional lengths are in months. Purchase (respectively BT) promo are equal to one if the originated card had a purchase (respectively balance transfer) promotional period. "Get Advertised APR" is a dummy equal to one if the individual obtains the APR advertised in the promotional materials.

Link back to summary statistics description

Table H.9: Summary statistics for card characteristics

Variable	Mean	SD	10%	25%	50%	75%	90%
Annual fee	10.34	37.37	0.00	0.00	0.00	0.00	24.00
Min income	6463.20	8356.91	0.00	2.08	4000.00	7500.00	20000.00
Min credit limit (£)	463.09	516.11	100.00	200.00	450.00	500.00	1000.00
Max credit limit (£)	19881.44	30651.74	1000.00	3000.00	15000.00	20000.00	30000.00
Interest free days	31.29	12.92	20.00	25.00	25.00	46.00	50.00
Eligibility							
Student Only	0.05	0.21					
Employed Only	0.07	0.26					
All	0.88	0.32					
Risk Segment							
Superprime	0.02	0.15					
Prime	0.51	0.50					
Subprime	0.21	0.40					
All	0.26	0.44					
Rewards							
Affinity	0.25	0.43					
Credit repair	0.21	0.41					
Cashback	0.09	0.29					
Purch protection	0.25	0.44					
Contactless	0.48	0.50					
Purchase rewards	0.34	0.47					
Airmiles	0.07	0.26					
Insurance	0.14	0.35					
Priority	0.12	0.32					

Notes: Unit of observation is the card-month (jt). Reward variables are all equal to one if the card-month offers the reward. Categorical variables' means may not sum to 1 because of rounding.

Link back to summary statistics description

Table H.10: Summary statistics on credit card statements

Variable	**Mean**	**SD**	**10%**	**25%**	**50%**	**75%**	**90%**
Credit Limit (£)	4213.90	3459.56	500.00	1600.00	3500.00	5900.00	9000.00
Purchase APR (%)	16.46	8.10	0.00	15.70	17.50	18.94	29.90
Account Balance (£)	1224.25	1956.57	0.00	0.00	395.12	1593.46	3669.04
Purchase Balance (£)	611.67	1255.25	0.00	0.00	75.95	660.18	1820.31
Value Transactions (£)	311.19	802.62	0.00	0.00	0.00	259.85	880.38
Repayment (£)	224.69	637.35	0.00	0.00	30.02	150.00	569.40
Total Interest (£)	8.23	20.52	0.00	0.00	0.00	6.01	26.58
Purchase Interest (£)	6.39	17.60	0.00	0.00	0.00	3.30	20.51
Account Status							
Up-To-Date	0.94	0.23					
1 Month Overdue	0.02	0.14					
2 Months Overdue	0.00	0.06					
3 Months Overdue	0.00	0.05					
4 Months Overdue	0.00	0.04					
5+ Months Overdue	0.00	0.06					
Charged Off	0.02	0.15					

Notes: Unit of observation is the statement-month. Account balance includes purchase, cash advance, money transfer, and balance transfer balances. Total interest includes purchase, cash advance, money transfer, and balance transfer interest. The variables 2 Months overdue to 5+ Months Overdue are zero rounded to 2 decimal places. Categorical variables' means may not sum to 1 because of rounding.

Link back to summary statistics description