Risk-Based Quantity Limits in Credit Card Markets*

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Abstract

Credit card lenders primarily individualize contracts through risk-based credit limits, not interest rates. To understand lenders' choice of credit limits, 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 the shape of lenders' credit limit distributions through a screening technology, which gives lenders a noisy signal of customers' risk. I identify model parameters using novel quasi-experimental variation in interest rates resulting from the April 2011 High Court case on the mis-selling of payment protection insurance. I use the estimated model to evaluate a counterfactual where lenders can freely individualize interest rates and credit limits, which the existing environment precludes. Individualized interest rates and credit limits emerge, profits increase on average, and borrowing becomes more dispersed as a result.

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

JEL Classification: D22, D82, 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 the extreme case, market unraveling (Akerlof, 1970; Rothschild and Stiglitz, 1976). The consequences can be severe, with the failure of credit markets described as "one of the major reasons for under-development" (Akerlof, 2001).

In credit markets, lenders attempt to minimize the deleterious effects of adverse selection by tailoring contract characteristics to predictions of customers' default risk. On the other hand, governments aim to ensure that contracts are simple and transparent so that consumers are not misled and can search effectively across lenders. Resultantly, 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 price 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, a finding difficult to rationalize with standard economic theory alone. 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 or the result of costs and constraints that affect lenders' willingness and ability to tailor interest rates according to risk.

Studying credit card lenders' choices of risk-based credit limits and interest rates is important because of 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] As a result, lenders' credit limit and interest rate choices have material effects on individuals' financial well-being. This is

[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.

especially true for subprime consumers, who are more likely to be credit constrained.

To establish my findings, I use novel, statement-level, administrative data on approximately 80 percent 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 origination, so I can check credibly if interest rates and credit limits are risk-based.

Using the data, I document that credit limits vary substantially across originations within lenders and credit cards, with the highest risk scores corresponding to the lowest credit limits. On the contrary, 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 advertize one interest rate (APR) for each credit card and (ii) at least 51 percent of customers on each card are granted the advertized APR or lower at origination. Nevertheless, 80 to 90 percent of customers are granted the advertized APR at origination, implying that the regulatory constraint is not the sole explanation for the limited within-card 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.

Towards this, I construct and estimate a structural equilibrium model of the UK credit card market. My primary modeling novelty comes through the supply side. I endow each lender with a screening technology that generates a noisy signal on each individual's private type, which is their risk. Differences across lenders in the granularity of these signals explain differences in the shape of lenders' credit limit distributions. 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 present substantial variation in lenders' screening technologies, matching the variation in lenders' credit limit distributions. Also, I find that the precision of lenders' screening technology correlates negatively with the proportion of cases within lender where the customer pays the full balance. This finding is consistent with a segmentation of credit card lenders in which lenders with the least sophisticated screening technologies serve a safer segment of the market on average. Lenders with more precise screening technologies are more willing to serve customers who may default on a revolving balance because they can set lower credit limits for customers they perceive as riskier more accurately.

On the demand side, I model borrowers' credit card choice, level of borrowing, and default decision, 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' income. 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 High Court case on the mis-selling of Payment Protection Insurance (PPI). Credit card lenders were forced to re-compensate thousands of consumers where the Court deemed that 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 fact that the regulatory APR constraint does not bind either implies 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 any 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 the cross-subsidization from safer to riskier individuals is diminished. Further, I find that credit limits remain individualized, borrowing becomes more dispersed, and lender profits increase.

The counterfactual findings suggest that lenders face costs and constraints that limit their willingness to set individualized interest rates. I offer two potential examples. First, lenders may face reputational costs in advertizing one APR yet giving customers an alternative individualized APR. 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.

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 counterfactual analyses. Section 8 concludes.

2 Related Literature

This paper relates to several literatures, and I detail my contribution to the closest in what follows. I describe the vast literature on credit card markets 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 Agarwal, Chomsisengphet, Mahoney, and Stroebel (2017), which shows that average credit limits increase with 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. To the authors, risk-based credit limits are a means more than an end: their paper focuses on the pass-through of credit expansions to customers. My contribution to this literature is to estimate a model of lenders' credit limit choices. In the model, heterogeneous lender screening technologies, which provide noisy signals on customers' private risk, justify differences in the shape and scale of lenders' credit limit distributions and can explain discontinuities in credit limits shown in Agarwal, Chomsisengphet, Mahoney, and Stroebel (2017).[2]

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 the absence of it 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 on risk-based pricing in credit card markets is limited. 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 following the adoption of risk-scoring methods. A large

[2] 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.

part of the literature focuses on credit scores' predictive, *statistical* quality (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. They note that if risk scores determine contractual terms, then risk scores confound underlying default risk with endogenous responses to contractual terms. I contribute to this literature by estimating lenders' underlying screening technologies, which provide a signal of underlying unobservable risk on a harmonized scale.

Finally, I contribute 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. Related to my work, they show that risk-based interest rate caps cause less harm.

Nelson (2022) and Agarwal, Chomsisengphet, Mahoney, and Stroebel (2014) study the second related regulatory context: the 2009 US Credit Card Accountability, Responsibility, and Disclosure (CARD) Act. Agarwal, Chomsisengphet, Mahoney, and Stroebel (2014) documents substantial consumer savings from the Act. Nelson (2022) focuses on how the Act limited lenders' ability to reprice credit card customers after origination. The estimated economic model implies that consumer surplus rose at the expense of lender profits. In my paper, I focus entirely on ex-ante risk-based pricing. Though I acknowledge the possible role of ex-post risk-based pricing, it is limited in the United Kingdom, 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 base prices on risk freely in the context of endogenous risk-based credit limits, in which risk-based interest rates emerge.

3 Data and Descriptive Findings

I start 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.[3] The FCA used its legal authority as the regulator of UK financial markets to obtain data on all credit cards active at 14 lenders between 2010 and 2015.[4] The data cover approximately 80 percent of the universe of cards active in 2010-2015, including 74 million cards. The CCMS databases are only available to restricted staff and associated researchers at the FCA. I summarize its three main databases in turn. I describe broader summary statistics of the data in Appendix B, where for example, I provide evidence that rewards are generally rare on UK credit cards relative to the US.

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 their card's interest rate and credit limit. The handiest feature of this dataset, however, is the lender-specific risk scores.

Documenting that credit limits are risk-based rather than interest rates is the foundation of my analysis. As a result, I need observations on 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.[5] As such, it is critical that I have available observations on 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. Public risk scores only explain a moderate proportion of the variation in lenders' 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. From these regressions, the proportion of variation explained is 21% on average.

The use of proprietary risk scores rather than public risk scores in the UK credit card market differs from the US, where FICO scores offer a measure of customer creditworthiness that

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

[4] 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.

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

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 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 can access.

Statement data

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 (implying 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 by which payment is overdue. In the event of numerous failures to repay, the lender charges off the account, which the dataset also details. Finally, these data contain observations on lenders' costs of servicing the account, including typically-unobserved funding costs and provisions for non-repayment of debt at the *statement* level.

Based on these data, I find substantial variation across lenders in the proportion of statements on 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 cards' 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 advertized Annual Percentage Rate (APR). With this variable, I calculate differences between advertized and obtained APR, which gives the intensive and extensive margins of risk-based pricing. At this point, a brief digression to explain the legal implications of advertized APRs is appropriate. I describe the UK and US APR regulations in more depth in Appendix C.

All UK credit card promotional material and documentation must include a "representative" APR. Before February 2011, at least 66 percent of customers each month had to obtain the advertized APR or lower. The regulation changed in February 2011 when the UK harmonized with the EU to reduce the threshold to 51 percent and has not changed since.

Other Sources

The CCMS data include a credit reference agency (CRA) dataset that matches cards to individuals. These data allow me to focus on those currently without an existing credit card when they originate. The CRA data confirm that, on average, UK adults hold fewer cards relative to the US population, with the majority holding only one card (see Figure H.3 and FCA (2015a)). Estimating my model on the sample currently without a credit card circumvents complications arising from (1) balance transfers and (2) 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 Descriptive Findings

The single aim of this subsection is to show robustly that the leading UK credit card lenders individualize credit card contracts through risk-based credit limits rather than interest rates. In what follows, most of the analysis is conducted within-lender or within-card. However, it is worth noting that even when pooling across all lenders and months, credit limits are much more dispersed than interest rates. The coefficient of variation (the ratio of standard deviation to mean) in credit limits is equal to 93 percent, compared to a value of 36 percent for interest rates.

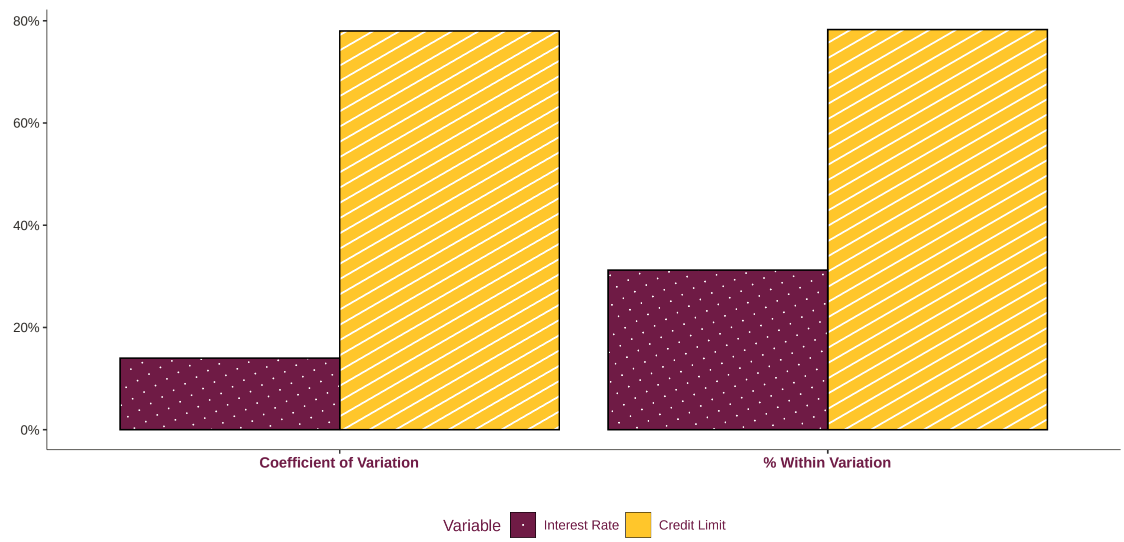
3.1.1 Limited Variation in Lenders' Interest Rates

Limited Total Variation

I start by documenting limited variation in lenders' interest rates across originations within a month. Table H.1 column (1) reports the average (over months) of lenders' interest rate coefficient of variation.[6] The values are below 23 percent, 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 percent. This implies that the standard deviation in interest rate is,

[6] 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 $\mathrm{sd}^2_{\ell t} = \frac{1}{I_{\ell t}} \sum_j \sum_i (r_{ij\ell t} - \bar{r}_{\ell t})^2$, and $I_{\ell t}$ is the total number of originations. The value in column (1) of Table H.1, for lender ℓ is $cv_{r\ell} = \frac{1}{T_\ell} \sum_t \dfrac{sd_{r,\ell t}}{\bar{r}_{\ell t}}$, 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 over origination share) of the lender-specific averages for the prime and superprime lenders.

on average, one-seventh 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 75^{th} to 25^{th} percentile (respectively 90^{th} to 10^{th}) 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 variation in interest rates is within credit card rather than across. 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 $V_{\ell t}^{B}$

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

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 $s_{j\ell t} = \dfrac{I_{j\ell t}}{I_{\ell t}}$ 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 percent of the total variation.[7] 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 percent of customers on a given credit card the same interest rate in *all* months so that practically all variation in interest rates at origination is at the card level.

Proportion Obtaining Advertized APR

To explain the lack of within-card variation in interest rates, I calculate the monthly percent of customers obtaining the advertized APR and plot its value in Figure H.5. The value across all credit cards in the sample hovers around 80 to 90 percent and it does not change in February 2011 when regulation on advertized APRs was relaxed. Even though regulation required lenders to give only 51 percent of their customers the advertized APR after February 2011, most lenders still gave almost all customers the advertized APR.[8] Further, Figure H.6 plots the proportion of *cards* giving at least 70 percent (solid) and 90 percent (dashed) of customers the advertized APR at origination in each month. Each month, around 85 percent of cards give at least 70 percent the advertized APR, and in 77 percent of card-months, over 90 percent of originations obtain the advertized APR. These statistics confirm that most *cards*, not just *lenders*, give the majority of their consumers the advertized APR. I embed this feature into my economic model by making borrowers' preferences over a credit card depend on card-level APRs, abstracting from the minimal within-card variation in interest rates.

I summarize my 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 percent of customers obtain the advertized APR at origination each month corroborates the limited within-card variation in interest rates.*

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

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

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 percent, it is over five times larger than the interest rate equivalent. As reported in columns (6) and (7) of Table H.1, the across-lender weighted average of 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 credit limits within each lender.

Substantial Within Variation

I perform the same within-card and between-card decomposition as in (1) for credit limits. Across lenders, as shown in the right-hand gold striped bar in Figure 1, the average percent of total variation found within credit cards is 81 percent. The lack of between variation suggests that lenders do not sort individuals onto cards of varying average credit limits.

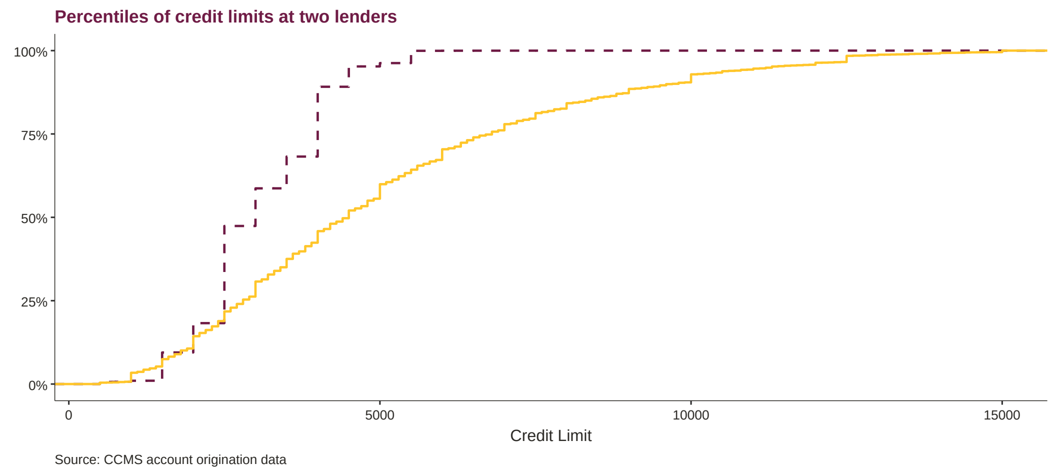
Shape and Scale of Credit Limit Distributions

The distribution of credit limits varies substantially across lenders in both shape and scale.[9] In Figure 2, I plot the empirical cumulative distribution function (CDF) of credit limits for two contrasting lenders. Two substantial differences are evident. The first relates to differences in the scale of the credit limit distributions. Credit limits at the golden solid lender are generally larger. The golden solid lender's credit limit distribution stochastically dominates that of the maroon dashed lenders for most of the distribution. All percentiles after the 25^{th} are larger at the golden solid lender relative to the maroon dashed lender. The second difference relates to the *shape* of the credit limit distributions. The maroon dashed lender's curve is step-like, implying a coarse process of assigning credit limits to individuals. The golden solid lender's smooth curve suggests a more finely tuned allocation mechanism for origination credit limits. Other lenders' credit limit empirical CDF at origination, which are plotted in Figure H.7, lie between the two in Figure 2. This range in shape and scale of distributions is consistent with lenders who vary in their coarseness of credit limit assignment.[10] Some

[9] 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 percent significance levels in all tests.

[10] 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



lenders offer large groups of customers the same credit limit, whereas others with smoother CDFs adjust their credit limits to each customer.

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

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

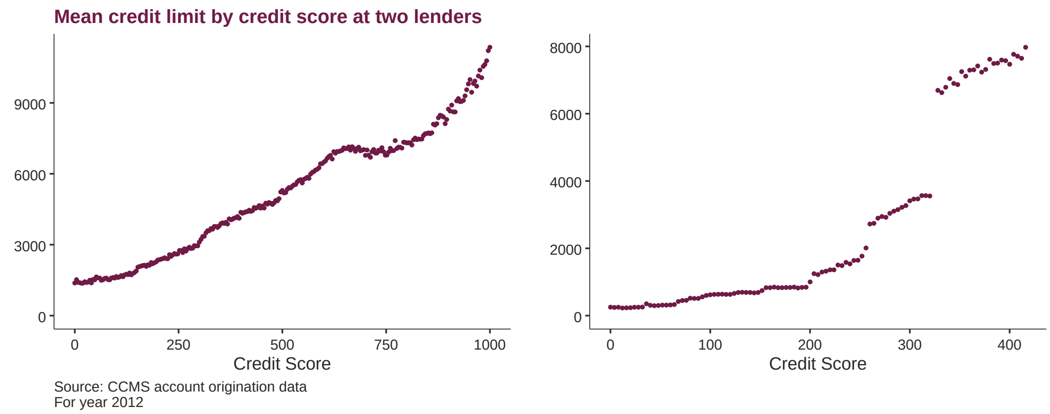
Since interest rates rarely vary within a credit card-month, they are unlikely to relate strongly to customers' default risk. I confirm this in Figure H.8, where most lenders' average interest rates are flat across the application risk score support. Exceptions exist for two subprime lenders, who, as 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.[11] In the period I study, there was limited repricing in the UK credit card markets. As detailed in Table H.3 and shown in Figure H.10, lenders reprice only 4 percent 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 origination credit limit along application credit scores for two

[11] 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.

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



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

contrasting lenders.[12] Optically, both curves are upward sloping, consistent with risk-based credit limits. Further, the left-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. The overarching aim of my model is to rationalize discreteness and discontinuities in lenders' credit limit distributions. 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. There is heterogeneity in how lenders map their credit scores into credit limits: some lenders exhibit discontinuities in their credit limits at certain credit score thresholds.*

[12] In Figure H.9, I plot the mean of origination credit limit for each lender, along application credit scores. In unreported plots, the same patterns emerge when produced by-month.

3.2 Implications of Descriptive Findings

This section revealed that the leading UK credit card lenders set card-level interest rates and individualize credit limits according to their assessments of customers' risk. Credit card regulation, which demands an advertized APR that most customers must obtain, rationalizes these findings. The next step is to learn about how lender heterogeneity and the regulatory environment impact and explain these findings. 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 follows next.

4 A Model of the Credit Card Market

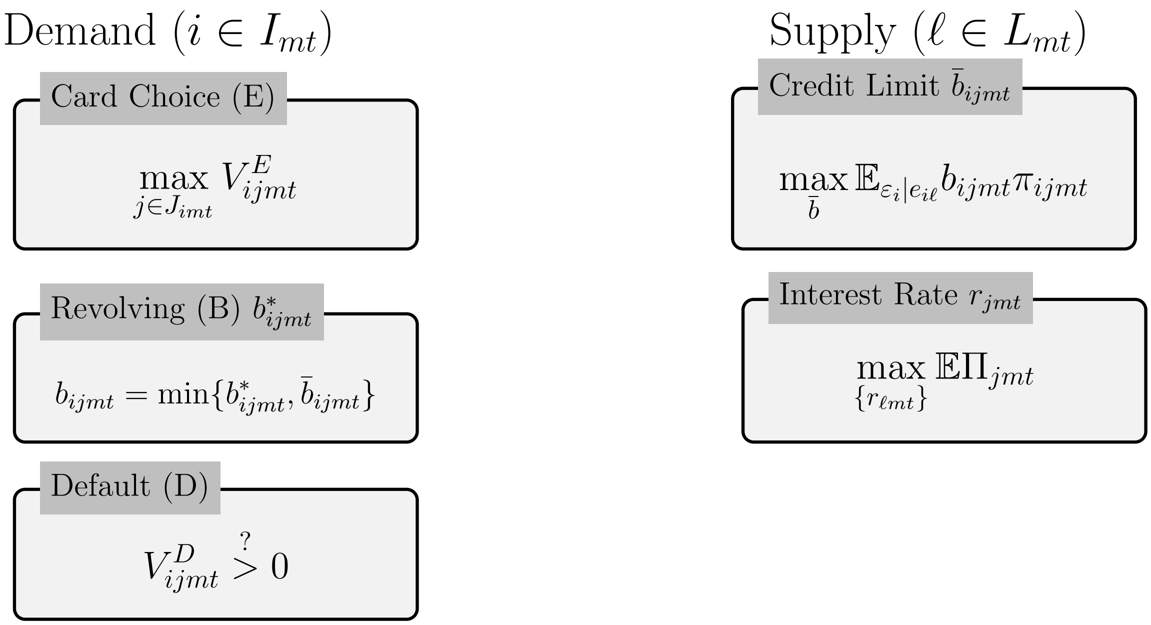
Now, I present a model of the UK credit card market. To help navigate the model, Tables H.4 and H.5 provide a glossary of notation and Figure H.11 depicts a timeline.

The market is a pair (m, t). Here t represents an origination month between January 2010 to June 2013, and m represents the distribution channel, split between those occurring in store and out of the store.[13] 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, the majority of UK adults hold only one credit card. Second, estimating my model on the sample currently without a credit card circumvents complications arising from (1) balance transfers and (2) balance matching heuristics in repayment across multiple cards (Gathergood, Mahoney, Stewart, and Weber, 2019). Figure 4 summarizes the building blocks of the model.

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, which are 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 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

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

Figure 4: Model overview



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.

4.1 Credit Card

Following Lancaster (1966), I model a credit card as a bundle of characteristics. There are four components. The first is the interest rate r_{jmt}. The second component is the income threshold $\underline{Y}_{jmt}$, explained in section 4.2. The third and fourth are characteristics: those I observe, denoted X_{jmt} (cashback and air miles), and those I do not, ξ_{jmt} (prestige and brand loyalty).

4.2 Consumer

My demand model is deliberately simple, with flavors of Crawford, Pavanini, and Schivardi (2018).[14] 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.

4.2.1 Card Choice

In the first nest, consumers choose whether to 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.[15] 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 parts of observed card characteristics 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.13 from the FCA Credit Card Market Study presents the results

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

[15] 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 percent have set up a direct debit, rising to 34 percent by six months. Of those who set up a direct debit at origination, around 40 percent 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 percent who set up a direct debit for an amount less than the full balance, 77 percent set up a direct debit to pay the *minimum repayment*, which is usually the maximum of (1) 1-2.5 percent of the balance, and (2) £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 percent 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 percent), “low fees (4 percent), and “good deal offered” (13 percent), 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

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

The random coefficient α^E_{imt} represents preferences over interest rates. Heterogeneous preferences over interest rates read[16]

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

implying that card-choice preferences over interest rate depend on individuals' income.

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 $\underline{Y}_{jmt}$; I discuss the rationale for lenders' use of income thresholds in 4.3. Resultantly, the set of cards available to customer i is

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

The utility from **transacting**, also linearized, is $V^E_{i0mt} = \delta_{0mt} + \nu_{i0mt} + \Omega^{E,cons}_{mt} y_i$, where δ_{0mt} is a market-level constant of transacting utility. If the individual chooses to borrow, they choose

[16]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 on 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.

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 $V^E_{ij^*mt}$.

4.2.2 Revolving

Next, **revolvers** choose their level of borrowing. Denote by b^*_{ijmt} the *desired* level of borrowing, which is their 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:

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

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 4.2.4.

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 ex-ante credit limits are consumers' overall borrowing over the 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 in a two-period consumption-savings model, or as a summary statistic (such as an average) of multiple choices of borrowing.[17] In either case, my setup does not require a model of multiple values of borrowing across periods as implied by a consumption-savings problem. Modeling a summary statistic of borrowing is a clear profitable abstraction for my context.[18]

[17]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.

[18]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.

4.2.3 Default

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

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

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

$$V_{imt}^{D} = \eta_{mt}^{D} + \Omega_{mt}^{D} y_i + \varepsilon_{imt}^{D} \tag{5}$$

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 (2010). 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 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.

4.2.4 Private Information Structure

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

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

for $h \in \{B, D\}$. The common component simplifies the lender signal structure (following in section 4.3) and generates correlation among unobserved private characteristics for each individual. The distribution of unobserved preferences varies over markets through σ_{mt}^{B} and σ_{mt}^{D}. Finally, I simplify further by setting $\tilde{\varepsilon}_i^{B}$ to zero and letting $(\tilde{\varepsilon}_i, \tilde{\varepsilon}_i^{D})$ be independently standard normal distributed. Henceforth, I simplify the notation, writing ε_i instead of $\tilde{\varepsilon}_i$.

4.3 Lender

My model of supply 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, along with some screening through interest rates. 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.

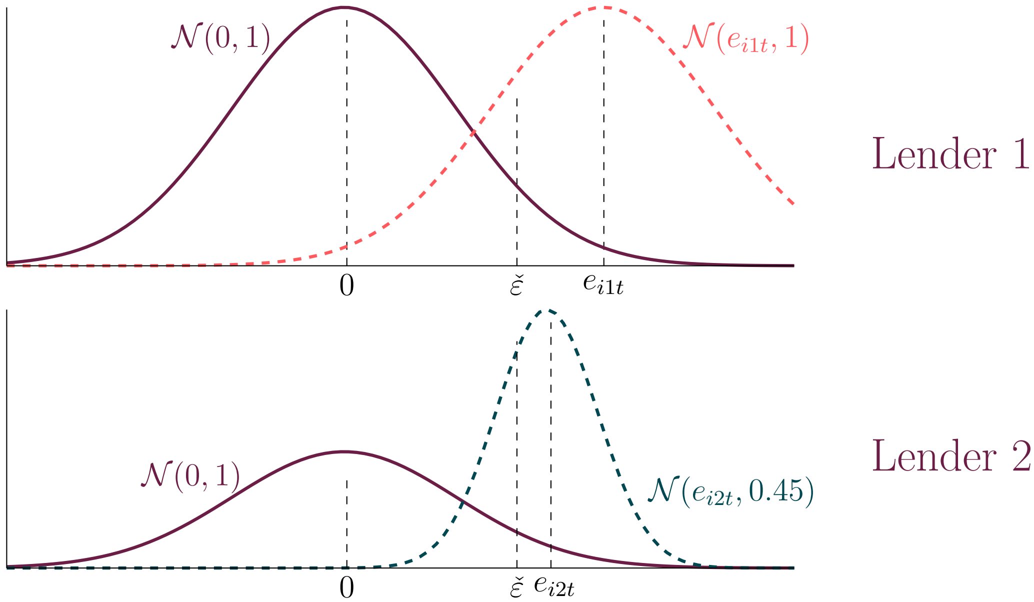
To match the institutional environment and my empirical findings in section 3.1, lenders choose credit limits for individuals non-competitively *after they have originated a card*. By the regulatory requirements, lenders set advertized APRs r_{jmt} at the card-month-market level. This institutional feature handily circumvents issues of equilibrium existence and uniqueness that are pervasive in the empirical literature on contract pricing in credit markets. Appendix E.2 presents one such model of how lenders set advertized APRs competitively for reference, though I do not use it to estimate any model parameters. 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.

4.3.1 Screening Technology

Each lender has a screening technology, which delivers a signal $e_{i\ell t}$ on the common risk component ε_i. With the signal, the lender updates its prior on the individual's risk from $\varepsilon_i \sim \mathcal{N}(0,1)$ to the posterior distribution $\varepsilon_i | e_{i\ell t}$. The signal is a discrete random variable,

FIGURE 5: Prior (solid) and posterior (dashed) distributions of ε 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.

and a finer support reflects a more finetuned screening technology. I write $\varepsilon_i | e_{i\ell t} \sim \mathcal{N}(e_{i\ell t}, \sigma^2_{\ell t})$. Equivalently $\varepsilon_i = e_{i\ell t} + w_{i\ell t}$ where $w_{i\ell t}$ reflects the lender's signal error. The signal noise $w_{i\ell t}$ is normally distributed with mean 0 and variance $\sigma^2_{\ell t}$, implying that the posterior follows the same distribution except with mean equal to $e_{i\ell t}$.

Figure 5 depicts the prior and posterior on ε_i for two fictitious lenders. The posterior distribution of risk for customer i at lender 1 is $\mathcal{N}(e_{i1t}, 1)$. The mean of the posterior distribution is relatively far from the customer i's true realization of $\varepsilon_i = \check{\varepsilon}$. Lender 2 has a better screening technology. The posterior 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 customer i, lender 2 will take expectation over the posterior distribution of risk and 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.

4.3.2 Credit Limit

To model lenders' credit limit choices requires a model of 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 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 some 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 percent of their card revenue (Evans and Schmalensee, 2005). The remaining 30 percent comes from three main factors, each of which are likely to account for a smaller percent of revenue for UK lenders. Appendix E.1 explains each of the three reasons in detail.

Each lender's profit from a transacting customer is Π_{i0mt}, unrelated to the credit limit and interest rate.[19] 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

[19]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

able to recover, which I set to zero in my empirical specification.[20]

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 $e_{i\ell t}$, the lender chooses the credit limit $\bar{b}_{ijmt}$ to maximize the expected profit from the individual, conditional on the signal:

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

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

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

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 error at which the individual wants to borrow exactly their credit limit, that is, the risk signal error 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.

[20] 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 percent 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.

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.

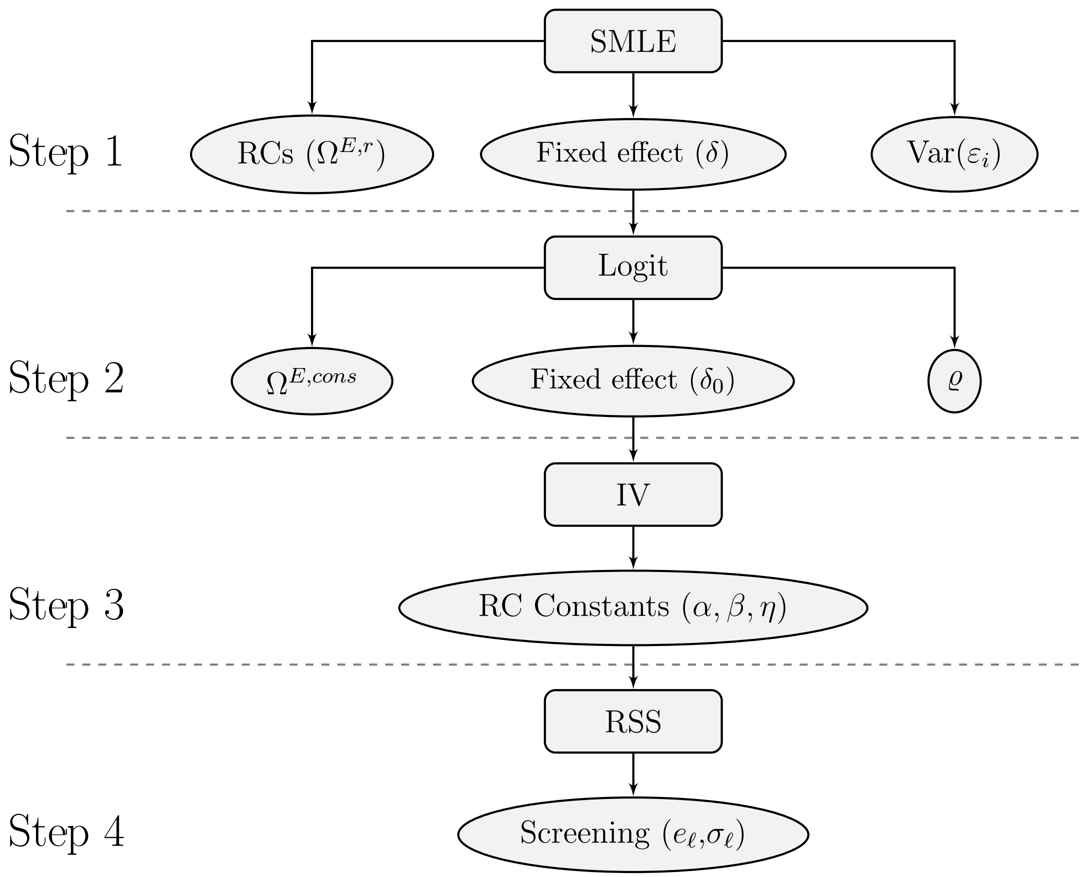
5.1 Demand

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

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.

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, 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

$$\begin{aligned} V^E_{ijmt} &= \delta^E_{jmt} + \nu_{ijmt} + u^E_{ijmt}, \\ \delta^E_{jmt} &= \beta^{E\prime} X^E_{jmt} + \xi^E_{jmt} + \eta^E_{mt} + \alpha^E r_{jmt}, \\ u^E_{ijmt} &= \Omega^{E,r}_{mt} y_i r_{jmt}, \end{aligned} \tag{11}$$

and

$$\begin{aligned} \log(b^*_{ijmt}) &= \delta^B_{jmt} + \varepsilon^B_{imt} + u^B_{ijmt}, \\ \delta^B_{jmt} &= \beta^{B\prime} X^B_{jmt} + \xi^B_{jmt} + \alpha^B r_{jmt} + \eta^B_{mt}, \\ u^B_{ijmt} &= \Omega^{B,cons}_{mt} y_i + \Omega^{B,r}_{mt} y_i r_{jmt}, \end{aligned} \tag{12}$$

where δ^E_{jmt} and δ^B_{jmt} are the card-channel-month fixed effects.

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

$$\log \mathcal{L}_{mt,E} = \sum_{i \in I_{mt}} \sum_{j \in J_{imt}} 1^E_{ijmt} \log(s^E_{ijmt|j \in J_{imt}}), \tag{13}$$

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 $\Omega^{E,cons}_{mt}$, 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 ($\delta^E_{jmt}, \delta^B_{jmt}$) onto distribution channel-month fixed effects, interest rates, and observed characteristics as in (11) and (12). 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.[21] 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.[22]

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 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. 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 technologies $e_{i\ell t}$ 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,

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

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

the corresponding signal $e_{i\ell t}$ satisfies

$$\int_{\omega_{i\ell t}(\bar{b}_{ijmt},e_{i\ell t})}^{\infty} \pi_{ijmt}(e_{i\ell t}, w_{i\ell t})\phi\left(\frac{w_{i\ell t}}{\sigma_{\ell t}}\right) dw_{i\ell t} = 0, \tag{14}$$

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

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

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 (14) 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 square deviations (over individuals) from the integral in (14). As in demand estimation, the integral in (14) has no closed form. Therefore, for each lender-month, I simulate the integral using 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, medians, and standard deviations of estimates over markets.

Table 1: First and second step demand estimates

Variable	Mean	Median	SD
η^D	-1.25	-1.30	0.46
Ω^D	-0.08	-0.08	0.05
σ^D	0.54	0.56	0.10
$\Omega^{B,cons}$	0.54	0.49	0.35
$\Omega^{B,r}$	-0.33	-0.17	1.13
σ^B	2.44	2.46	0.30
$\text{Corr}(\varepsilon^B, \varepsilon^D)$	0.47	0.49	0.07
$\Omega^{E,r}$	-0.92	-0.12	1.95
$\Omega^{E,cons}$	-0.20	-0.10	0.66
ϱ	0.47	0.40	0.38

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 0.54 for σ^D indicates unobserved heterogeneity in default, justifying the role of lenders' screening technology.

Moving to the borrowing equation, the intensive margin income elasticity estimate of 0.54 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 0.47, 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.[23] This 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.

Finally, the parameters of the card choice equation and the utility for transacting. I estimate

[23] 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 2: Summary statistics for variation in signal mismeasurement across lenders

Variable	Mean	SD	10%	25%	50%	75%	90%
σ_ℓ	0.097	0.249	0.006	0.008	0.012	0.0222	0.171

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 0.47, indicates a reasonable substitution between transacting and borrowing choices.

6.1.2 Third Stage Estimates

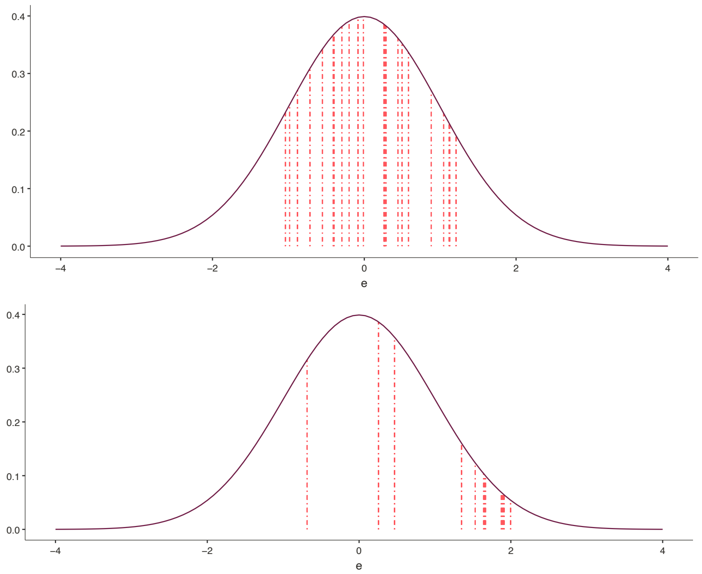
Table H.6 reports estimates and bootstrapped standard errors of the demand parameters recovered in the third stage of demand estimation. Coefficients on dummies for most rewards in the card choice equation are positive, with air miles providing a stronger incentive than cashback and contactless. Air miles also enter positively in the borrowing equation.

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 2.57, 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 7 shows the estimated screening technologies for two contrasting lenders superimposed onto a standard normal distribution. I superimpose the values onto a standard normal distribution since the signals partition the standard normally distributed signal, ε_i. The top lenders' screening technology contains many values, and represents a sophisticated screening technology, providing sharp signals on borrowers' type. The bottom lenders' screening technology offers only a few values, implying less precise signals on borrowers' unobservables. Figure H.12 shows the screening partitions for other lenders. Like

FIGURE 7: Screening technology at two lenders



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 0.83 ($p = 0.01$). This estimate is consistent with the notion that the lenders with the least sophisticated screening technologies focus on the observably safest consumers, who have the smallest risk of default. Lenders with more precise screening technologies are more willing to serve customers who may default on a revolving balance because they can set lower credit limits for customers they perceive as riskier more accurately.

7 Counterfactual Analysis

In the final part of my analysis, I run counterfactual scenarios that give lenders more scope to individualize interest rates. In the current environment, lenders can fully individualize credit limits but face constraints on individualizing interest rates. In what follows, I provide three possible examples of these costs and constraints. First and foremost, as described in section 3, UK regulation requires lenders to post an advertized APR for each credit card, which at least

51 percent of customers originating the card must obtain. This directly limits lenders' ability to engage in individualized pricing. As a result of the regulation, and a second example of a cost of individualizing interest rates, lenders face potential reputational costs if they advertize a particular APR yet give customers an alternative individualized APR. Finally, there are administrative costs in setting up infrastructure and software to set individualized prices optimally. Despite these costs, lenders could still engage in some degree of individualized pricing, if it was profitable to do so.

In my main counterfactual, I allow lenders to set individualized interest rates with no costs or constraints in doing so. I follow the baseline model by assuming that individuals know their potential interest rate at each lender when choosing their card.[24]

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

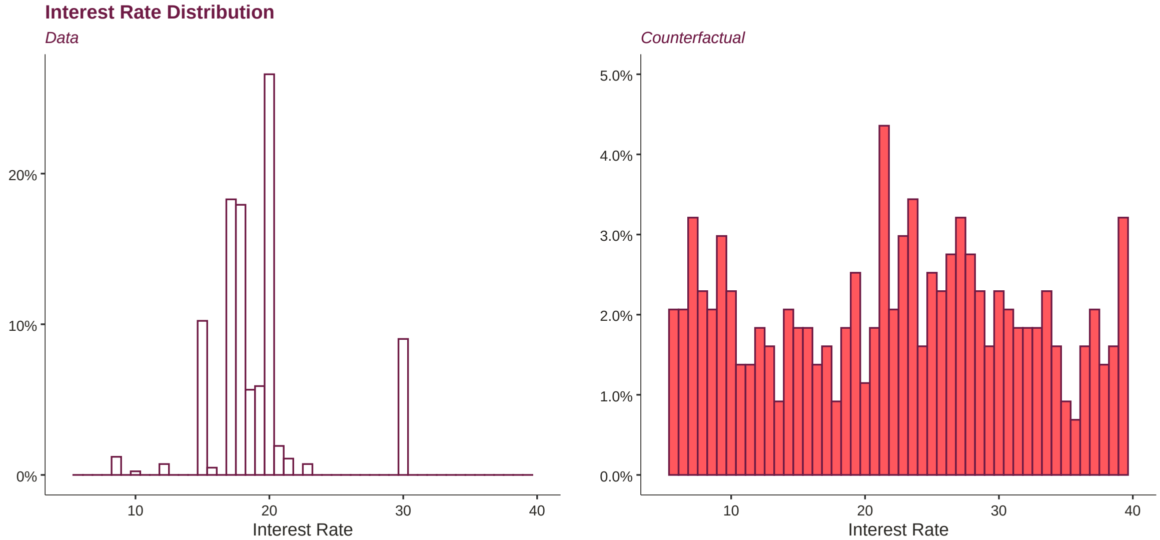
$$\max_{\boldsymbol{r}_{i\ell},\bar{\boldsymbol{b}}_{i\ell}} \sum_{j\in J_{i\ell}} s^E_{ij}(\boldsymbol{r}_{i\ell}, \boldsymbol{r}^*_{-i\ell})\mathbb{E}_{\varepsilon_i|e_{i\ell}}\left[\min\{b^*_{ij}, \bar{b}_{ij}\}\pi_{ij}\right] \tag{15}$$

Similar to supply estimation, I minimize the residual from the first order conditions to (15) to calculate $\boldsymbol{r}_{i\ell}$ and $\bar{\boldsymbol{b}}_{i\ell}$ for all individuals i. This is a computationally intensive procedure, since I have to solve the optimization problem for each consumer separately. Resultantly, I use a random sample of 1000 consumers. Appendix G provides the first order conditions that I use for the calculation of counterfactual interest rates.

Figure 8 displays the distribution of interest rates in the baseline and in the counterfactual. As shown on the left-hand side, interest rates in the data are discretely distributed, with a few values (14.9%, 16.9%, 29.9% for example) each having large probability mass. In the counterfactual, as shown on the right-hand side, the distribution is smoother, with a larger set of values for interest rates, each having a small probability mass. The coefficient of variation in interest rates increases from 0.21 in the baseline to 0.73 in the counterfactual. Similarly, borrowing becomes more dispersed, with its coefficient of variation increasing from 1.12 to

[24] I maintain the assumption that consumers do not know their credit limit to ensure that I am only changing one thing 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.

FIGURE 8: Distribution of interest rates in the data and the counterfactual



1.65. Credit limits remain individualized, with a coefficient of variation of 1.62. Finally, average profits increase by 15%.

One intuition for why lenders combine individualized interest rates and credit limits is because prices also affect individuals' choice of card, through the term s_{ij}^E in the profit function for individual i. This implies that individualized prices are also a device for standard third-degree price discrimination, along with their role as a tool for competition amongst lenders. Across lenders, interest rates rise by 8.2 percentage points (on a base of 20.2%) for the most inelastic customers, and fall by 1.8 percentage points (on a base of 18.8%) for the least inelastic. Credit limits do not affect individuals' card choice, 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.

In the absence of any costs and constraints, interest rates are individualized, whereas in the data, they are set at the card-level, not individualized. The difference in the shape of the distribution of interest rates implies that the costs and constraints described above impose meaningful restrictions on lenders' willingness to adopt individualized prices, and motivate lenders' use of risk-based credit limits in the baseline model.

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, which provides noisy signals on borrowers' unobserved type. 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 where lenders can freely individualize interest rates and credit limits, which the existing regulatory environment precludes. Individualized interest rates and credit limits emerge, and profits increase on average. My findings imply that the current environment imposes meaningful restrictions on lenders' willingness to adopt risk-based pricing, motivating lenders' use of risk-based credit limits instead.

There are two immediate avenues for extensions. The first is the role of consumer search and inattention. Throughout, I assume that consumers are fully aware of interest rates at all lenders and are aware of all cards they qualify for, 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 to learn their interest rate and credit limit: some lenders allow consumers to learn their contractual terms before origination. In contrast, others 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 over-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.

My model also 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. In future work, I also intend to analyze counterfactuals that change lenders' screening technologies. One example would be where lenders share their screening technologies. Alternatively, I could consider mergers where lenders also merge 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 measure the private benefit of screening technologies. The model can also *measure* an element of the cost synergies from the merger, which is typically challenging.

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 amongst 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 USA.

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; Nosal and Drozd, 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.

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 percent of individuals set up a direct debit at origination, approximately 52 percent of cardholders report being female, 57 percent are homeowners, and 76 percent are employed (not including self-employed). Finally, most customers (53 percent) originate online, 32 percent originate in a store, 12 percent originate via post, and 4 percent do so by telephone.

B.2 Cards

Table H.8 provides summary statistics on card features at the origination level. The mean credit limit is £3390, and the mean purchase APR at origination is 21.5 percent. 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. Promotional deal lengths for purchases are short, typically around three or six months where they exist, and over 25 percent of cards have no purchase promotional deal. Across all cards, 83 percent of customers obtain the advertized APR, a fact I describe in depth in section 3.1.1. Finally, 28 percent 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 percent of card-months offering cashback and 7 percent offering air miles. The table also shows the following facts. First, over 75 percent of cards have no annual fees. 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 percent reserved for students and 7 percent 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 individuals are repriced or eventually close their card. Over 25 percent 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 two percent of statement months have an overdue payment, and two percent 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.[25] FCA (2015c) offers a general summary of UK credit card regulation.

C.1 Definitions and UK Advertized APR Regulation

A credit card's *purchase balance* is the total amount spent on the card relating to non-cash transactions currently not repaid.[26] A *purchase interest rate* for a credit card is the percentage rate at which interest is added to a credit card purchase balance.

In what follows, I 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 typically 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 which interest is added to an unpaid balance daily. The consumer is notified of the interest charged on their monthly statement, where the

[25] 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.

[26] 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.

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 percent. An *Annual Percentage Rate* (APR) is similar to the annual purchase rate, except it accounts for all mandatory fees that an individual must pay each year on the card and interest 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 all 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 *advertized 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 percent 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 advertized APR was 66 percent. After February 2011, the UK harmonized regulation with the EU and the proportion changed from 66 percent to 51 percent.

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 advertized 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.14 by plotting the distribution of percentage point differences (rounded to the nearest integer) between advertized APRs and those customers actually received. The differences are minor and often favorable to consumers. In the most commonly occurring case, 42 percent of customers received an interest rate six percentage points *lower* than that advertized. Very few customers (around 2.6 percent) received interest rates more than eight percentage points above the APR advertized.

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 percent) (Evans and Schmalensee, 2005). Further, the remaining 30 percent contains revenue sources that are likely to be smaller proportions in the UK relative to the US. I detail three alternative revenue sources.

The first is interchange revenue, which accounts for 15 percent 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.[27]

The second part of the remaining 30 percent 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 after last, as most lenders did before the regulation.

The final source of revenue is fee revenue. 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.[28] 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 (including late, dormancy, over-limit, and foreign transaction) were at most £12, around 50 percent lower than in 2003 (House of Commons Treasury, 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

Within each market, lenders set profit-maximizing advertized APRs on their cards.[29] Lenders choose rates strategically so that interest rates form a Bertrand-Nash equilibrium. Let $\boldsymbol{r}^*_{-\ell mt}$

[27] 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 percent of the transaction for credit cards. The UK adopted these changes in late 2015.

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

[29] I abstract here from the small percentage of borrowers on which the main lenders engage in some risk-based pricing.

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

$$\max_{\boldsymbol{r}_{\ell mt}} \sum_{i \in I_{mt}} \sum_{j \in J_{i\ell mt}} s^E_{ijmt}(\boldsymbol{r}_{\ell mt}, \boldsymbol{r}^*_{-\ell mt}) \Pi_{ijmt}(r_{jmt}). \tag{16}$$

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 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 $\bar{b}$.[30] 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

$$\int_{\omega_{i\ell t}}^{\infty} \pi_{ijmt}(e_{i\ell t}, w_{i\ell t}) \phi\left(\frac{w_{i\ell t}}{\sigma_{\ell t}}\right) dw_{i\ell t} \tag{17}$$

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.

[30] 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

$$\frac{\partial \log(b_{ijmt})}{\partial \log(r_{jmt})} = r_{jmt}\alpha^B_{ijmt}\Phi\left(\frac{\bar{\mathcal{Q}}^B_{ijmt}}{\sigma^B_{mt}}\right). \tag{18}$$

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

$$\frac{\partial s^E_{ijmt}}{\partial r_{jmt}} = \alpha^E_{ijmt} s^E_{ijmt} \left[\frac{1 - s^E_{ijmt|j\in J_{imt}}}{\varrho_{mt}} + s^E_{ijmt|j\in J_{imt}} s^E_{i0mt} \right]. \tag{19}$$

Multiplying (19) by $\frac{r_{jmt}}{s^E_{ijmt}}$ provides the product choice price elasticity of demand for individual i, given by

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

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

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

where

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

with all terms defined as in the main text and in the notation tables H.4 and H.5. 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 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

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

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 (13). 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^E_{i0mt} exceeds the maximal utility from borrowing. The probability that this occurs for individual i is

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

where

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

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

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

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

G Additional Counterfactuals Details

I derive the first order conditions to the optimization problem in equation (15). 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

$$s^E_{ij}(\boldsymbol{r}_{i\ell}, \boldsymbol{r}^*_{-i\ell})\mathcal{E}_{ij} + \sum_{k\neq j} s^E_{ik}(\boldsymbol{r}_{i\ell}, \boldsymbol{r}^*_{-i\ell})\mathcal{E}_{ik}. \tag{21}$$

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

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

Equation (19) provides an expression for $\frac{\partial s^E_{ij}}{\partial r_{ij}}$. Finally, I provide expressions for $\frac{\partial \mathcal{E}_{ij}}{\partial r_{ij}}$ and $\frac{\partial s^E_{ik}}{\partial r_{ij}}$ when $k \neq j$. The former of these two terms is

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

The expression for $\frac{\partial s^E_{ik}}{\partial r_{ij}}$ is more involved. To start,

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

Then

$$\frac{\partial s^E_{ik|k\in J_i}}{\partial r_{ij}} = -s^E_{ij|j\in J_i} s^E_{ik|k\in J_i} \frac{\alpha^E_i}{\varrho}$$

and

$$\frac{\partial s^E_{i0}}{\partial r_{ij}} = -\alpha^E_i s^E_{i0} s^E_{ij}.$$

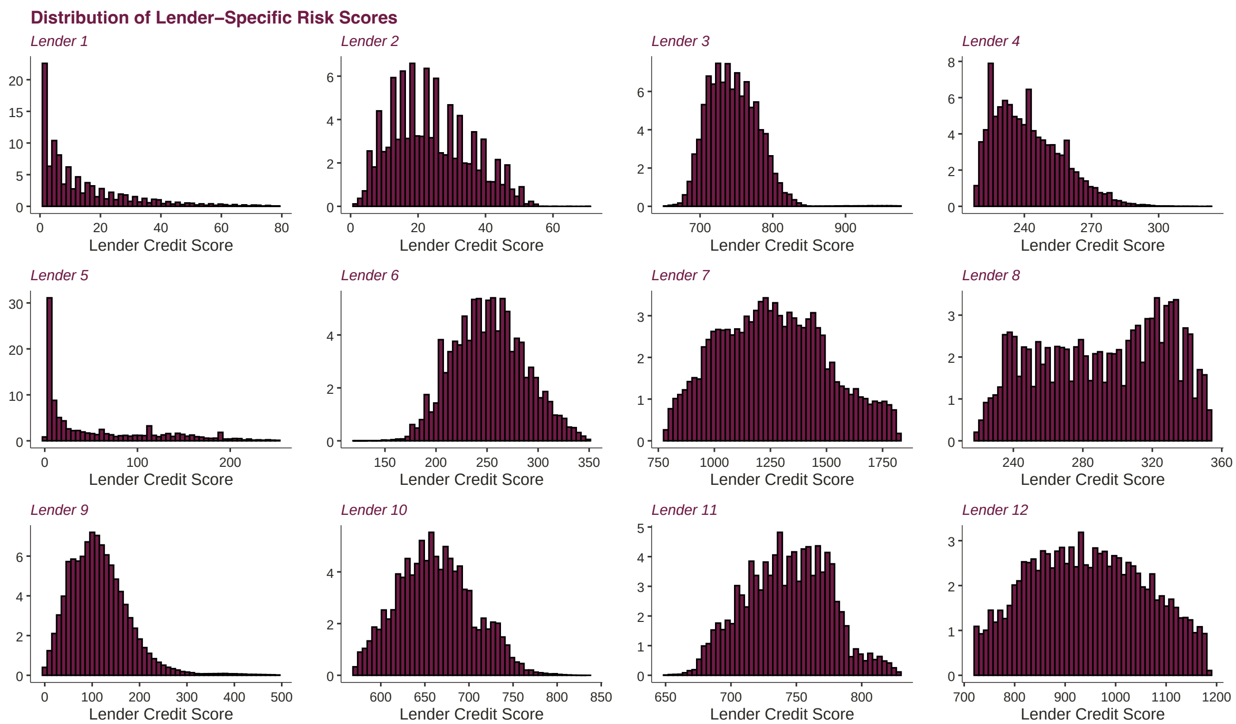
Putting these together yields

$$\frac{\partial s^E_{ik}}{\partial r_{ij}} = s^E_{ij} s^E_{ik|k\in J_i} \alpha^E_i \left[s^E_{i0} - \frac{1}{\varrho} \right].$$

H Additional Figures and Tables

H.1 Figures

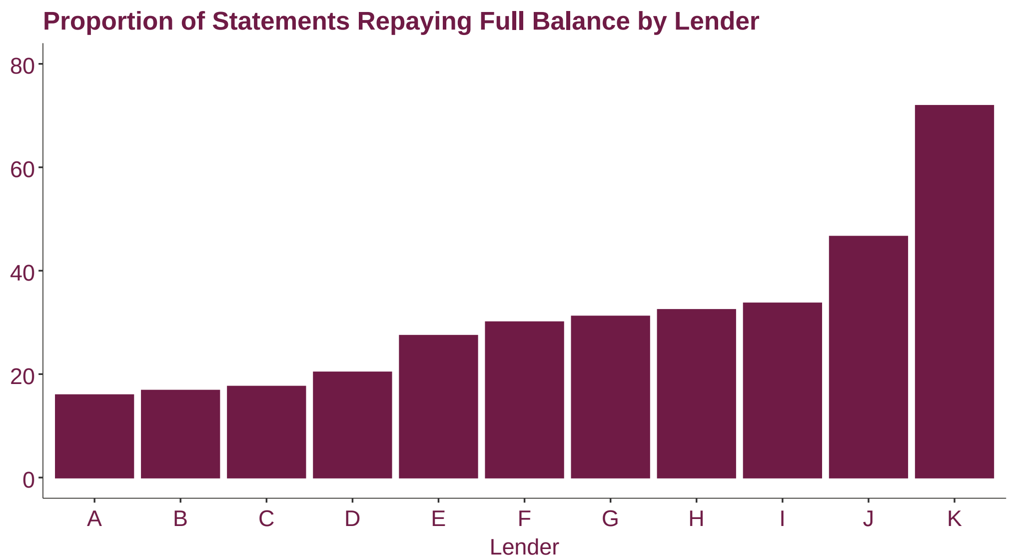
FIGURE H.1: Distribution of proprietary credit scores across lenders



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

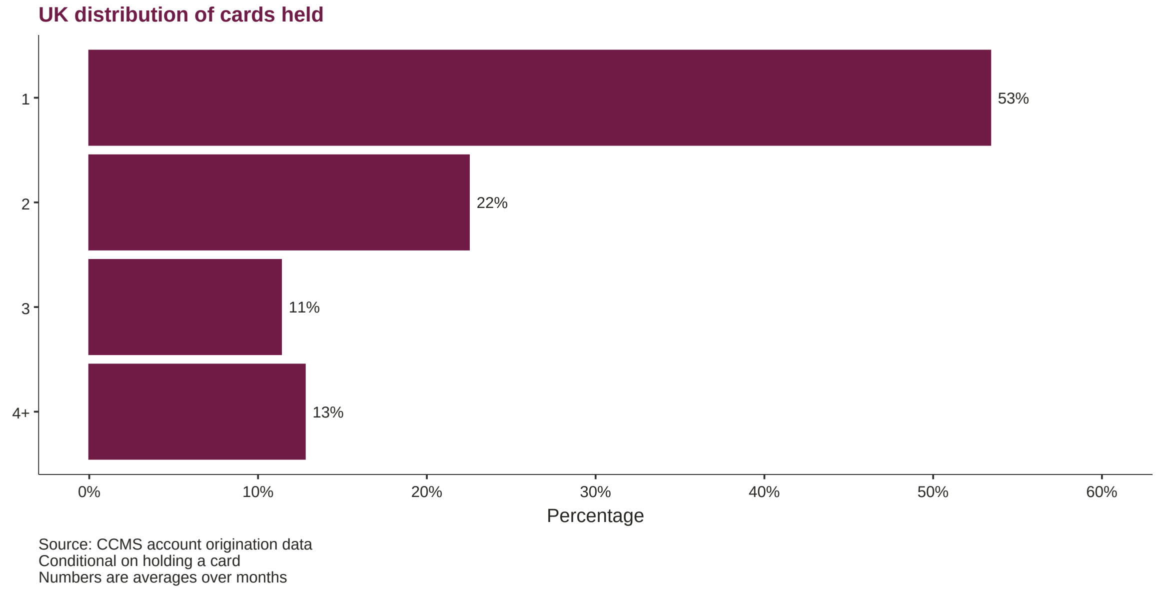
Figure H.2: Proportion of statements where full balance is repaid



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

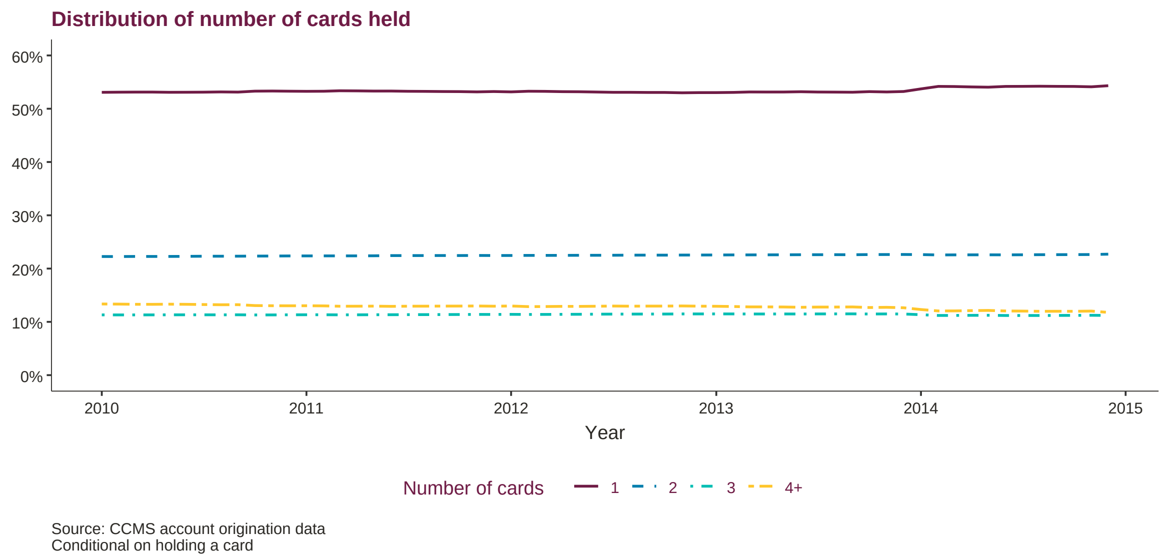
Figure H.3: Distribution of the number of cards



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.

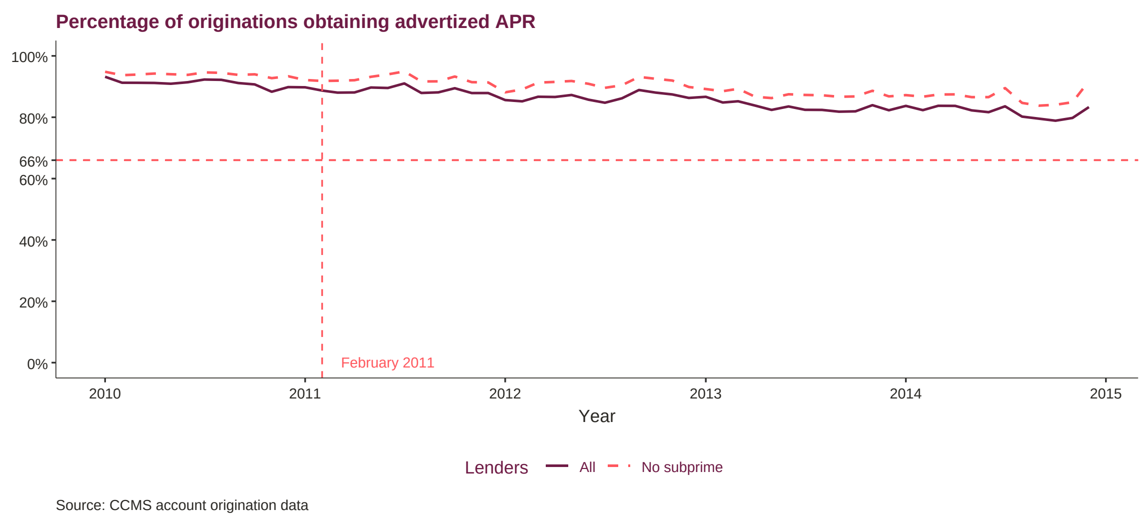
Link back to data section

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.

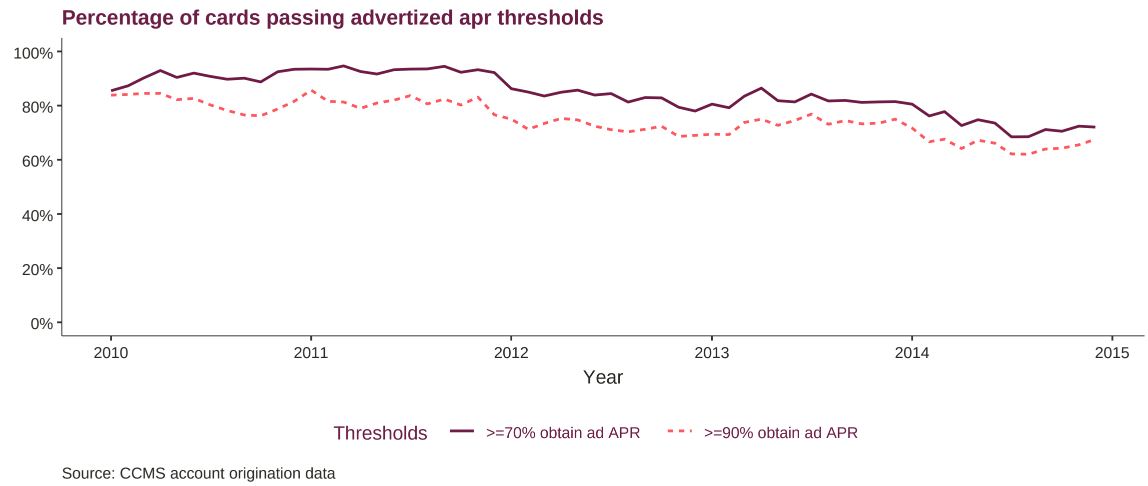
Figure H.5: Percentage of originations each month that obtain the advertized APR



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 advertized APR or below fell from 66 percent to 51 percent.

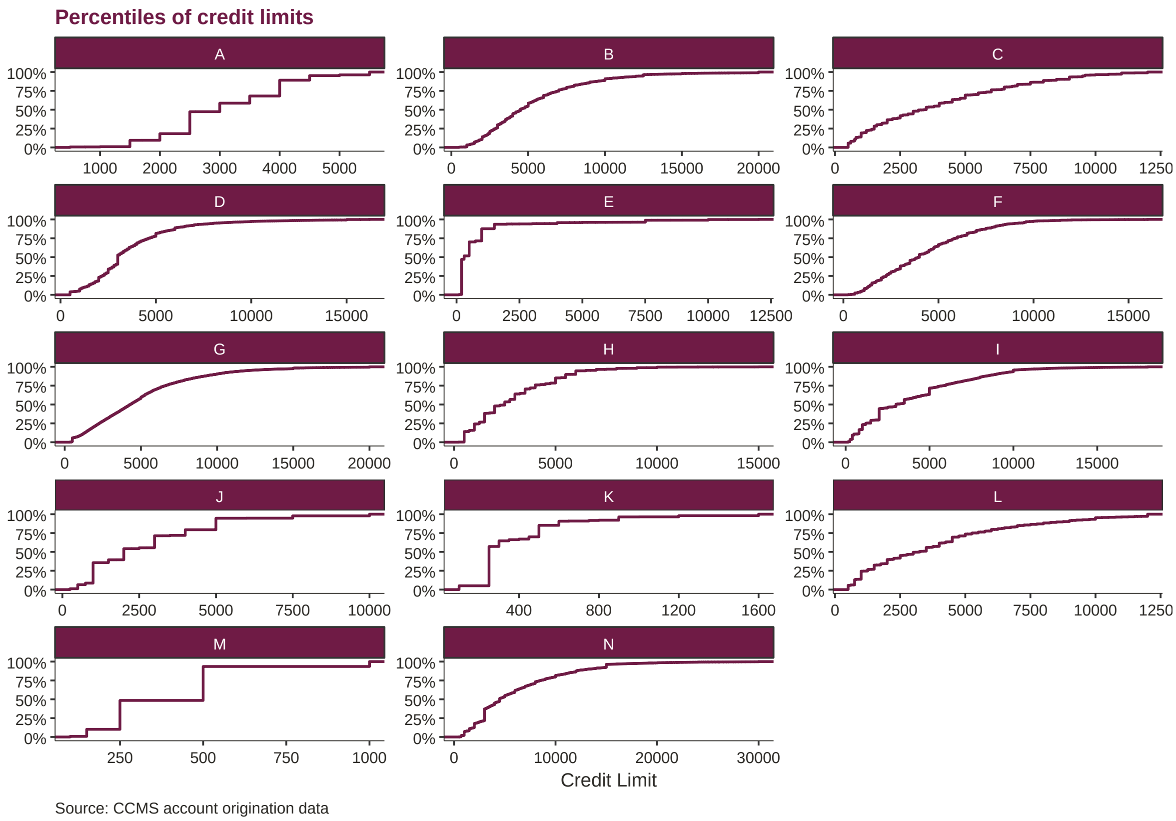
Link back to descriptive findings

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



Link back to descriptive findings

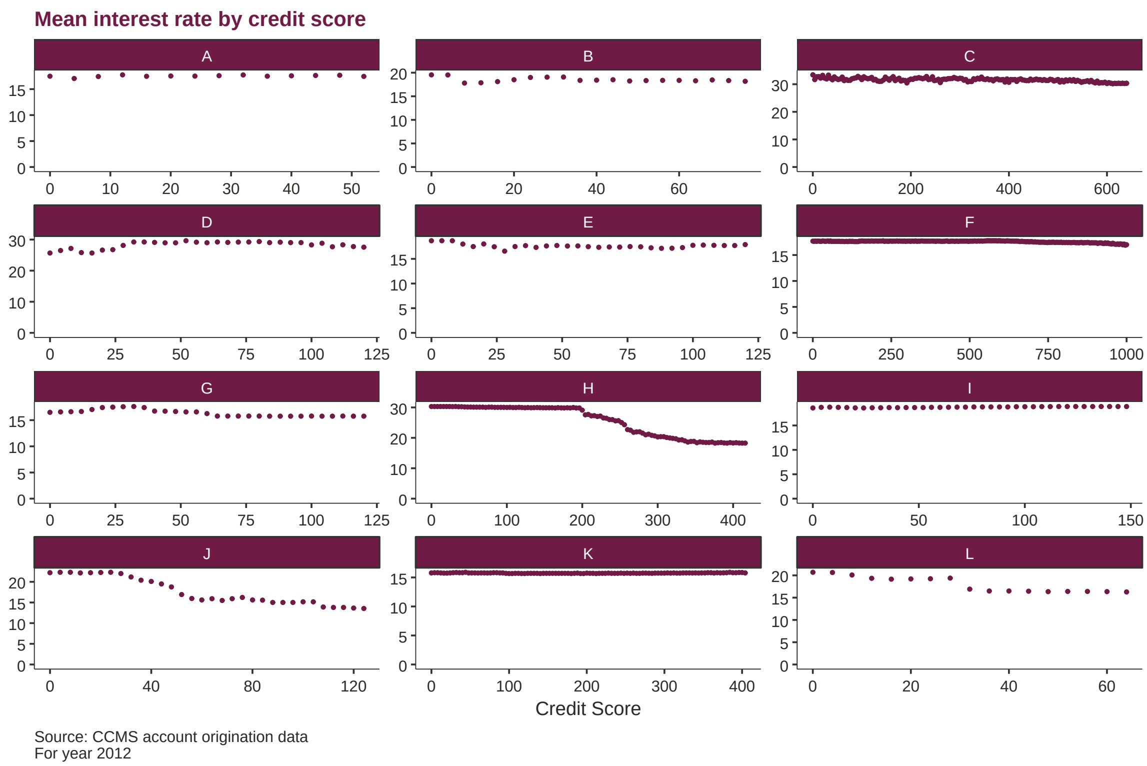
FIGURE H.7: Empirical CDFs of credit limits at all lenders, pooled over time



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

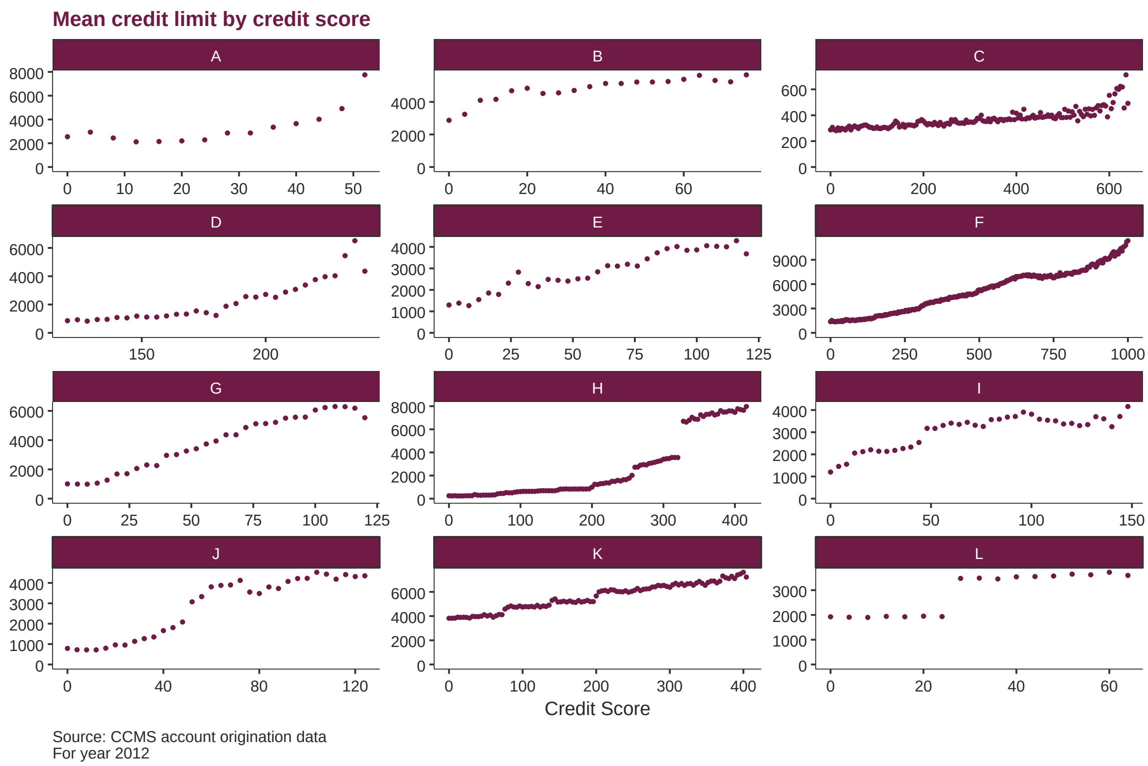
FIGURE H.8: Mean interest rates across lenders' risk scores



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

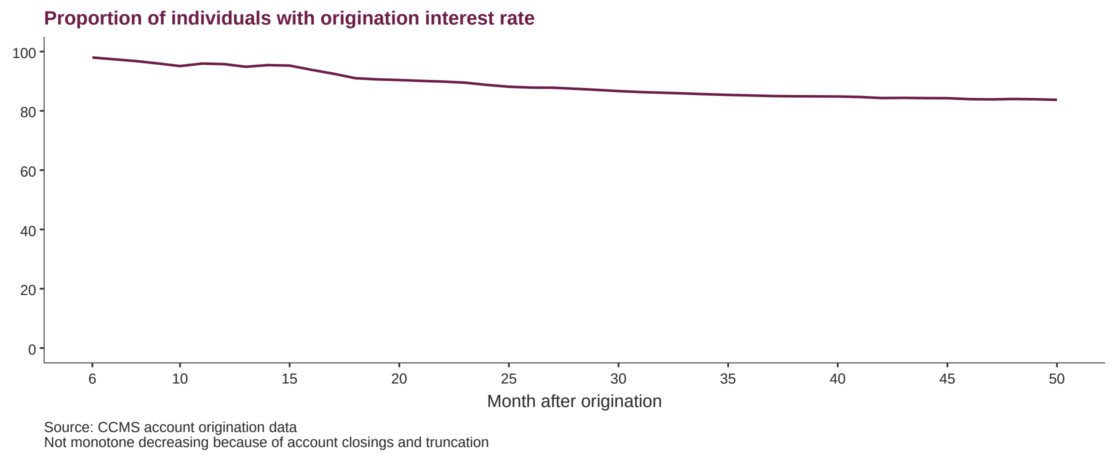
FIGURE H.9: Mean credit limits across lenders' risk scores



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

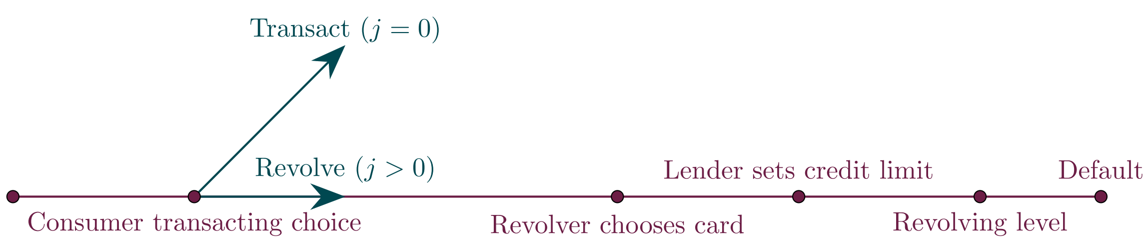
Figure H.10: Percentage of cards with origination interest rate by month after origination



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

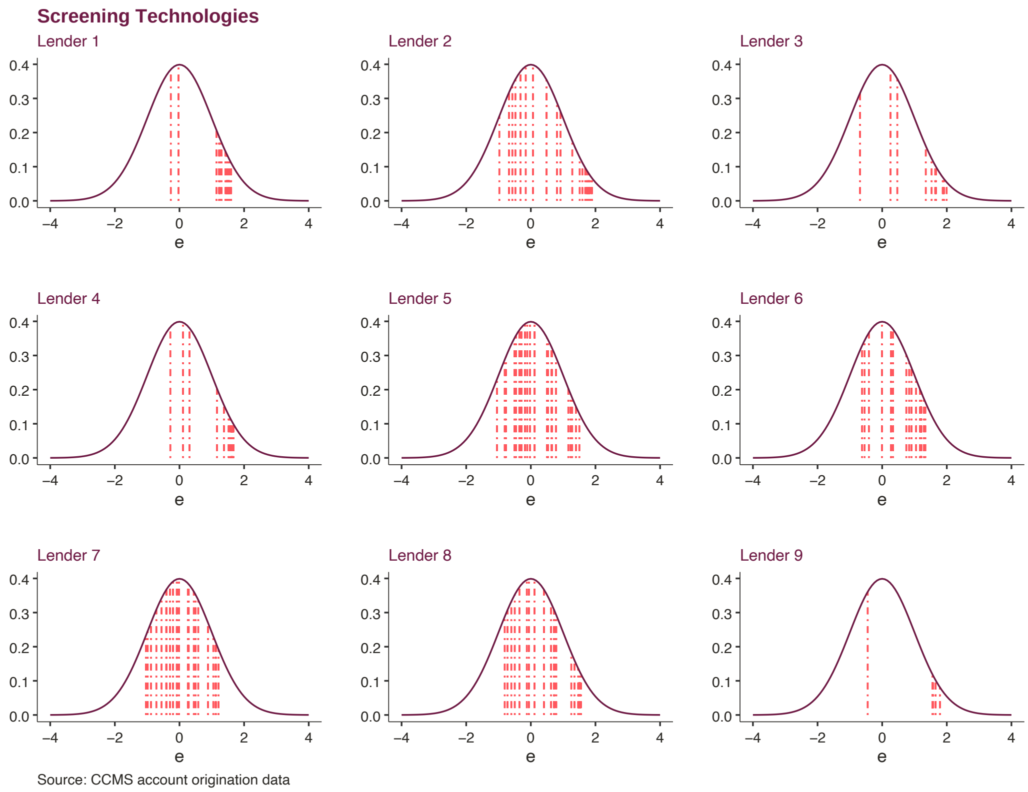
Link back to repricing discussion

Figure H.11: Model timeline within a market



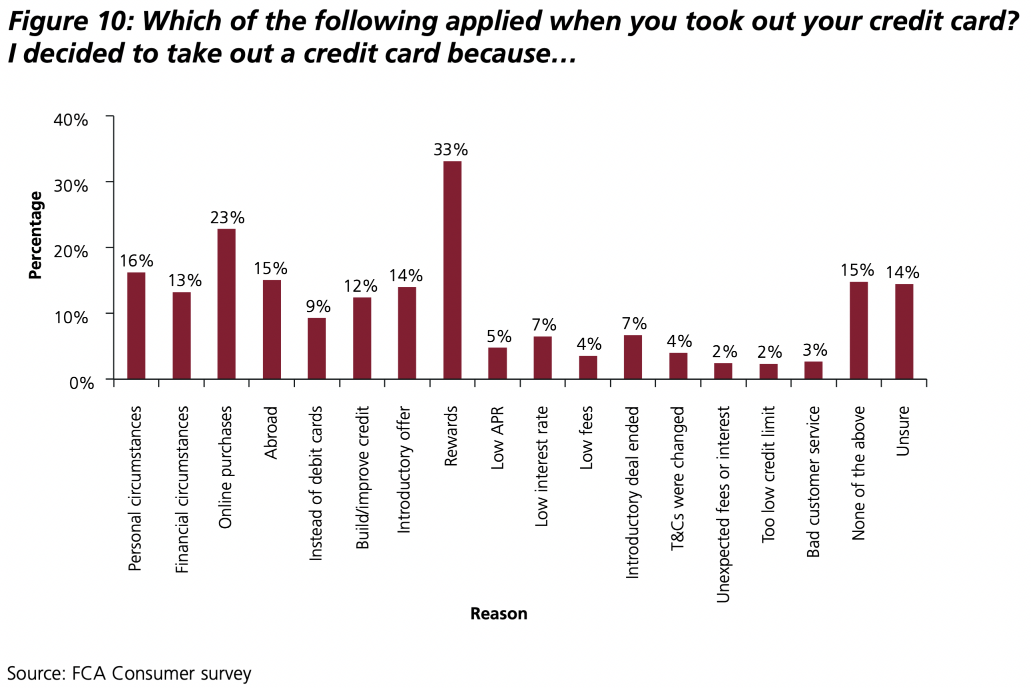
Link back to model section

FIGURE H.12: Screening technologies at nine main lenders



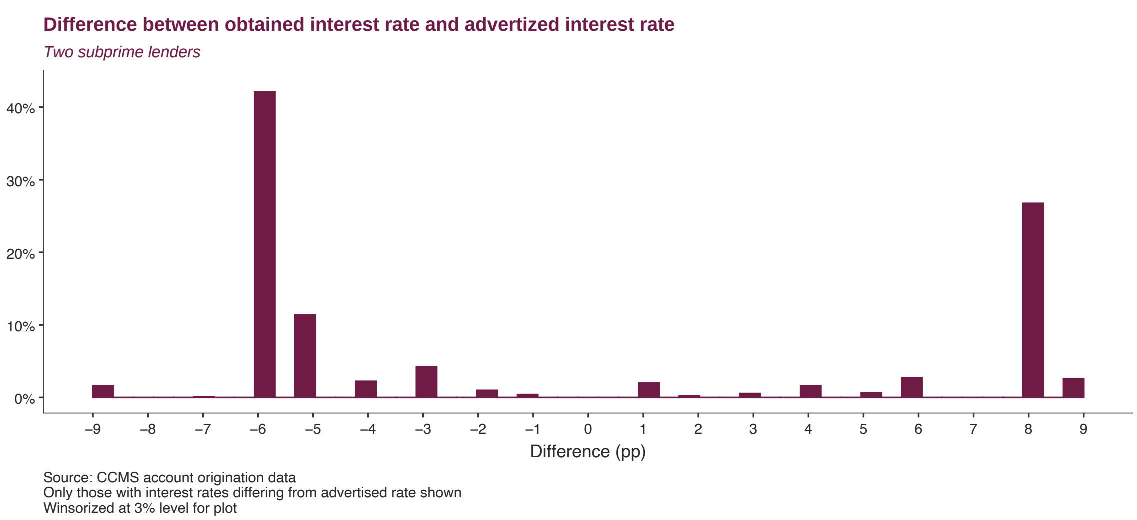
Link back to supply estimates

Figure H.13: Answers to question on reasons for taking out a credit card



Link back to card utility discussion

Figure H.14: Histogram of differences between obtained APR and advertized APR at two subprime lenders (conditional on not obtaining advertized 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: Percent of cards with origination interest rate across months

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
$\underline{Y}$	Minimum income threshold
z	Instrument

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 "correlation" 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

Variable	Notation	Estimate	SE
Panel A: Card choice equation			
Airmiles	$\beta^{E}_{\text{airmiles}}$	0.73	0.18
Contactless	$\beta^{E}_{\text{contactless}}$	0.12	0.11
Cashback	$\beta^{E}_{\text{cashback}}$	0.24	0.11
First-stage F Statistic	21.79		
Panel B: Borrowing choice equation			
Airmiles	$\beta^{B}_{\text{airmiles}}$	0.83	0.64
First-stage F statistic	11.80		

Notes: This table provides the estimates and bootstrapped standard errors of the demand parameters recovered in the third stage of demand estimation. Based on the equation $\hat{\delta}^{h}_{jmt} = \eta^{h}_{mt} + \alpha^{h} r_{jmt} + \beta^{h'} X^{h}_{jmt} + \xi^{h}_{jmt}$ I use IV estimation with cost shifters as instruments for interest rate. I include distribution-month, and network fixed effects in both 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 Advertized 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 Advertized APR" is a dummy equal to one if the individual obtains the APR advertized 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. 2 Months overdue to 5+ Months Overdue are 0, rounded to 2 decimal places. Categorical variables' means may not sum to 1 because of rounding.

Link back to summary statistics description