Risk-Based Borrowing Limits in Credit Card Markets*

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Abstract

I use novel statement-level data on the 2010–2015 UK credit card market to show that lenders primarily individualize contracts through risk-based credit limits. Though shared with other European credit markets, this feature contrasts with the US counterpart, where interest rates are also individualized. To quantify the welfare implications of this distinction, I estimate a structural model that explains credit limit distributions with lender-specific credit scores. I evaluate a counterfactual where lenders can freely individualize prices and credit limits, which the existing environment precludes. Lenders control default risk with credit limits and use prices to extract surplus from inelastic borrowers.

Keywords: Risk-based credit limits, risk-based pricing, adverse selection, credit cards
JEL Classification: D22, D82, E51, G21, G51, L13, L50

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1 Introduction

US credit card lenders individualize interest rates and credit limits according to assessments of customers' default risk. This paper shows that the leading UK lenders tailor credit limits but keep interest rates constant across customers of varying default risk. Other European credit markets follow suit, in line with EU-wide regulations limiting credit lenders' ability to price discriminate. How does this striking institutional difference affect consumers' and lenders' welfare? Further, why might lenders tailor both credit limits and interest rates in equilibrium?

The central contribution of this paper is to estimate a structural model of the credit card market to shed light on these hitherto unanswered questions. The model includes two interrelated channels through which lenders could tailor contracts: default risk and price elasticity. My model and counterfactual results imply that lenders tailor credit limits to mitigate potential default risk associated with adverse selection, and tailor interest rates to maximize interest revenues. Risk-based interest rates benefit lenders and price-elastic borrowers at the expense of higher interest rates for inelastic borrowers, who are typically most at risk of default.

Beyond the standalone interest in the functioning of consumer credit markets, two specific factors underscore the importance of answering these questions. The first is the longstanding interest in credit rationing. Several theoretical papers study why similar borrowers have, in the past, varied in their ability to obtain credit (Stiglitz and Weiss, 1981). Nowadays, credit is widely accessible, but credit rationing occurs through credit limits.[1] Despite theoretical interest, there have been almost no *empirical* attempts to explain how lenders ration credit on the intensive margin. This gap in the literature persists despite the relevance of rationing to information economics (Akerlof, 2001), the macroeconomy (Blinder and Stiglitz, 1983), and economic development (McKinnon, 1973).

Second, this topic is important because of its regulatory implications, which extend beyond credit markets. The academic literature and policy discourse generally focus on regulating price discrimination.[2] Recently, interest in tailored prices has increased in response to the tension between the rapid development of AI (used for algorithmic pricing) and government regulatory interventions aimed at limiting its scope. Firms, though, set multidimensional contracts with many levers for discrimination. Effective regulation requires an understanding of how firms discriminate multiple variables and how multidimensional individualization adjusts in response to regulation. This paper is a first attempt at studying credit market quantity *and* price discrimination in tandem.

At least two challenges have stymied efforts to establish the implications of interest rate and credit limit discrimination in credit card markets. First, studies generally focus on the US market, where

[1] In July 2023, approximately 80% of US adults owned at least one of the 578 million credit cards in circulation (see `https://www.newyorkfed.org/newsevents/news/research/2023/20230808`).

[2] A leading example of a US Act that limits price discrimination is the Affordable Care Act, which prohibits health insurers from tailoring premiums based on gender, health status, medical history, or occupation.

lenders can and do tailor both interest rates and credit limits. This collinearity limits the variation available to disentangle their impacts. I overcome this by studying a European context, in which credit market regulation limits lenders' ability to tailor interest rates. Thus, I can focus on the sole role of credit limits in the baseline setting and analyze interest rates in a counterfactual scenario.

The second challenge is the scarcity of administrative, statement-level panel data that includes credit scores, interest rates, and credit limits. To address this, I use a new source of statement-level data on approximately 80% of UK credit cards active between 2010 and 2015. The data include cardholder demographics and card characteristics for every card, along with monthly spending, repayment, default decisions, and lenders' funding (marginal) costs. Among other advantages, the data contain lenders' proprietary credit scores for every credit card originated. Hence, I can check whether lenders tailor interest rates and credit limits to their own predictions of customers' risk. The data reveal significant intensive margin credit rationing. Around 40% of individuals use over 90% of their credit limit on at least one occasion in the first two years of owning the card.

In my formal empirical analysis, I document significant variation in credit limits within and across lenders. This variation persists within credit card products, with higher credit scores corresponding to larger credit limits. In contrast, interest rates vary minimally across cards, remain almost constant at the card-month level, and are not risk-based. This pattern extends beyond EU credit regulation, which mandate lenders to advertise a single annual percentage rate (APR) for each card and ensure that the majority of customers receive the advertised APR or lower. I also report substantial heterogeneity in the shape and scale of credit limit distributions across lenders.

To investigate the welfare impacts of individualized interest rates and credit limits on cardholders and lenders, I develop and estimate a structural model of the credit card market. My primary modeling novelty relates to the supply side. I endow each lender with a screening technology that generates a noisy signal of each individual's private type, which is their risk. Optimal credit limits trade off maximizing interest revenues from larger balances when the cardholder does not default, with adverse selection that generates a correlation between unobservables driving the desired balance and default probability. The model represents the first quantitative analysis of credit card lenders' screening technologies and credit limit choices. The model's primary contribution lies in explaining how credit card markets function in the absence of risk-based pricing.

My supply-side estimates reveal substantial variation in lenders' screening technologies, which aligns with observed differences in credit limit distributions. Lenders with precise screening technologies face fewer statements where the customer repays their entire balance. This finding is consistent with a segmentation of credit card lenders, in which those with the most precise screening technologies serve a riskier but more profitable market segment. Lenders with precise screening technologies are more willing to serve customers who will borrow but may default because they can more accurately set lower credit limits for customers they perceive to be riskier. The role of risk-based credit limits is to control downside risk from customers that may default.

The demand model explains borrowers' credit card choices, borrowing levels, and default decisions, incorporating observed and unobserved heterogeneity in all endogenous demand-side variables. For credit card and borrowing choices, preferences over interest rates vary with individuals' incomes. To identify demand parameters, I leverage a novel source of quasi-experimental price variation: the cost shock resulting from the 2011 High Court ruling on the mis-selling of payment protection insurance (PPI). Banks were forced to compensate thousands of consumers after the court deemed they had mis-sold PPI, which led to rises in interest rates on some credit cards.

My demand estimates show that individuals with the lowest income have the most inelastic demand, both in their borrowing and credit card choices. Consequently, individuals with a high default probability also have inelastic demand. They are thus susceptible to high interest rates due to their inelasticity, not just their increased cost.

Finally, counterfactual simulations illustrate how the option of fully individualized prices affects consumers' and lenders' welfare. Like in the US, in the counterfactual lenders face no constraints in individualizing interest rates and credit limits. Interest rate and credit limit discrimination emerges as a result. Low-income, inelastic individuals experience increases in interest rates and thus reductions in consumer surplus, but consumer surplus increases for elastic borrowers. Tailoring interest rates increases lenders' profits by 23%. The profit increases in the counterfactual suggest that the costs to lenders of tailoring rates in the EU environment must be substantial. Understanding these costs is an important endeavor. Though it is not the question I answer in this paper, I conclude by discussing potential sources of these costs, focusing on reputational risk.

Relative to the US, the EU context tilts the market in favor of low-income individuals and away from lenders, whose profits are lower because of constrained abilities to price discriminate. My counterfactual reveals that in consumer credit markets, tailoring prices and tailoring quantities are complementary tools rather than substitutes. The punchline of my counterfactual analysis is that in unregulated environments, interest rates are risk-based to maximize interest revenues, and credit limits are risk-based to cover downside default risk from adverse selection.

A central and non-obvious insight of my analysis is that those most likely to default receive high interest rates because they have the least elastic demand, and not because they have the highest costs. Indeed, individuals in the counterfactual with high default risk signals but elastic demand obtain *lower* interest rates in the counterfactual relative to the baseline. Further, there is no difference between the interest rate to elasticity gradient for those with low and high risk signals. This suggests that the negative correlation observed in the US between FICO scores and interest rates may be driven as much by standard price discrimination as by firms pricing in default risk.

2 Related Literature

Credit Rationing

Credit limits are a device for credit rationing, and since the early work of Hodgman (1960) and the seminal work of Stiglitz and Weiss (1981), there has been a longstanding interest in credit rationing in credit markets (Calomiris, Longhofer, and Jaffee, 2017). In the Stiglitz and Weiss model, market-level interest rates do not rise to clear the market because higher interest rates attract riskier borrowers (adverse selection effect) and may induce more defaults (moral hazard effect). As a result, amongst similarly risky projects, some receive a loan, and others do not.

Motivated by recent empirical findings, which I detail in Sections 3 and 5, my model of credit rationing differs from Stiglitz and Weiss (1981) along three main dimensions. First, I argue that the credit card market is not perfectly competitive, so lenders set their own prices. Second, several recent papers have documented the price-invariance of default, so I exclude moral hazard. Finally, in my framework, lenders obtain signals on borrowers' risk, whereas lenders in Stiglitz and Weiss (1981) infer default risk based on borrowers' willingness to accept higher rates. In prior work, credit rationing occurs as a result of the aversion of the to raise rates to clear the market. I contribute by producing a model that generates *intensive margin* (rather than extensive margin) credit rationing through lenders choosing to set credit limits that may bind for some individuals.

The limited existing empirical work focuses on the causal effect of credit limits on borrowers' outcomes. Agarwal, Chomsisengphet, Mahoney, and Stroebel (2017) and Gross and Souleles (2002a;b) estimate the causal effect of credit limits on borrowing and default.[3] I am the first to estimate a model that explains credit limit distributions as a function of lenders' risk signals.

Risk-Based Pricing

My work also contributes to the literature on risk-based pricing. Papers have documented the presence of risk-based pricing in some financial markets (e.g., Edelberg, 2006; Adams, Einav, and Levin, 2009) and its absence in others (e.g., Benetton, 2021). Livshits, Mac Gee, and Tertilt (2016) is a key contribution to this literature. The authors argue that credit has become widely available, or "democratized," in response to financial innovations such as credit scoring and risk-based pricing. Their empirical work shows that in the US, the availability of credit to riskier borrowers coincided with a significant rise in interest rate dispersion, consistent with their model's predictions. I show that the functioning of the UK credit card market up to 2015 differs: credit has become widely available at almost all levels of risk despite limited variation in interest rates across the distribution. My work shows that in the UK market, the widespread availability of credit occurs alongside risk-based credit limits and not risk-based interest rates.

[3] Aydin (2022) presents an interesting experiment randomizing credit limit shocks across credit card accounts in the United States.

Regulation of Credit Markets

My final primary contribution is to the literature on regulating credit markets. Much of the existing work focuses on the effects of the 2009 US Credit Card Accountability, Responsibility, and Disclosure (CARD) Act.[4] Agarwal, Chomsisengphet, Mahoney, and Stroebel (2014) documents substantial consumer savings due to the Act. Nelson (2022) focuses on how the Act limited lenders' abilities to reprice credit card customers after origination. I focus entirely on pricing and credit limits at origination since risk-based repricing has limited application in the UK (see Section 4). I contribute to this literature by arguing that the limited risk-based pricing in the EU credit market context tilts the market in favor of low-income consumers and away from lenders and their profits.

3 Data and Context

My primary data source is the Financial Conduct Authority (FCA) Credit Card Market Study (CCMS) Database (FCA, 2015b). The FCA used its regulatory authority to collect data on all active credit cards at 14 lenders between 2010 and 2015.[5] This dataset covers approximately 80% of all UK cards active during this period, amounting to around 74 million cards. Their data collection resulted in three main datasets, which are yet to be used for economic research.

The first dataset includes cardholder and card information at origination, such as demographics (age, income, gender, employment, and home-ownership status, etc.), acquisition channel (whether in branch, online, by post, via telephone, etc.), and initial interest rate, credit limit, and 0% promotional deal length. Notably, this dataset includes lender-specific credit scores at origination, a unique feature I analyze comprehensively in Section 4.1. Since there is no single equivalent of the FICO score in the UK, this addition is particularly valuable because, without data on the credit scores that lenders actually use, I cannot accurately assess whether interest rates and credit limits are risk-based. Table A.1 provides detailed summary statistics, already revealing stark differences in credit limit and interest rate variation. For instance, the coefficient of variation (the ratio of standard deviation to mean) for credit limits is 93%, compared to 36% for APRs. Sections 4.2 and 4.3 further decompose these variations by lenders and cards in what is a central element of my descriptive findings.

The second dataset is a monthly panel of statement data for credit cards between January 2010 and January 2015. It includes balances (opening and closing), repayments, the number and value of

[4] Another related context is the Chilean credit market, 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 equilibrium prices. Related to my work, they show that risk-based interest rate caps mitigate welfare decreases.

[5] 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.

transactions, fees, interest, and defaults. Further, it provides the evolution of credit scores, interest rates, *and* credit limits, which is often lacking in existing ones used for research on the US market.

I use the statement data to assess the extent of credit rationing from binding credit limits. Credit is considered rationed through credit limits if individuals' spending on the card is at or close to the credit limit.[6] I define credit limit utilization by calculating the closing balance as a percentage of the credit limit. Across all statements with a positive closing balance, 23% close with a balance over 90% of the credit limit, and 27% have a closing balance exceeding 85% utilization. Thus, on over one in five statements on which the card is used, the card's closing balance is at or close to the credit limit. At the individual level, in the first two years post-origination, approximately 40% use over 90% of their credit limit on at least one occasion. So near- or full-utilization is a prominent UK credit card market feature.

The decision of a customer to repay the entire balance—also known as transacting—is another prevalent feature of the statement data. Repayment covers the entire balance on approximately 50% of statements, and approximately 25% of cardholders repay in full every month in the first 12 months post-origination. Further, there is substantial variation in the proportion of transacting statements across lenders, ranging from 22% to 85% (see Figure A.1 for all values). These findings motivate the inclusion of an extensive margin transaction decision for consumers in my model and discipline the model to sort customers across lenders by their potential transacting decisions.

The third dataset is a monthly panel of card characteristics covering January 2010 through January 2015, capturing annual fees, rewards, income thresholds, and advertised APRs. Additionally, the dataset includes rarely observed lender funding costs. The statistics on funding rates in Table A.1 suggest that credit card lenders enjoy substantial markups. Mean yearly funding rates are 2.28%, and less than 3% of borrowers default each year. Even under the conservative assumption that lenders cannot recover any part of a defaulted balance and ignoring interchange revenue, this implies a markup (price to marginal cost ratio) of approximately four. Since the marginal lender prices above marginal cost, I am inclined to consider an alternative to a perfectly competitive model. Furthermore, the Herfindahl-Hirschman Index (based on the value of borrowing) is 1,496, where a value exceeding 1,000 implies a concentrated industry (FCA, 2015a).

Finally, the CCMS data package also includes a credit reference agency (CRA) dataset that matches cards to individuals. Also, I occasionally complement my analysis and motivate modeling choices with an FCA survey of cardholders, detailed in FCA (2015c).

UK Credit Card Market and EU Regulation

The UK credit market differs from the US equivalent in several ways. First, the UK market is more

[6]Individuals using, say 90% of their credit limit are considered as credit constrained because they might not make a purchase on credit because it would push them over their credit limit, which incurs a fee and will lead to a decrease in credit score.

passive regarding rewards, fees, and purchase promotional deals. In the UK, cashback and airmiles are scant, present in only 11% and 6% of card product-months, respectively, and annual fees are zero in 88% of card product-months. In understanding these discrepancies, it is worth noting that EU regulation limits interchange fees to 0.3%, as compared to typical values of 2% in the US (see Wang, 2023 for more details on the positive relationship between interchange fees and rewards).

Second, US individuals own more credit cards than UK individuals. My CRA data confirm that most UK individuals have only one card each (see Figure A.2). The 2015 US mean number of cards per person was 2.24.

Third, regulatory differences exist. All promotional material and documentation for a credit card product in an EU credit market must include a "representative" ("advertised") APR. Before February 2011, at least 66% of customers each month had to obtain the advertised APR or lower. The regulation changed in February 2011 when the UK harmonized with the EU to reduce the threshold to 51% and it has not changed since. The US has no such regulation. Also, UK customers cannot discover their personal interest rate or credit limit until after they have been accepted. The 1974 Consumer Credit Act mandates a "cooling-off period" during which consumers can freely cancel their card, though my data show that this option is exercised in only 0.2% of originations. These shopping periods are also common in the US, though the law does not mandate them.

In Section 4.2, I describe two other notable features of the UK credit card market (limited lender product portfolios and limited ex-post repricing) as they pertain to ruling out alternative mechanisms through which lenders could implement risk-based pricing.

4 Descriptive Evidence

The main aim of this section is to present robust descriptive evidence that up to 2015, the leading UK credit card lenders individualized credit card contracts through risk-based credit limits rather than interest rates. I organize my discussion around three primary variables: credit (risk) scores, credit limits, and interest rates. Though not described in the text, rewards, fees, and promotional fees are almost always constant at the card-month level. At the end of each subsection, I summarize the descriptive facts presented and explain their implications for a model of the UK market.

4.1 Credit Scores

This subsection highlights two features of the credit score data: (i) credit scores differ across lenders and are based on proprietary information, and (ii) there is substantial within-card variation in credit scores across cardholders at origination.

To start, I plot the distributions of origination credit scores across different lenders (see Figure A.3). The figures highlight that lenders' scores differ in their numerical scales and distributions.

These features suggest that lenders construct their own scores, but this could result from a mere rescaling process or the selection of customers with differing default risks across different lenders.

To explore potential discrepancies in lenders' credit scores further, I regress each lender's proprietary credit scores on a fine set of demographics collected by lenders during the application process, including percentile bins for income and age, employment and home-ownership status dummies, and month fixed effects. In these regressions, the proportion of variation in private credit scores explained is 21% on average, varying from 7% to 34% (see Figure A.4 for the range of values).[7] These findings imply that most lenders' proprietary credit scores are based on much more than the readily available customer demographics, though it suggests that some lenders rely on these demographics more than others. The fact that the R-squared values vary greatly suggests that each lender's proprietary credit scoring algorithms differ.

The use of proprietary credit scores in the UK contrasts with the US, where FICO scores provide a standardized measure of customer creditworthiness that many banks use as part of their lending decisions (Agarwal, Chomsisengphet, Mahoney, and Stroebel, 2017). Recent academic research justifies why lenders might create their own risk scores. For example, Albanesi and Vamossy (2019) shows that machine learning (specifically deep learning) methods consistently outperform standard credit scoring models, even when trained on the same data source.[8]

Next, I investigate whether lenders sort customers of similar risk onto different cards. For each lender-month, I perform a one-way Analysis of Variance (ANOVA), decomposing the variation in proprietary credit scores into a within-card and between-card component (see Online Appendix Subsection B.1 for a mathematical formulation). Table A.2 column (1) contains the results across lenders. When averaging over lenders and months, the within-card variation accounts for 87% of the total variation, indicating substantial variation in customers' credit scores within each card product. This fact implies that lenders do not sort customers of varying risk onto separate cards. As described in the next section, lenders do not offer many products in their portfolio anyway, and their cards differ in alternative features such as their network (e.g., Visa/Mastercard), rewards, and branding. To summarize:

[7] Similar findings emerge when I perform the same exercise, replacing demographics with the main publicly available UK credit score, though I have only have data on the public credit score for a limited set of months. In these regressions, the mean R-squared across lenders is around 22%, and it varies from 6% to 36%. These findings imply that public credit scores only explain a moderate proportion of the variation in each lender's proprietary credit scores: lenders either input private data sources into their algorithms or use alternative algorithms to the public credit score providers.

[8] Einav, Jenkins, and Levin (2013) documents significant profit increases for lenders following the adoption of risk-scoring methods. Also, see FCA (2023) for a recent report on the UK credit information market and credit reference agencies. The report confirms that the credit information market is concentrated, and points to "several areas where it [the market] could be working better."

Empirical Finding 1 (Credit Score Variation) *Each lender constructs its credit score, differing from publicly available scores and not well-explained by typical demographics such as income or age. Additionally, substantial within-card variation in credit scores indicates that lenders do not sort customers by risk onto separate cards.*

Model Implication 1 (Screening Technologies) *Lender-specific credit scores, termed "screening technologies," should be a lender-specific variable in a model of the supply side of the UK credit card market. Credit scores observed are a combination of demographics, such as income, and private signals on customers' risk.*

4.2 Interest Rates

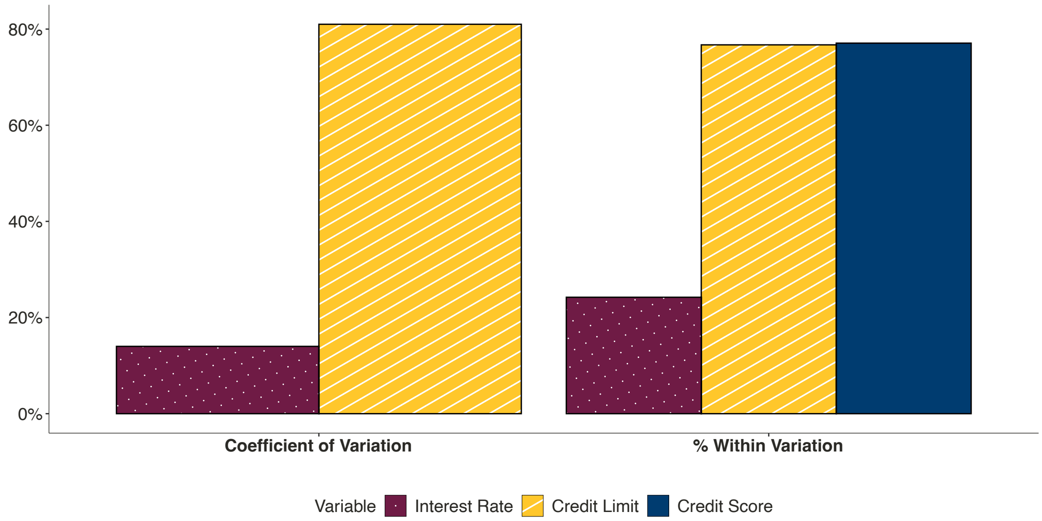
4.2.1 Limited Total and Within-Card Variation in Lenders' Rates

Next, I document limited variation in interest rates across originations at each lender. Table A.2 column (2) reports the average (over months) of lenders' interest rate coefficient of variation. The values are below 23%, and, as shown in the left-hand dotted maroon bar in Figure 1, the average across prime and superprime lenders (weighted by originations) is 14%. This finding implies that the standard deviation in the interest rate is, on average, one-seventh of the mean at a lender in a given month. Further, as detailed in Table A.2 columns (3) and (4), the across-lender weighted average of the ratio of the 75^{th} to 25^{th} percentile (respectively 90^{th} to 10^{th}) for interest rates is 1.19 (respectively 1.38), further illustrating limited UK variation in interest rates within lenders. In contrast, Galenianos and Gavazza (2022) show that for US interest rates, the ratio of 90^{th} percentile to 10^{th} percentile is as large as 3, even after controlling for borrower and card characteristics. Finally, the coefficient of variation in interest rates is 0.36 when calculated across all lenders. This is over 2.5 times larger than the within-lender average, indicating some differences in lenders' average interest rates.

For the leading UK credit card lenders, a modest proportion of the already small total variation in interest rates is found across the individuals on a given credit card product. To show this feature, I perform the same one-way ANOVA as in Section 4.1, but this time for interest rates. As plotted in the right-hand dotted maroon bar in Figure 1, within variation for prime and superprime lenders is, on average, 24% of the total variation.[9]

[9]The weighted average including subprime lenders is 33%. I discuss subprime lenders separately in Online Appendix B.2. Table A.2 column (5) reports the values of the percentage of within-card variation for all lenders. In the extreme case, one lender gives all customers on a given credit card the same interest rate in *all* months. In that case, all the variation in interest rates at origination is at the card level.

Figure 1. Coefficient of variation and proportion of within-card variation in credit scores, interest rates, and credit limits



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

4.2.2 High Proportion of Customers Obtaining Advertised APR

To explain the lack of within-card variation in interest rates, I calculate the percentage of customers in each month that obtain their card's advertised APR. I plot the time series in Figure A.5. The proportion of customers receiving the advertised APR across all credit cards in the sample remains consistently high at 80 to 90%, and this stability persists even after the regulatory change in February 2011 that relaxed the requirements for advertised APRs. Even though regulation required lenders to give the advertised APR (or lower) to only 51% of their customers after February 2011, most lenders still gave almost all their customers the advertised APR. Further, in 77% of card-months, over 90% of originations obtain the advertised APR. This statistic confirms that most *cards*, not just *lenders*, give most of their holders the advertised APR.

4.2.3 Ruling Out Alternative Forms of Risk-Based Pricing

Lenders could employ risk-based pricing by adjusting interest rates after origination, *repricing* customers according to their evolving risk and behavior. However, limited repricing occurs in the UK credit card markets. Outside of promotional deals, lenders reprice 3% of individuals within nine months of origination and 5% within one year of origination.

Furthermore, lenders could employ risk-based pricing by offering multiple distinct cards and sorting customers of differing average risk onto different cards. Empirical Finding 1 already rules out that customers are sorted onto cards by risk score and the above evidence shows that there is limited between-card variation in interest rates within a lender. Furthermore, as shown through several statistics in Table A.3, lenders offer a minimal set of cards each month. For example, the share of originations on the top two cards at each lender is 86% at the mean and 91% at the median.

Finally, lenders may refrain from using risk-based pricing because they are colluding on interest rates in a cartel. I provide brief empirical evidence inconsistent with this notion in Appendix B.3.

Empirical Finding 2 (Interest Rate Variation) *Rates exhibit limited total and minimal within-card variation. Between 80-90% of customers obtain the advertised APR at origination each month, corroborating the limited within-card variation in interest rates. Interest rates are not risk-based within credit card, and alternative means by which lenders could employ risk-based pricing (through sorting or dynamics) are also absent.*

Model Implication 2 (Card-level interest rates) *It is a sensible abstraction to treat interest rates as constant at the card-month level so that interest rates* $r_{ij} = r_j$ *for all customers* i *who choose card* j.

4.3 Credit Limits

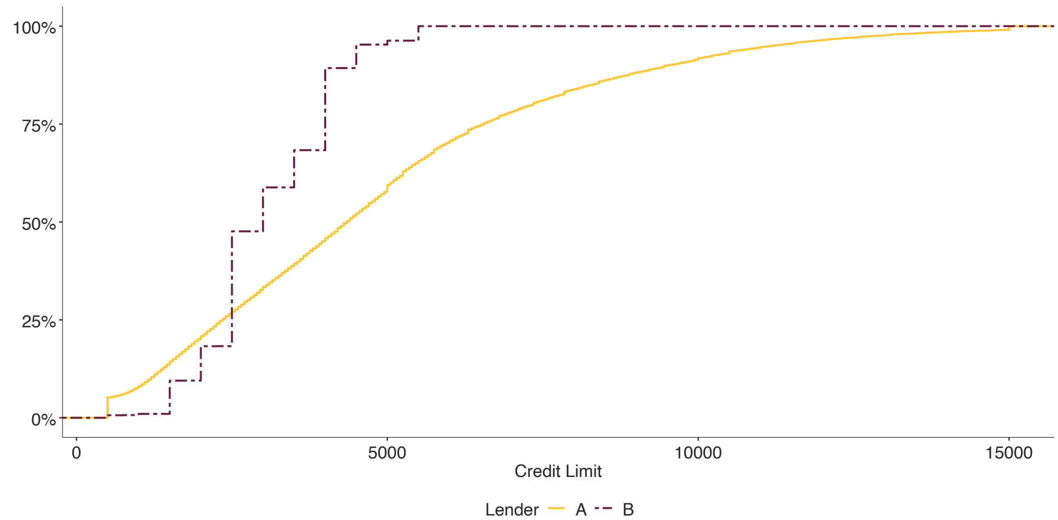
4.3.1 Substantial Variation in Lenders' Credit Limits Across and Within Cards

Having confirmed the lack of variation (particularly within-card variation) in interest rates, I now turn to credit limits, which, unlike interest rates, exhibit substantial variation. The coefficient of variation in credit limits across lenders is 78% on average (when weighted by originations). This value is over five times larger than that for interest rates. Columns (7) and (8) of Table A.2 report the across-lender weighted average of the 75th to 25th percentile and the 90th to 10th percentile credit limit ratios, which are 3.34 and 9.18, respectively, indicating significant variation in credit limits within each lender.[10]

Once again, I perform a within-card and between-card decomposition of credit limit variation. Across lenders, as shown in the right-hand gold striped bar in Figure 1, the percentage of total variation found within credit cards is 80%. Like credit scores, the dominance of within variation suggests that lenders do not sort individuals onto cards with varying average credit limits. Instead, there is considerable variation in credit limits, even within a credit card product and month.

[10]These ratios are not well-documented in the literature for the US credit card market.

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



Notes: Monetary values here and everywhere that follows are quoted in 2015 Great British Pounds (GBP).

4.3.2 Variation in the Shape and Scale of Lenders' Credit Limit Distributions

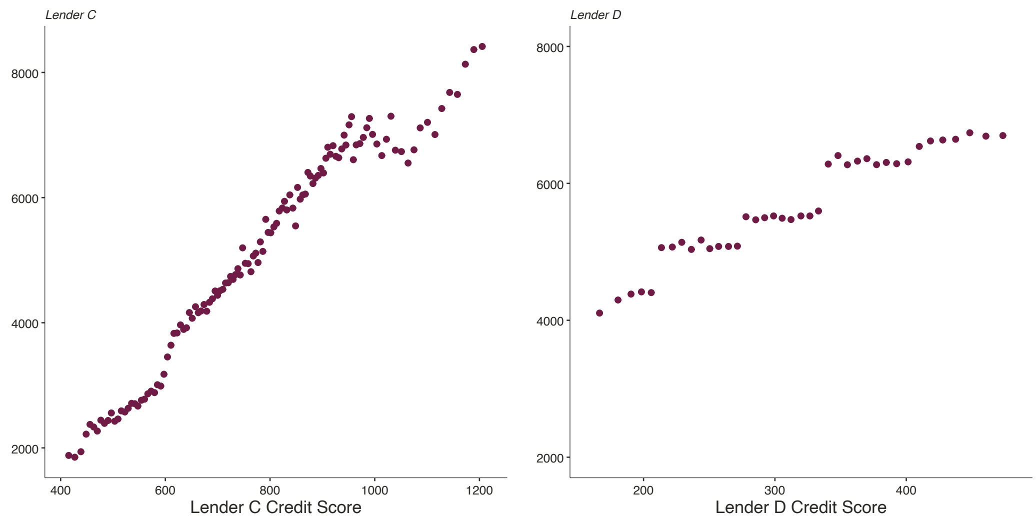
The distribution of credit limits varies substantially across all lenders, both in shape and scale.[11] I illustrate this in Figure 2, where I plot the empirical cumulative distribution function (CDF) of credit limits for two contrasting lenders, lenders A and B. Two substantial differences are evident. The first relates to the *shape* of the credit limit distributions. Lender B's curve is step-like, implying a coarse process of assigning credit limits to individuals, where groups of consumers obtain the same credit limit. Lender A's smooth curve is consistent with a more finely tuned allocation mechanism for origination credit limits. The second difference relates to the *scale* of the credit limit distributions. Lender A has lower values of credit limits than lender B for the first 25 percentiles; however, all percentiles after the 25^{th} are larger. The range of lender A's credit limit distribution is indeed much larger.

Other lenders' credit limit CDFs, plotted in Figure A.6, lie between the two lenders in Figure 2. This range in the shape and scale of distributions is consistent with lenders who vary in the coarseness of their credit limit assignment. Some lenders offer large groups of customers the same credit limit, while others with smoother CDFs adjust their credit limits more precisely.

As expected, lenders link each individual's credit limit to an assessment of their default risk. In Figure 3, I plot the mean of the origination credit limit along application credit scores for two

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

Figure 3. Mean credit limits across credit scores for two particular lenders



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

contrasting lenders for 2013.[12] Both curves are upward-sloping, consistent with risk-based credit limits. Further, the right-hand lender has discontinuities in credit scores at credit score thresholds similar to those exploited in Agarwal, Chomsisengphet, Mahoney, and Stroebel (2017). Accordingly, my model aims to rationalize discreteness and discontinuities in lenders' credit limit distributions through coarse (discrete) assessments of customers' risk.

Empirical Finding 3 (Risk-Based 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. Credit limits vary with lender-specific credit scores, and heterogeneity exists in how lenders map their credit scores into credit limits.*

Model Implication 3 (Risk-Based Credit Limits) *Lenders should choose credit limits optimally according to their predictions of customers' risk. Differences in their screening technologies should deliver lender-specific distributions of credit limits that vary in scale and coarseness.*

4.4 Implications of Descriptive Findings

This section reveals that leading UK credit card lenders individualize credit limits based on their assessments of customer risk but do not individualize interest rates. These empirical facts align with EU credit card regulation, which mandates a card-level advertised APR that most customers must

[12]In Figure A.7, I plot the mean of origination credit limit for each lender, along application credit scores. All curves are upward-sloping, consistent with risk-based credit limits. In unreported plots, the same patterns emerge when produced by month and by card.

receive. The next step is understanding how lender heterogeneity and regulatory environments impact consumers' and lenders' outcomes and welfare. The empirical setting is not insightful on how lenders would set interest rates if they were not required to set and advertise a card-level APR. In the absence of meaningful exogenous variation in the regulatory environment or the makeup of lenders, the best—and perhaps only—way to achieve this aim is to build an economic model of the credit card market. This model follows in the next section.

5 Model of the Credit Card Market

In this section, I develop a model of lenders' credit limit choices and individuals' credit card, borrowing, and default choices. The model is specifically designed to explain how lenders set credit limits and to analyze the implications of these limits on borrower utility and lender profitability under different market conditions. Before providing the details, I intend to clarify what the model is not intended for. First, the previous section showed that lenders give 80–90% of customers the advertised APR at origination, even though the regulation allows for 49% of individual interest rates to exceed that which is advertised. The aim of this model is not to rationalize this fact. I take it as given that there are some underlying features, beyond the regulatory 51% proportion, that drive lenders to set interest rates at the card level. I provide some details on what these possible factors could be in Online Appendix E.2. While this is a fundamental question, it is not the one I answer in this paper.

Second, in the previous section, I argue that lenders do not offer an extensive menu of cards with a broad spectrum of advertised interest rates. Lenders also do not sort consumers of similar risk across their limited set of cards. I am not trying to rationalize these two features with my supply-side model either. I take lenders' menus of cards as given and do not estimate how they set advertised rates; instead, I estimate a model of lenders' credit limits through their screening technologies. The model is fit for the purpose of simulating how lenders would set interest rates (admittedly, on the same set of cards) in the absence of *any* limitations on how they are individualized – I develop that model of interest rate setting in the counterfactual section. This modeling setup is sufficient to shed light on the two research topics at hand, which are (1) the implications of constant interest rates on lenders' profits and borrowers' outcomes and (2) the respective roles of tailored interest rates and credit limits, as seen in the US context.

5.1 Preliminaries and the Credit Card Product

I define the market as a pair (m, t), where t represents an origination month between January 2010 and June 2013, and m represents one of three distribution channels: branch, online, or other channels such as telephone or post.[13] I describe the model through its three features: the credit card $j \in J_{mt}$, consumers without a credit card $i \in I_{mt}$ (representing demand), and lenders $\ell \in L_{mt}$ (representing supply).

I focus on the preferences of those currently without a credit card for two reasons. First, as discussed in Section 3, most UK adults hold only one credit card, making it a relevant subset for empirical analysis. Second, estimating my model on the sample currently without a credit card circumvents complications arising from (i) balance transfers and (ii) balance-matching heuristics in repayment across multiple cards (Gathergood, Mahoney, Stewart, and Weber, 2019).

My demand model of card origination, borrowing, and default can be microfounded in a typical consumption-savings setup. However, since my focus is lenders' credit limit choices, I prefer to specify demand-side estimating equations as a set of linearized equations agnostic to the behavior that generates them. Matcham (2024) discusses the costs and benefits of this approach and the approaches in other credit market models.

Following the tradition of Lancaster (1966), I model a credit card product as a bundle of features. There are four components. The first is the advertised interest rate r_{jmt}. The second is the income threshold $\underline{Y}_{jmt}$, explained in Section 5.2. The third and fourth are characteristics: those I observe, denoted X_{jmt} (e.g., air miles), and those I do not, ξ_{jmt} (e.g., prestige and loyalty).

5.2 Consumer

Like Crawford, Pavanini, and Schivardi (2018), I model three primary endogenous demand-side variables: card choice, borrowing level, and default. I detail each of these in turn.

5.2.1 Card Choice

Consumers choose a card and whether to use the card for transacting or revolving. Choosing to transact, denoted $j = 0$, involves paying off the balance in full every month. Revolvers leave some balance unpaid, accruing interest.[14] The consumer's utility from revolving on card j is

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

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

[14] That consumers choose whether they will use the card for revolving or transacting is one of few substantive assumptions on consumer behavior I impose. I impose it as it simplifies the lender's problem. 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, 25% have set up a direct debit, rising to 31% by six months. Of those who set up a direct debit at origination, around 40% set up a direct debit to automatically pay off their entire balance each month, suggesting they intend to be a transactor. Of the remaining 60% who set up a direct debit for an amount less than the full balance, 76% set up a direct debit to pay the *minimum repayment*, which is usually the maximum of (i) 1-2.5% of the balance, and (ii) £5 (around $6).

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

To justify my choice of components for $\bar{V}^E$, I draw on the results of a question from a cardholder survey (FCA, 2015c). Participants were asked, "Which of the following applied when you took out your credit card?" The most common response is rewards, which 33% of respondents provide. For this reason, I include X^E_{jmt} in $\bar{V}^E$. Twelve percent of customers mention the card's interest rate. Hence, I include r_{jmt} in $\bar{V}^E$.

Other non-price, non-reward, and non-promotional deal responses comprise some of the remaining survey responses, implying the importance of ξ^E_{jmt}. Such responses include "use abroad" (15%), "low fees (4%), and "good deal offered" (13%), all of which are examples of unobserved characteristics contained in ξ^E_{jmt}. Finally, there is little to no mention of individualized credit limits $\bar{b}_{ijmt}$, which I omit from $\bar{V}^E$ directly. However, through ξ^E_{jmt}, I allow individuals to prefer certain cards because they know (or think) these cards have higher *average* credit limits.

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

$$V^E_{ijmt} = \beta^{E\prime} X^E_{jmt} + \xi^E_{jmt} + \nu_{ijmt} + \alpha^E_{imt} r_{jmt} + \eta^E_{mt}. \tag{1}$$

The random coefficient α^E_{imt} represents individual-specific preferences over interest rates. Since my counterfactual scenarios explore how lenders may choose individualized interest rates, I must allow for the possibility that preferences over interest rates differ across individuals. Heterogeneous preferences over interest rates read

$$\alpha^E_{imt} = \alpha^E + \Omega^{E,r}_{mt} \tilde{y}_{imt}. \tag{2}$$

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

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

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

I discuss the rationale for lenders' use of income thresholds in Subsection 5.3.

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

5.2.2 Borrowing

Revolvers choose the amount of spending to leave unpaid on their card. I refer to this as the borrowing and revolving level interchangeably. To be clear, this is not the level of spending; it is the amount of spending that remains *after repayment*. Denote by b^*_{ijmt} the *desired* level of borrowing, which represents the individual's level of balance unpaid in the absence of any credit limit. The word "desired" reflects that individuals may wish to borrow more than their credit limit $\bar{b}_{ijmt}$ allows. The value of b^*_{ijmt} satisfies the following borrowing function

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

and as in card choice utility, the log of borrowing is linear in parameters:

$$\log(b^*_{ijmt}) = \beta^{B\prime} X^B_{jmt} + \xi^B_{jmt} + \alpha^B_{imt} r_{jmt} + \eta^B_{mt} + \Omega^{B,\text{cons}}_{mt}\tilde{y}_{imt} + \varepsilon^B_{imt}. \tag{3}$$

The terms X^B_{jmt}, ξ^B_{jmt}, α^B_{imt}, and η^B_{mt} in (3) have analogous definitions to those in (1) and (2), swapping E for ***B***orrowing. The random variable ε^B_{imt} reflects a revolver's unobserved demand for borrowing. For example, ε^B_{imt} would be high if an individual has an unreported health issue that requires them to quit their job. Both the lender and I do not observe ε^B_{imt} perfectly. I define its distribution in Subsection 5.2.4.

In the data, revolvers are likely to make monthly borrowing choices, such as those implied by the solution to an inter-temporal consumption-savings problem. However, this paper concerns lenders' choices of origination credit limits. What matters to lenders when choosing origination credit limits are consumers' overall borrowing over the immediate period they use the card and less so the dynamics of borrowing within that period.[15] Hence, my setup does not require a model of multiple borrowing values across periods, as a consumption-savings problem implies. Modeling borrowing as static is a clear-cut, profitable abstraction for my context.

5.2.3 Default

Finally, revolvers choose whether to default on their balance. The net utility from defaulting reads

$$V^D_{imt} = V^D(\eta^D_{mt}, y_i, \varepsilon^D_{imt}; \theta^D_{mt}),$$

[15] As such, "borrowing" can be interpreted either as the result of a borrowing choice in a two-period consumption-savings model, or as a summary statistic (such as an average) of multiple borrowing choices. 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.

where, again, all terms are analogous to those defined in (1) and (3), swapping E for ***D***efault. The individual defaults if $V^D_{imt} > 0$. Once again, I linearize V^D_{imt}, implying

$$V^D_{imt} = \eta^D_{mt} + \Omega^D_{mt}\tilde{y}_{imt} + \varepsilon^D_{imt}. \tag{4}$$

Following Nelson (2022), I omit the interest rate from 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. Much of the research on default implies that short-run liquidity drives default rather than the long-run value of a loan (Ganong and Noel, 2020; Indarte, 2023). Also, making default invariant to price follows other structural models of selection markets without moral hazard, for example, Cohen and Einav (2007) and Einav, Finkelstein, and Schrimpf (2010b).

Also, as in Nelson (2022), default is not a direct function of the credit limit. Empirical work supporting this choice includes (i) Gross and Souleles (2002b), which shows that increases in credit limit do not explain increases in default, and (ii) Agarwal, Chomsisengphet, Mahoney, and Stroebel (2017), which provides evidence that credit limits do not affect default rates for prime customers. In Online Appendix C.1, I show that the association between credit limit and default in my data is consistent with there being no positive causal effect of credit limit on default.

5.2.4 Private Information Structure

I decompose private characteristics $(\varepsilon^B_{imt}, \varepsilon^D_{imt})$ into a common component $\tilde{\varepsilon}_i$ and an idiosyncratic component $\tilde{\varepsilon}^h_i$ so that

$$\varepsilon^h_{imt} = \sigma^h_{mt}\tilde{\varepsilon}_i + \tilde{\varepsilon}^h_i$$

for $h \in \{B, D\}$.[16] The common component simplifies the lender signal structure (following in Subsection 5.3) and generates a correlation among unobserved private characteristics for each individual. I simplify by setting $\tilde{\varepsilon}^B_i$ to zero and letting $(\tilde{\varepsilon}_i, \tilde{\varepsilon}^D_i)$ be independently standard normal distributed. This approach greatly reduces the complexity of estimation while still allowing for arbitrary correlation between ε^B_{imt} and ε^D_{imt}, which I term as intensive margin selection. Henceforth, I simplify the notation, writing ε_i instead of $\tilde{\varepsilon}_i$.

5.3 Lender

This part presents my model of lenders' exogenous screening technologies and credit limit optimization, which contains the central modeling novelty. Existing approaches, which are theoretical or calibrated against limited data, focus on how lenders *choose* the coarseness of their screening

[16] I do not include private characteristics in the card choice equation. This is partly for tractability in modeling lenders' optimal supply-side choices, but also motivated by the fact that their inclusion would only capture characteristics driving the extensive margin choice to revolve, which are already captured in some part by ε^B_i.

technology in the context of fixed costs of creating "scorecards" (e.g., Livshits, Mac Gee, and Tertilt, 2016 and Agarwal, Chomsisengphet, Mahoney, and Stroebel, 2017). Instead, I treat screening technologies as exogenous, which is reasonable in a given month since investing in higher-quality proprietary data and setting up new credit scoring algorithms are costly and time-consuming. My novelty is to design a model that can estimate lenders' screening technologies off lenders' optimal credit limit distributions.

5.3.1 Preliminaries

Lenders observe individuals' incomes Y_i and take X_{jmt}, ξ_{jmt}, and $\underline{Y}_{jmt}$ as given in each market. Card characteristics are exogenous for three reasons. First, in the data, lenders do not individualize rewards, which are sticky and rarely change over the entire five-year period on which I have data. Second, lenders cannot adjust several unobserved characteristics, such as loyalty, in a given month. Third, contract pricing introduces issues in equilibrium existence and uniqueness that are profitable to abstract from where justified.

Income thresholds determine the set of individuals qualifying for a given card. UK lenders use income thresholds partly because they 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). Consequently, lenders base decisions on *eligibility*, at least in part on income.

To match the institutional environment, lenders choose credit limits for individuals non-competitively *after they have originated a card*. The regulatory climate mandates that lenders set advertised APRs r_{jmt} at the card-month-market level at the beginning of each month. This institutional feature handily circumvents issues of equilibrium existence and uniqueness pervasive in the empirical literature on contract pricing in credit markets.

I estimate the supply side model entirely off lenders' credit limit choices and, therefore, do not need to take a stance on how lenders set interest rates in the baseline. By not estimating parameters of how lenders set interest rates and taking advertised interest rates from the data, I avoid making specific assumptions about the nature of competition or conduct. Online Appendix C.3 presents one model—the standard Nash-Bertrand pricing model—of how lenders may set advertised APRs. In principle, I can use the estimated model to test how well the Nash-Bertrand model fits the card-level interest rates found in the data. Finally, although I do not estimate a model of advertised interest rate setting, interest rates are still endogenous on the demand side in the econometric sense. In the following demand estimation, interest rates are considered to be correlated with unobservable product characteristics ξ_{jmt}, which will be the error term.

5.3.2 Screening Technology

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

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

Figure 4 depicts distributions of ε_i and $\hat{\varepsilon}_i$ for two fictitious lenders. The risk distribution provided by lender 1's screening technology for customer i is $\mathcal{N}(e_{i1t}, 0.95)$. The mean of the conditional distribution e_{i1t} is far from the customer i's actual realization of $\varepsilon_i = \breve{\varepsilon}$. Lender 2 has a better screening technology. Its screening technology gives the signal e_{i2t}, which is closer to $\breve{\varepsilon}$. 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 put more weight (relative to lender 1) on potential values close to $\breve{\varepsilon}$ and less on incorrect values, such as those near zero.

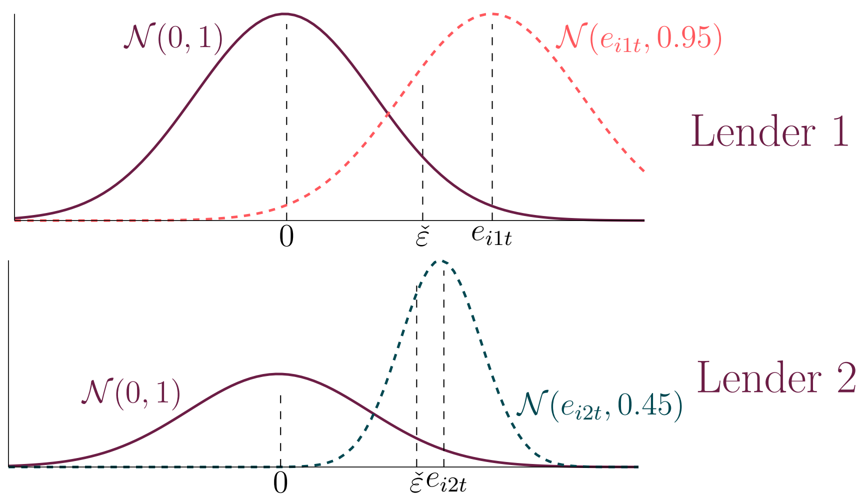
5.3.3 Credit Limit

Modeling lenders' credit limit choices requires an expression of their profits. Regarding costs, I focus on the cost of funds, denoted c, and charge-off (default) costs. 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 mainly of fixed costs (overhead and operational), which I can ignore since they do not affect lenders' margins in choosing credit limits or interest rates.

Regarding revenue, I focus entirely on finance charges coming from interest. For US lenders in 2001, this accounted for 70% of their card revenue (Evans and Schmalensee, 2005). The remaining 30% comes from three main factors: interchange revenue, fees, and cash advances. Online Appendix C.2 describes the three factors in more detail and explains why they are less relevant in the UK credit card market than in the US.

Each lender's profit from a transacting customer, denoted Π_{i0mt}, is unrelated to the credit limit

Figure 4. Distribution of ε (solid) and $\hat{\varepsilon}_i$ (dashed) across two lenders for a customer with unknown value $\varepsilon_i = \check{\varepsilon}$



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

and interest rate.[17] 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 the 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 can recover, which I set to zero in my empirical specification.[18] Hence, the expected profit per unit credit for individual i on card j is

$$\pi_{ijmt} = (1 - \Delta_{imt})(r_{ijmt} - c_{jmt}) + \Delta_{imt}(-1 - c_{jmt}). \tag{5}$$

Given the signal $e_{i\ell t}$ and the implied screening technology distribution, the lender chooses the

[17]The revenue and costs from transactors do not relate to the interest rate, since they do not revolve a balance on which interest accrues. 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.

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

credit limit $\bar{b}_{ijmt}$ to maximize the expected profit from the individual:

$$\Pi_{ijmt} \quad = \quad \max_{\bar{b}_{ijmt}} \mathbb{E}\left[\min\{b^*_{ijmt}, \bar{b}_{ijmt}\}\pi_{ijmt}\right]. \tag{6}$$

As derived in Online Appendix C.4, the first order condition is

$$\mathbb{E}\left[\pi_{ijmt} | b^*_{ijmt} \geq \bar{b}_{ijmt}\right] = 0. \tag{7}$$

The intuition behind 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, for instance, the expected profit per unit credit were positive, the lender should raise the credit limit because the expected benefit of safer types using the entire credit limit exceeds the expected costs of riskier types using the whole credit limit. The converse is true if the expected profit per unit credit were negative. Notably, the first order condition here is not a zero-profit condition. Expected profit per unit credit over those infra-marginal individuals with unobservables that drive them to use less than their full credit line is positive.

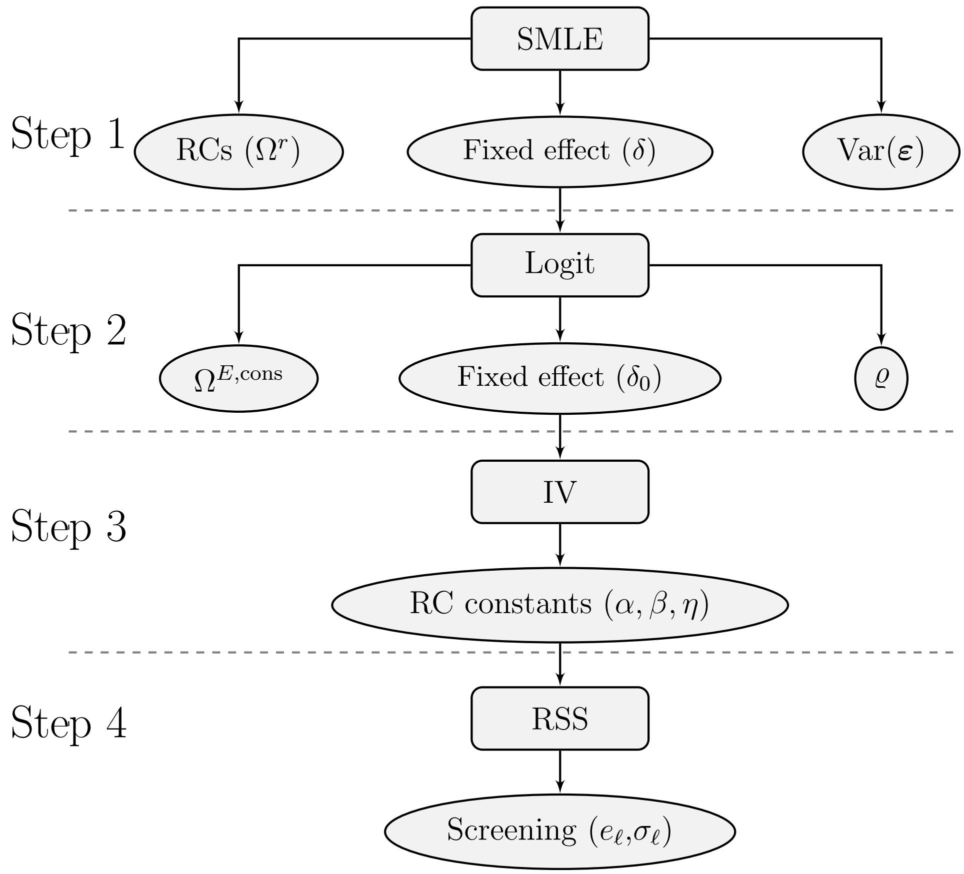
This intuition and the technical conditions behind the first order condition rely on a positive correlation between the unobservables driving borrowing and default, which I term intensive margin adverse selection. Existing studies of credit markets estimate significant adverse selection (Nelson, 2022; Crawford, Pavanini, and Schivardi, 2018). My demand estimates, which I estimate entirely *independently* from the supply side, verify this assumption (see Sections 6 and 7 for details).

Because default probability is not a direct function of borrowing, the lender's optimization problem would be piecewise linear in credit limit if there were no adverse selection. In this case, the corner solution would make lenders give zero credit to those with negative expected profit per unit credit and unboundedly large limits to those with positive expected profit per unit credit.

However, in the presence of adverse selection, an interior solution arises because, conditional on observables, sufficiently large credit limits will only be utilized by those with the highest unobserved default risk, that is, those with negative expected profit per unit credit. Of course, the lender does not want to offer extra credit to these individuals. To summarize, in the context of adverse selection, the choice of credit limit must be made with consideration of the distribution of default risk *among those* utilizing that amount of credit. This insight reveals the effect of adverse selection on lenders' optimal credit limit choices.

My descriptive findings 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 a 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. I leverage this link between credit limits

Figure 5. Four steps of model estimation



Notes: Step 1 refers to simulated maximum likelihood estimation of the demand parameters, for those who revolve. Step 2 refers to the choice between transacting and revolving 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.

and signals to estimate the distribution of signals from each of the unique credit limit values. I detail this estimation process in the following section.

6 Estimation

In this section, I outline my method for model parameter estimation. My approach to demand estimation shares features with Benetton (2021) and Benetton, Gavazza, and Surico (2022). Figure 5 displays the four steps of the estimation procedure.

6.1 Demand

6.1.1 Log-likelihood Conditional on Borrowing

I start with Step 1 in Figure 5. My demand model for those who revolve a balance consists of equations for card choice (equation 1), borrowing (equation 3), and default (equation 4). The equations map cardholders' demographics along with lenders' interest rates, credit limits, and card characteristics into card choice, borrowing level, and default. Together with stochastic assumptions on unobservables, the three equations imply a log-likelihood function for observed decisions.

The log-likelihood $\log \mathcal{L}_{mt}$ comprises two parts: the log-likelihood for card choice $\log \mathcal{L}_{mt,E}$, and the joint log-likelihood for borrowing and default choices $\log \mathcal{L}_{mt,BD}$. This form follows from the fact that unobservables for card choice are uninformative about the unobservables driving borrowing and default. Online Appendix D.1 provides detailed expressions for the terms of the likelihood. In the text below, I focus on how the estimation approach overcomes two primary challenges and discuss the exogenous variation I exploit to identify the parameters.

The truncation in borrowing is the first of two primary challenges in estimating the parameters of the likelihood function. 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 the desired borrowing for any revolvers who borrow their entire credit limit. Revolvers either use their entire credit line (full utilization) or not (interior utilization) and do or do not default. 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 individual i being in group I_g. Then the expression for $\log \mathcal{L}_{mt,BD}$ is

$$\log \mathcal{L}_{mt,BD} = \sum_{i \in I_{mt}} \sum_{j \in J_{imt}} \sum_{g=1}^{4} 1^{(g)}_{ijmt} \log(s^{(g)}_{ijmt}), \tag{8}$$

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 Online Appendix D.1.

Individuals exhibiting full utilization create the most complication. Since their desired borrowing is not observed, their contribution to the likelihood is an integral with no closed form. Hence, I use simulated maximum likelihood (Gouriéroux and Monfort, 1996) with Halton draws.

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. Without addressing this issue, estimates might suggest that individuals prefer higher interest rates when, in fact, they prefer products with attractive unobservable features that are resultantly priced higher. To deal with this endogeneity in the likelihood estimation, I estimate a full set of product-channel-month fixed effects δ_{jmt} in the card choice and borrowing equations that subsumes the endogeneity between r_{jmt} and ξ_{jmt}.

Formally, I rewrite equations (1) and (3) respectively as

$$\begin{aligned} V^E_{ijmt} &= \delta^E_{jmt} + \nu_{ijmt} + u^E_{ijmt}, \\ \delta^E_{jmt} &= \beta^{E'} X^E_{jmt} + \xi^E_{jmt} + \eta^E_{mt} + \alpha^E r_{jmt}, \\ u^E_{ijmt} &= \Omega^{E,r}_{mt} \tilde{y}_{imt} r_{jmt}, \end{aligned} \tag{9}$$

and

$$\begin{aligned} \log(b^*_{ijmt}) &= \delta^B_{jmt} + \varepsilon^B_{imt} + u^B_{ijmt}, \\ \delta^B_{jmt} &= \beta^{B'} X^B_{jmt} + \xi^B_{jmt} + \alpha^B r_{jmt} + \eta^B_{mt}, \\ u^B_{ijmt} &= \Omega^{B,\text{cons}}_{mt} \tilde{y}_{imt} + \Omega^{B,r}_{mt} \tilde{y}_{imt} r_{jmt}, \end{aligned} \tag{10}$$

where δ^E_{jmt} and δ^B_{jmt} are the card-channel-month fixed effects. Because of the typical identification issue in discrete choice models, I normalize $\delta^E_{0mt} = 0$ and take interest rates and card characteristics in (9) and (10) as differences from the outside option.

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

$$\log \mathcal{L}_{mt,E} = \sum_{i \in I_{mt}} \sum_{j \in J_{imt}} 1^E_{ijmt} \log(s^E_{ijmt|j \in J_{imt}}), \tag{11}$$

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 Online Appendix D.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, the first step of demand estimation involves market-by-market simulated maximum likelihood estimation on the log-likelihood for card choice, borrowing, and default, conditional on borrowing, to estimate product-market fixed effects (δ^E_{jmt} and δ^B_{jmt}). Estimating the fixed effects sidesteps 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 $\Omega^{B,\text{cons}}_{mt}$).

6.1.2 Log-likelihood for Borrowing and Transacting

In the second step of demand estimation (Step 2 in Figure 5), I maximize a log-likelihood for the choice between transacting and revolving, which estimates δ_{0mt} and outside option utility term $\Omega^{E,\text{cons}}_{mt}$, along with the correlation coefficient for the extreme value shocks, ϱ_{mt}. I provide details and an expression for the log-likelihood of revolving/transacting in Online Appendix D.2.

6.1.3 Constant Demand Parameters

In the third and final step of demand estimation (Step 3 in Figure 5), 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 market fixed effects, interest rates, and observed characteristics as in (9) and (10). The same endogeneity problem persists, so I estimate the equation using an instrumental variable.

As an instrument for interest rates, I exploit a cost shock to lenders in 2011 relating to the mis-selling of payment protection insurance (PPI). PPI is a form of insurance designed to cover a loan if an individual cannot make repayments due to adverse events such as unemployment, illness, or disability. In the late 20^{th} Century, UK lenders started bundling PPI with credit products such as credit cards. In the mid-2000s, it was claimed that lenders were mis-selling PPI to borrowers. For example, lenders were selling PPI to self-employed individuals who could not use it because of their employment status. In 2006, the Financial Services Authority (FSA) started imposing fines on financial institutions for mis-selling PPI.

A significant development in the case came in January 2011, when the British Bankers' Association (BBA) took the FSA to court over its decision to impose standards on the correct selling of PPI *retrospectively*.[19] The British Bankers' Association lost the case, and in mid-2011, banks informed the BBA that they were withdrawing their support for an appeal of the decision. The ruling forced banks to reopen thousands of claims for PPI mis-selling. 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.[20] The court case loss in mid-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 cards in their portfolios.[21]

I create an instrument for interest rates from this cost shock by interacting lender fixed effects with a "post" treatment dummy. The assumption is that the only channel through which the court case ruling affects individuals' card choice and subsequent borrowing is the impact of cost increases on cards' interest rates. I know no other events in the same period that affected lenders' unobservable

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

[20]See https://www.fca.org.uk/ppi/ppi-explained, last accessed 26 July 2024.

[21]Previous work argued that in the US, credit card rates are sticky relative to the cost of funds (Ausubel, 1991). However, this doesn't seem to be the case in the time series or cross section in the UK, at least in the period for which I have data. Regarding the former, monthly average funding rates are almost exactly always 10% of interest rates, with both rising by 14% between 2010 and mid-2013. And they are not merely trending together: when I regress logged interest rates on logged funding costs along with distribution channel and *month* fixed effects, the elasticity of interest rates with respect to funding costs is 0.16 and significant at lower than 1% significance level.

card characteristics. I find no significant changes in characteristics or credit limits in the same period. I confirm the instrument's relevance empirically through tests provided in Table A.4.

6.2 Supply

The final step (Step 4 in Figure 5) estimates the supply side. The parameters to estimate in the supply model are the screening technology signals $e_{i\ell t}$ and the standard deviation of the signal noise, $\sigma_{\ell t}$. I estimate these by minimizing the residual sum of squares from the first order condition of the credit limit optimization problem. As derived in Online Appendix C.4, for each unique observed credit limit $\bar{b}_{ijmt}$ on card j at lender ℓ in month t, the corresponding signal $e_{i\ell t}$ satisfies

$$\int_{\omega_{i\ell t}(\bar{b}_{ijmt}, e_{i\ell t})}^{\infty} \pi_{ijmt}(e_{i\ell t}, w_{i\ell t}) \phi\left(\frac{w_{i\ell t}}{\sigma_{\ell t}}\right) dw_{i\ell t} = 0, \tag{12}$$

where I define π_{ijmt} in (5). Towards an estimation strategy, note that under the distributional assumptions on private characteristics, the probability of default, as featured in π_{ijmt} is given by

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

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

For each observed credit limit and income, equation (12) provides an equation in which the only unknowns are the screening technology $e_{i\ell t}$ and $\sigma_{\ell t}$ (once demand parameters have been replaced with their estimates). The basis of the strategy is to estimate the screening technologies as the values that minimize the sum of squared deviations (over individuals) from the integral in (12). As in parts of demand estimation, the integral in (12) has no closed form. Therefore, for each lender-month, I simulate the integral using H 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. While it is possible to estimate the model at the lender-month level, I prefer more parsimonious models that either (i) pool months within a year (estimating at the lender-year level) or (ii) pool over all months.

7 Model Estimates and Findings

7.1 Demand 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.

Table 1. First and second step demand estimates

Variable	Parameter	SE
η^D	-1.90	0.02
Ω^D	-0.15	0.02
σ^D	0.48	0.02
$\Omega^{B,\text{cons}}$	0.24	0.02
$\Omega^{B,r}$	-1.16	0.02
σ^B	3.70	0.06
$\text{Corr}(\varepsilon^B, \varepsilon^D)$	0.38	0.02
$\Omega^{E,r}$	-0.22	0.00
$\Omega^{E,\text{cons}}$	-0.11	0.01
ϱ	0.29	0.00

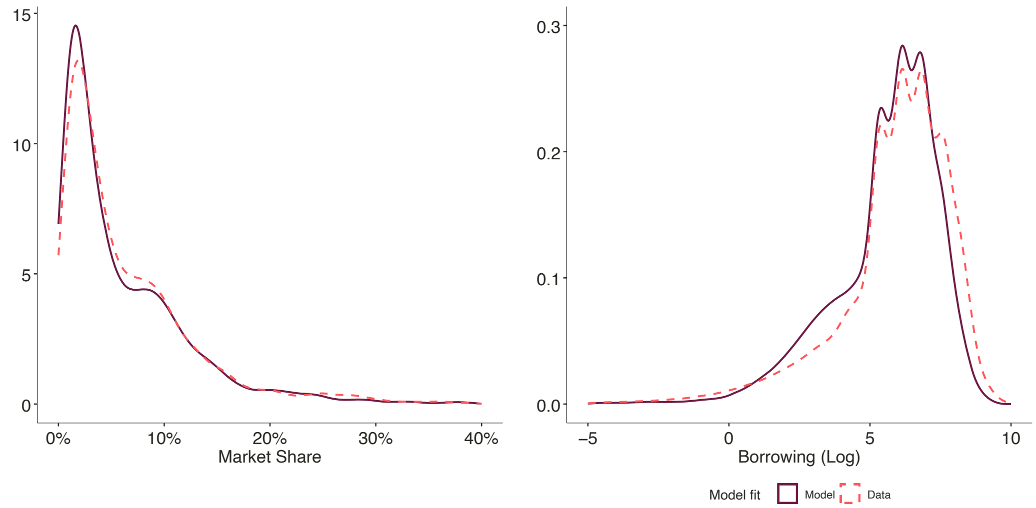
I report means (over markets) of parameter estimates and standard errors. Standard errors are asymptotic, coming from the inverse of the corresponding Hessian matrices.

First, I consider gradients of default utility, transacting utility, and the level of borrowing with respect to income. The negative value for Ω^D implies that higher-income borrowers are less likely to default. The estimate of 0.24 for $\Omega^{B,\text{cons}}$ means that higher-income individuals desire to borrow more. And the negative value for $\Omega^{E,\text{cons}}$ in the transaction utility indicates that higher-income individuals are less likely to transact. These findings are consistent with the Relative Income Hypothesis (Duesenberry, 1949), which posits that higher-income individuals are influenced by the consumption patterns of peers, leading to increased spending and use of credit.

The most notable insight comes from the gradients of interest rate sensitivities (i.e., α_i^E and α_i^B). I estimate negative values of $\Omega^{B,r}$ and $\Omega^{E,r}$, implying that lower-income individuals who decide to borrow are less sensitive to interest rates (i.e., more inelastic) when choosing their card and how much to borrow. By a standard price discrimination argument (Lerner, 1934), this implies that lenders have an incentive to set higher interest rates for lower-income individuals. Since low-income individuals are more likely to default, the negative correlation between credit scores (e.g., FICO) and interest rates, as observed in other countries and markets, may result from standard price discrimination instead of/alongside the pricing of default risk. I elaborate on this finding when discussing the counterfactual results in Section 8.

Regarding the distribution of private characteristics, the mean value of 0.48 for σ^D indicates unobserved heterogeneity in default, underscoring the importance of lenders' screening technologies. The correlation between unobserved preferences for borrowing and default is 0.38, implying that revolvers with an unobserved preference to borrow a larger amount have an unobserved prefer-

Figure 6. Distributions of market share and borrowing in the data and the model



ence to default. This finding is strong evidence of adverse selection along the intensive borrowing margin. The presence of adverse selection justifies the model intuition for how lenders set optimal credit limits. The estimate is larger than the estimate of 0.14 obtained by Crawford, Pavanini, and Schivardi (2018), whose context is the Italian market for small business loans between 1988 and 1998. Finally, the parameter ϱ, estimated at 0.29, indicates a reasonable substitution between the choice to transact or revolve.

Next, I consider model fit. Figure 6 displays the model-implied and data distributions of market shares and borrowing. The fit is good, indicating that the model captures the heterogeneity in borrower behavior, adding credence to the subsequent policy simulations.

Table A.4 reports estimates and standard errors of the demand parameters recovered in the third stage of demand estimation. OLS coefficients on interest rates in both card choice (α^E) and borrowing (α^B) equations are positive, whereas IV estimates are negative. This finding indicates the severity of interest rate endogeneity. Coefficients on dummies for most rewards (i.e., airmiles and purchase protection) in the card choice equation are positive across specifications, except for cashback. Cashback rewards are rare in the UK and the cashback rate tends to be lower than in the US, due to lower interchange fees in the UK.

Finally, I turn to interest rate elasticities (see equations (14) and (17) in Online Appendix C.5 for formulas). Figure A.8 plots the distribution of elasticities over individuals. Three noteworthy features emerge. First, individuals are much more elastic to the interest rate in their card choice relative to their borrowing choice: this suggests that individuals do shop over advertised interest rates, but their choice of how much revolve is not so sensitive to them. Second, there is a large degree of dispersion in both elasticities. The coefficient of variation of card choice and borrowing

Table 2. Summary statistics for variation in signal mismeasurement

Variable	Mean	SD	10%	25%	50%	75%	90%
σ_ℓ	0.13	0.19	0.02	0.02	0.06	0.16	0.23

elasticity is over one. This implies substantial heterogeneity in responsiveness to changes in interest rates across individuals. Third, both distributions are skewed. The distribution of card choice elasticities has a long tail, and the distribution of borrowing elasticities has a large mass close to zero, implying several consumers who are completely inelastic to the interest rate. Finally, the elasticities are similar to other experimental estimates of interest rate elasticities in credit markets (e.g., Alan and Loranth, 2013; Karlan and Zinman, 2018).

7.2 Supply Estimates

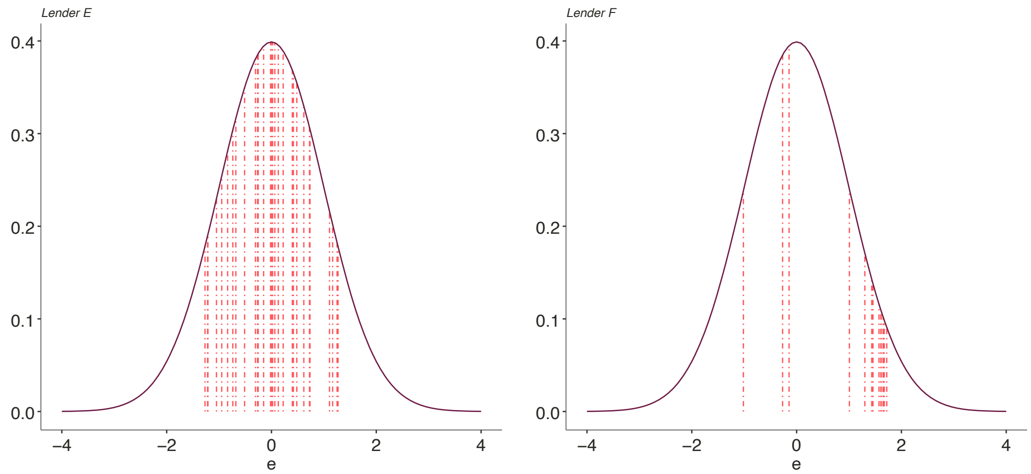
Estimation of the supply side delivers two sets of parameter estimates, where the first is the variation in signal mismeasurement across lenders, σ_ℓ. Table 2 reports summary statistics in the values of σ_ℓ across lenders. The coefficient of variation is 1.46, indicating substantial differences in the precision of lenders' screening technologies.

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. Each vertical line represents one of the lender's possible signals. I superimpose the values onto a standard normal distribution since the signals partition the standard normal distribution of ε. The left lender (lender E) has a screening technology that produces several possible signals. It is a sophisticated screening technology that provides sharp signals of borrowers' type. Lender F on the right side has a screening technology that offers only a few values, implying less precise signals on borrowers' unobservables. Figure A.9 shows the screening partitions for other lenders. Like with the values of σ_ℓ, there is substantial variation in the values and the coarseness of the screening technology across lenders.

In Section 3, I described the substantial variation across lenders in the proportion of transactors. Having estimated the structural model, I can check whether this variation correlates with the quality of lenders' screening technologies. Indeed, the correlation between σ_ℓ and the proportion of periods in which individuals repay the entire balance is 0.25. This estimate is consistent with a segmentation of credit card lenders in which lenders with the most precise screening technologies serve a riskier, but more profitable, market segment, on average. Lenders with more precise screening technologies are willing to serve customers who will borrow but may default because they can accurately set lower credit limits for customers they perceive to be riskier.

In the context of endogenous screening technologies, it would be insightful for further work to

Figure 7. Screening technology at two lenders



assess the direction of causality between the quality of a lender's screening technologies and the risk profile of their customers. One possibility is that lenders face external factors that drive them to serve safer customers and, consequently, set high-income thresholds and do not invest in screening technologies. Another possibility is that external factors drive lenders to invest in (or be endowed with) higher-quality screening technologies, encouraging them to set lower income thresholds and accept more profitable borrowers.

8 Counterfactual Analysis

This paper's central empirical finding is that credit limits are the only contractual variable individualized by lenders in the UK credit card market. Related to this empirical fact is the regulatory environment, which requires lenders to market an interest rate for each credit card product offered. Despite the requirement to advertise a card-level interest rate, lenders could still individualize interest rates to some extent. Under the assumption of profit maximization, my empirical findings imply that either (i) it is optimal for lenders to individualize credit limits only, i.e., there is no extra revenue available from individualizing interest rates, or (ii) there exist costs/constraints restricting lenders' willingness or ability to individualize interest rates.

To shed light on what drives lenders' lack of individualized pricing, I use my estimated model to simulate a counterfactual scenario that changes lenders' optimization problem. In my counterfactual, I allow lenders to set interest rates subject to no costs or constraints, and analyze the resulting distribution of interest rates and credit limits. In this setup, which mimics the US context, lenders are not required to advertise an interest rate. Since UK lenders do not individualize interest rates in the data, any profit increases measured in the counterfactual serve as a lower bound on any potential shadow costs of individualizing interest rates.[22] However, the extent to which lenders will individualize interest rates, credit limits, or both in the counterfactual is, *a priori*, not obvious.

8.1 Implementation

To implement the counterfactual, I simulate the February 2013 in-branch market under the new regime, taking the income thresholds and card characteristics from the data. In the counterfactual, for customer i, lender ℓ now solves simultaneously for all interest rates and credit limits across their cards $J_{i\ell}$ that consumer i is eligible for. Formally, given other lenders' optimal interest rate choices $\boldsymbol{r}^*_{-i\ell mt}$, for customer i, lender ℓ solves

$$\max_{\boldsymbol{r}_{i\ell},\bar{\boldsymbol{b}}_{i\ell}} \sum_{j\in J_{i\ell}} s^E_{ij}(\boldsymbol{r}_{i\ell},\boldsymbol{r}^*_{-i\ell})\mathbb{E}\left[\min\{b^*_{ij},\bar{b}_{ij}\}\pi_{ij}\right], \tag{13}$$

where s^E_{ij} represents card choice probability, $\min\{b^*_{ij},\bar{b}_{ij}\}$ reflects the constrained borrowing level, and π_{ij} denotes per-unit profit. With knowledge of interest rates, customer i chooses their card, borrowing level, and whether to default.[23] Similar to supply estimation, I minimize the residual from the first order conditions to equation (13) to calculate $\boldsymbol{r}_{i\ell}$ and $\bar{\boldsymbol{b}}_{i\ell}$ for all individuals i. Appendix E.1 provides the first order conditions I use to calculate counterfactual interest rates and credit limits. This implementation is computationally intensive because I have to solve a separate optimization problem for each consumer. Consequently, I draw a representative sample of approximately 20% of the market.

I measure three sets of endogenous variables in the baseline and counterfactual scenarios. The first is the set of equilibrium origination interest rates and credit limits. The second set—the demand-side variables—includes consumers' card choice, borrowing level, and consumer surplus. I calculate individuals' card choice and borrowing using indirect card utility (equation 1) and borrowing equation (equation 3), respectively, replacing r_{jmt} with r_{ijmt} in the counterfactual. As a result of the type-1 extreme value assumption, consumer surplus is

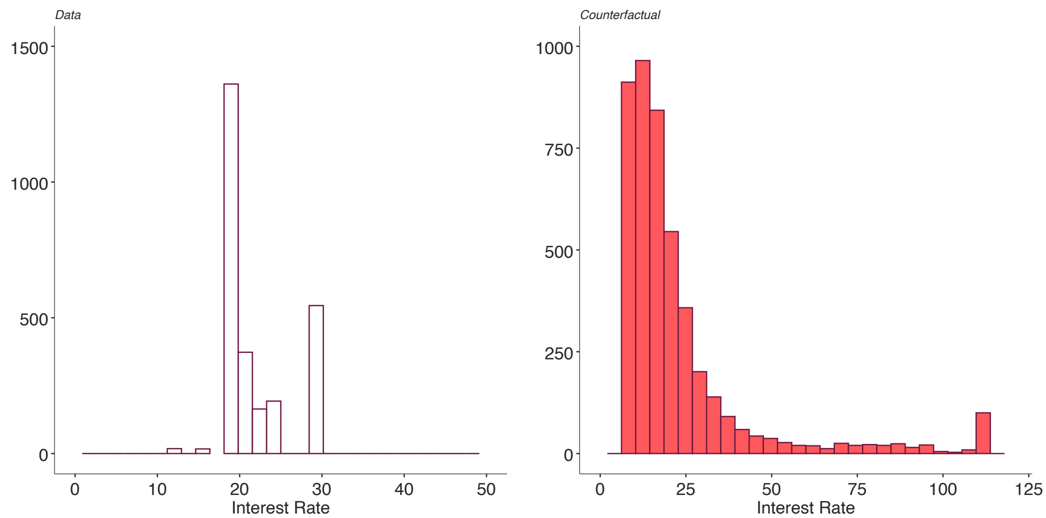
$$CS_i = \frac{1}{\alpha_i}\log\left(\sum_{j\in J_i}\exp\left(\bar{U}^E_{ij}\right)\right),$$

where $\bar{U}^E_{ij}$ is equal to $\bar{V}^E_{ij}/\varrho$, a scaled version of indirect utility. The third set of endogenous variables

[22]If profits increase by $\hat{\pi}$ in the counterfactual, then the underlying costs that deter (profit-maximizing) lenders from individualizing interest rates must exceed $\hat{\pi}$, else we would observe lenders individualizing rates in the data.

[23]In the counterfactual, I follow the baseline model by assuming that individuals know their potential interest rate at each lender when choosing their card; results from the case in which consumers do not know interest rates are available on request. I maintain the assumption that consumers do not know their credit limit to ensure that I am only changing one object at a time and also due to the absence of any credible method to measure what individuals' preferences over credit limits would be, were they known to the consumer.

Figure 8. Distribution of interest rates in data and counterfactual



includes supply-side variables. I focus on ex-post profit, which for a revolver i is given by

$$\pi_{ij}^{\text{post}} = b_{ij}\Bigg[(1-\mathcal{D}_i)(r_j - c_j) + \mathcal{D}_i(-1-c_j)\Bigg],$$

where $\mathcal{D}_i$ is equal to 1 if borrower i defaults.

8.2 Counterfactual Results

8.2.1 Interest Rates and Credit Limits

The main variable driving changes in the counterfactual is the interest rate. Figure 8 shows the distribution of interest rates in the baseline and the counterfactual scenarios. The distribution becomes highly individualized in the counterfactual, with thousands of unique interest rate values compared to few distinct values in the baseline. The coefficient of variation in interest rates increases from 20% in the baseline to 92% in the counterfactual, and the standard deviation increases from 0.04 to 0.21. These together imply a significant increase in interest rate dispersion. This finding means there must be some underlying cost of individualizing interest rates in the 2010–2015 UK market beyond the 51% proportion alone; otherwise, we would expect lenders to individualize interest rates to some extent in the baseline. Though this is not the question I answer in this paper, I discuss possible factors in Subsection 8.2.3 and further in Online Appendix E.2.

The net directional effect on the values of interest rates is *ex ante* ambiguous. Average interest rates may increase because lenders can now price discriminate, but they could also decrease because lenders need not pool interest rates across risk types. The former dominates in the counterfactual, with interest rates increasing by three percentage points, equivalent to a 13% increase.

The net increase in interest rates in the counterfactual masks vast heterogeneity in interest rate changes across borrowers. In the counterfactual, lenders practice traditional price discrimination. Individuals with below median (that is, *inelastic*) elasticity of demand receive an average interest rate increase of 12 percentage points. On the contrary, interest rates fall by six percentage points for the most elastic individuals.

Since the most inelastic individuals are those with the lowest incomes and thus have the highest average default risk, it is the case that interest rate and default probability are positively correlated in the counterfactual. However, this is not caused by lenders pricing in default risk. In the counterfactual, individuals with high overall default risk but elastic demand obtain a lower interest rate than in the baseline.

To shed further light on this finding, in Figure 9, I plot baseline and counterfactual interest rates as a function of interest rate sensitivity $|\alpha_i^E|$. I do this separately for those with small and large risk signals $\breve{\varepsilon}$. Three features are noteworthy. First, as expected, there is no relationship between rates and sensitivity (nor rates and risk signals) in the baseline. This finding follows from the absence of within-card and across-card variation in rates. Second, the counterfactual gradient is negative for both low and high default risk signals, consistent with the price discrimination mentioned previously. Third, the counterfactual curves and patterns are almost identical for those with high and low risk signals, confirming that interest rates do not price in this default risk.

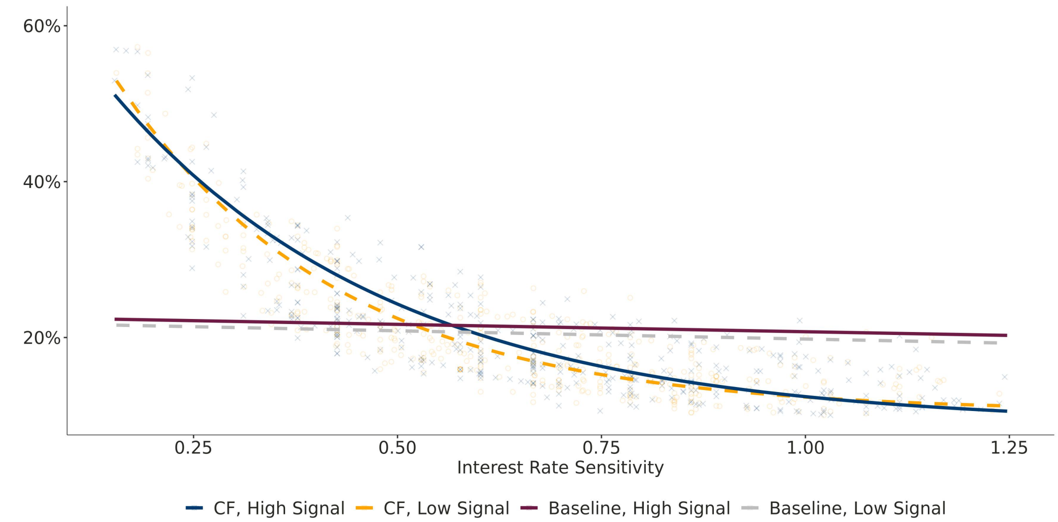
The lenders' second screening instrument is the credit limit. Figure A.10 displays the distribution of credit limits in the data and the counterfactual scenario. Credit limits remain individualized and become more dispersed, with the coefficient of variation in credit limits increasing by 38% and the standard deviation rising by 24%. Credit limits fall by 10% on average in the counterfactual. The coincidence of rising interest rates and falling credit limits follows the intuition of downward sloping cost curves in Einav, Finkelstein, and Cullen (2010a) and Einav and Finkelstein (2011).

The intuition for why counterfactual lenders combine individualized interest rates and credit limits is as follows. Credit limits do not affect individuals' card choices or desired borrowing and *only* serve to manage downside risk from default. Interest rates, however, affect an individual's choice of card and level of desired borrowing through the terms s_{ij}^E and b_{ij}^* in the profit function for individual i. Individualized prices are thus a device for standard price discrimination. As an example, lenders set lower interest rates for individuals with elastic demand to encourage individuals to pick their cards and generate interest revenue. Then, among these with elastic demand, they set low (respectively, high) credit limits if the unobserved risk signal is large (respectively, small).

8.2.2 Demand-Side Variables

Next, I explore changes to borrowers' outcomes. In the counterfactual, 10% of customers switch cards and 8% switch lenders. That the vast majority of customers choose the same card in the context of changing interest rates highlights the importance of card characteristics (X_{jmt} and ξ_{jmt}) along with the relative price-inelasticity of demand. Though the borrowing level does not adjust

FIGURE 9. COUNTERFACTUAL INTEREST RATES AND PRICE ELASTICITIES BY RISK TYPE



Notes: The solid downward-sloping curve represents the least squares fit between observations of interest rates and interest rate sensitivity in the counterfactual scenario for those with default risk signal above the 85^{th} percentile; the dashed downward-sloping curve represents the analog of the solid curve except estimated on those with default risk below the 15^{th} percentile. The solid horizontal line represents the best fit between interest rate and interest rate sensitivity in the baseline for those with default risk signal above the 85^{th} percentile; the dashed horizontal line represents the analog except estimated on those with default risk below the 15^{th} percentile.

materially on net, it increases by approximately 11% for those with above-median income and decreases by 15% for those with below-median income. This result is consistent with lenders' motives to price-discriminate: lenders decrease interest rates for safe, elastic individuals to incentivize them to borrow/borrow more.

In the counterfactual, consumer surplus falls by 1% on average relative to the baseline. However, as with interest rates, this decrease in the average masks heterogeneity across borrowers. In Figure A.11, I plot the distribution of percentage changes in consumer surplus for high-elasticity and low-elasticity individuals. Consumer surplus generally increases in the counterfactual for the high-elasticity group—a 15% increase on average—because they benefit from lower interest rates. Consumer surplus falls by 2% on average for the low-elasticity group.

8.2.3 Lenders' Profits

By price discriminating, lenders' ex-post profits increase by 23% on average. Such increases imply the existence of non-trivial frictions restricting lenders' willingness to adopt individualized prices.

Identifying the exact sources of these frictions is not the focus of this paper. Still, in Online Appendix E.2, I consider a small set of likely candidates. Industry and policy documents allude to potential reputational risk to lenders from adopting risk-based pricing in the EU regulatory context (House of Commons Treasury Committee, 2003). There could be significant backlash, were lenders to advertise a low interest rate and then set high individualized APRs after individuals have chosen their card. Indeed, in 2003, the UK Government Treasury Committee described this kind of risk-based pricing as an "unacceptable practice" raising "serious transparency issues."[24] In the aftermath of a global financial crisis and a "PPI scandal," any further erosion of trust in UK banks may have come at significant reputational cost.

9 Concluding Remarks

I investigate how credit card lenders manage customers' unobserved default risk by individualizing contracts through risk-based credit limits. Using novel, statement-level microdata, I estimate a structural model of the credit card market. The model features credit rationing on the *intensive margin* as lenders set binding credit limits. The central model innovation is the lender screening technology that provides noisy signals on borrowers' unobserved types. Lenders make credit limits contingent on these signals, and the coarseness of the set of signals offered by the screening technology corresponds to the coarseness of their equilibrium credit limit distribution. Indeed, supply-side estimates imply marked differences in lenders' screening technologies.

My demand estimates imply that lower-income borrowers have more inelastic demand. This finding highlights an alternative motive for "risk-based" pricing in line with price discrimination. Lenders use credit limits to manage default risk, whether risk-based pricing is used or not.

I use the estimated model to evaluate a counterfactual scenario where lenders can fully and freely individualize interest rates and credit limits. The resulting interest rate discrimination results in consumer surplus gains for high-income individuals and losses for low-income individuals, while lenders' profits increase on average. My findings imply that, relative to the US context, the current UK environment imposes restrictions on lenders' willingness to adopt individualized prices, which protects high-risk consumers at the expense of lenders' profits and low-risk consumers.

Important questions remain regarding why UK credit card lenders do not base interest rates on risk, be it through (i) exploiting the full extent that the regulation allows, (ii) offering a broader menu of cards of varying advertised rates, or (iii) repricing customers after origination. I describe some relevant considerations in Online Appendix E.2, but a more thorough investigation is warranted.

There are several possible extensions of this paper. First, future work could analyze counterfactuals that change lenders' screening technologies. One example would be a scenario in which lenders must share their screening technologies. This counterfactual would create a setting closer to the

[24]See House of Commons Treasury Committee (2003) for a detailed discussion of the transparency of credit card charges.

US, where many lenders use FICO scores.[25] Second, building on the empirical work of Panetta, Schivardi, and Shum (2009), my model can analyze the welfare effects of mergers in which the merging lenders combine their screening technologies. Along with the typical trade-off between cost synergies and increased concentration, mergers would benefit from improved screening technologies. The model can measure this element of merger synergies, which is typically challenging.

Regarding external validity, consumer credit markets across different countries and time periods have used varying combinations of individualized prices and quantities. No general theory exists to explain how product features and regulatory environments interact to influence how lenders individualize contracts. Deriving conditions on the market that deliver tailored prices or quantities is a natural sequel to this work.

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