Risk-Based Borrowing Limits in Credit Card Markets

Supplemental Appendices

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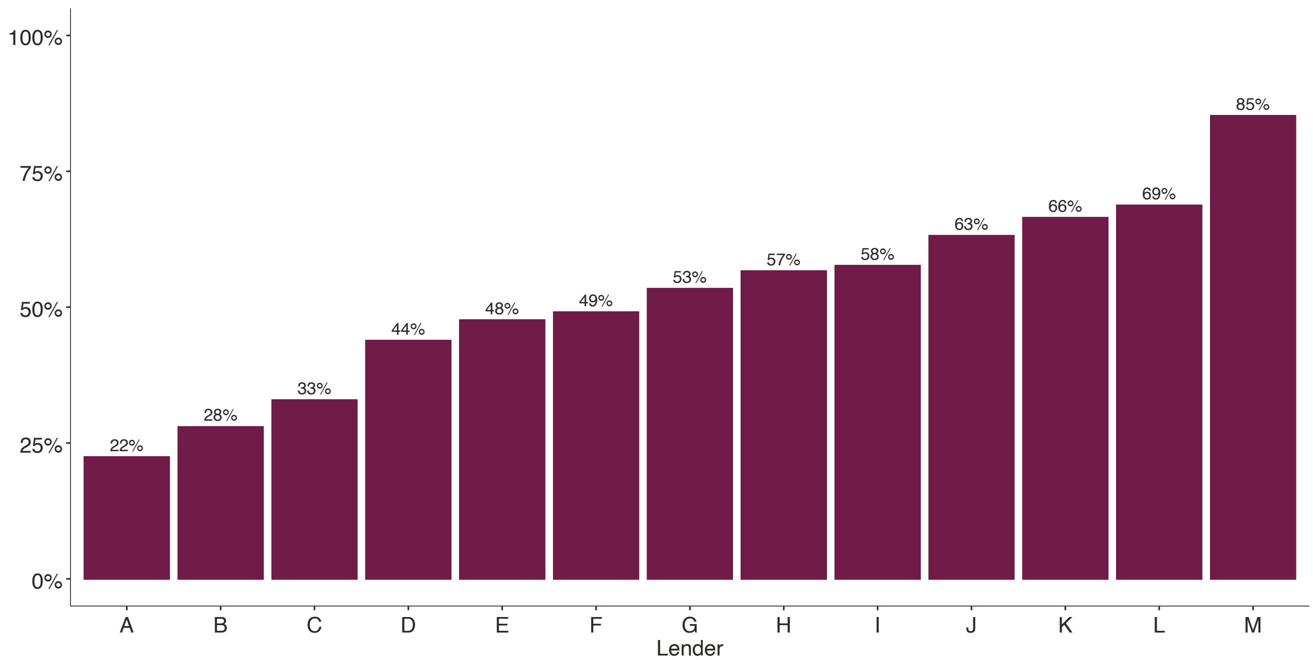
A Additional Figures and Tables

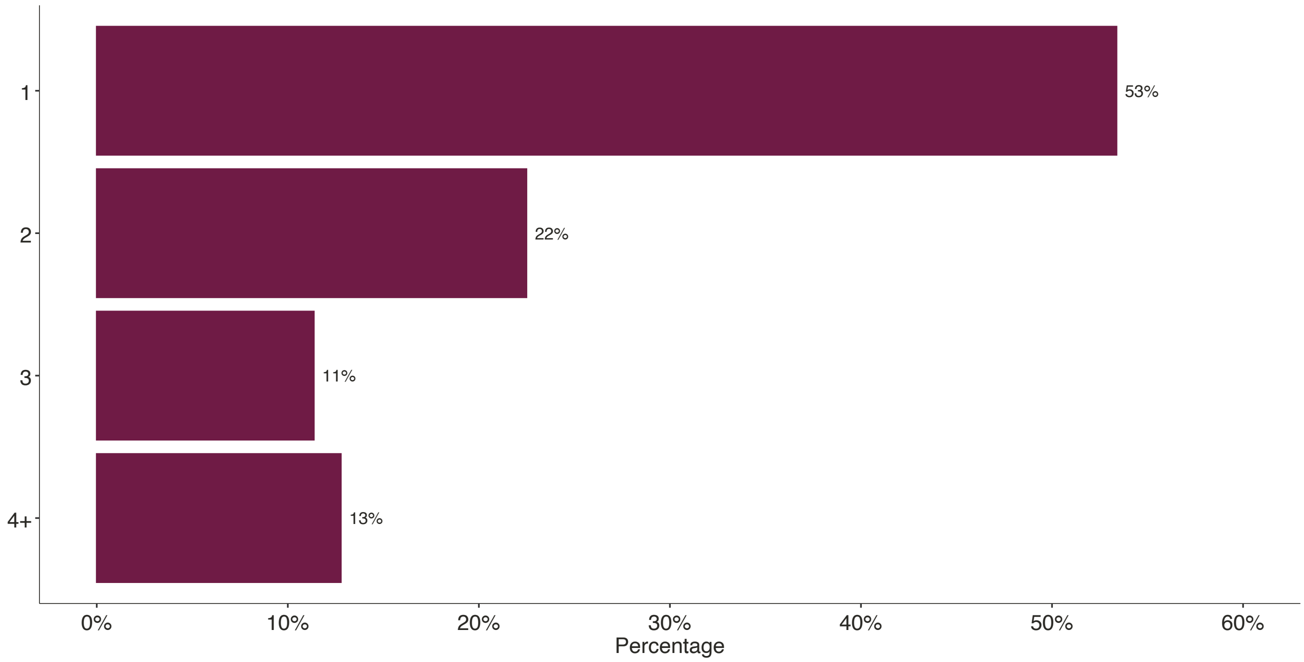
A.1 Figures

Figure A.1. Proportion of statements in which entire balance is repaid



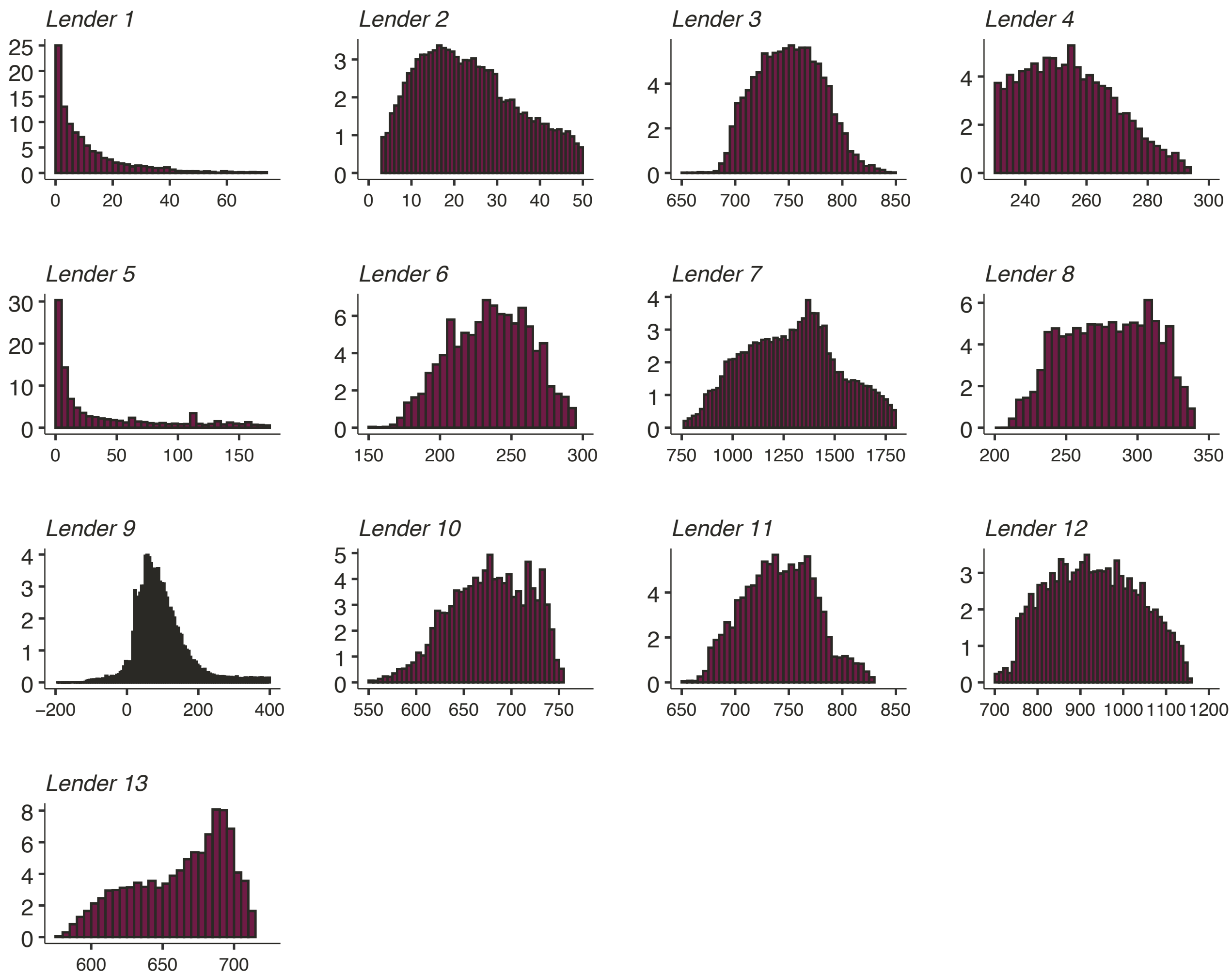
Notes: I scramble lenders' identities to preserve anonymity, so labels do not necessarily match the identities in other tables and figures.

Figure A.2. UK conditional distribution of cards held



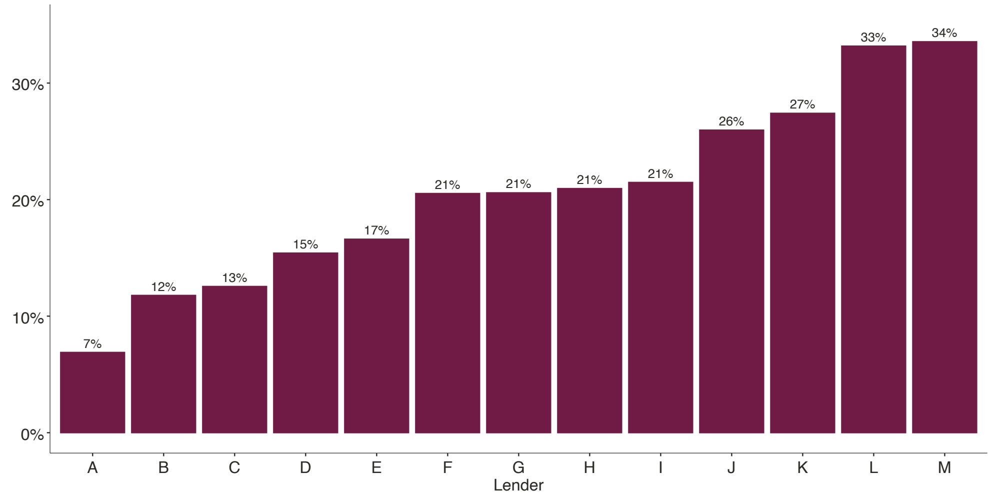
Notes: Distribution of the number of cards held by individuals with at least one credit card in the UK. I calculate the distribution of cards held, conditional on holding a card, in each month, and then average over months. Shares do not add up to 100 because of rounding.

Figure A.3. Histogram of proprietary credit scores across lenders



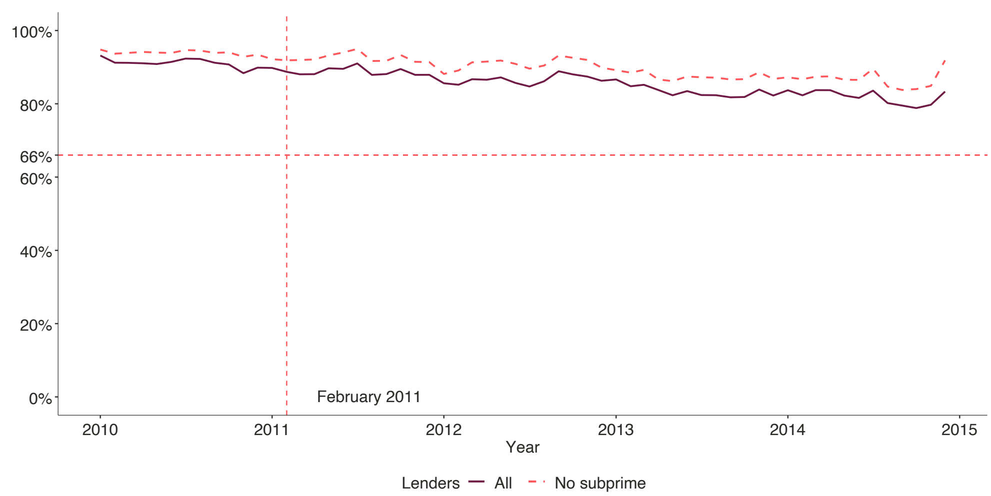
Notes: I scramble lenders' identities to preserve anonymity, so labels do not necessarily match the identities in other tables and figures. Plot is constructed using 2013 data.

Figure A.4. R-Squared from regressing lender proprietary credit score on demographics



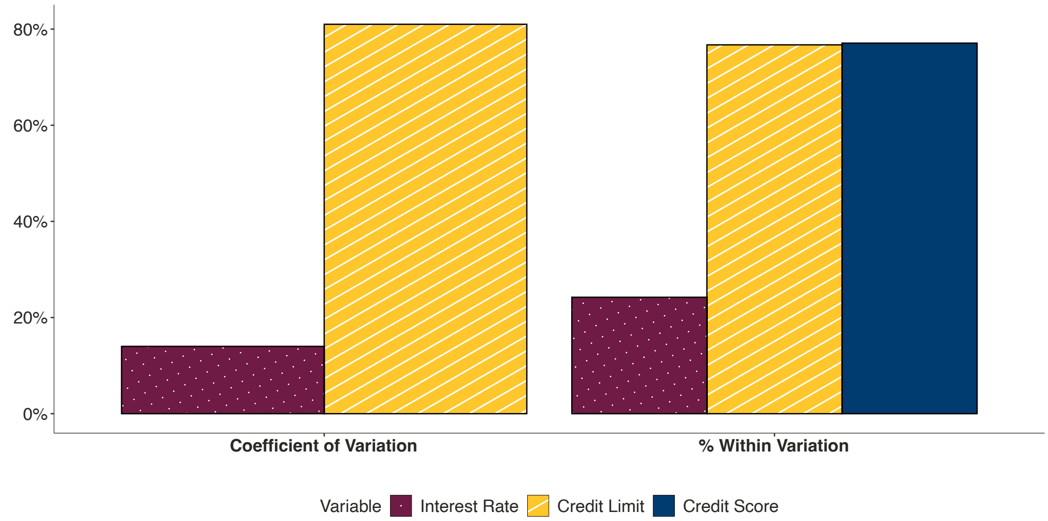
Notes: For each lender, I regress their proprietary credit score on a fine set of demographics including income and age percentile bins, dummies for employment and homeownership status, and origination month. I scramble lenders' identities to preserve anonymity, so labels do not necessarily match the identities in other tables and figures.

Figure A.5. Proportion of originations that obtain advertised APR



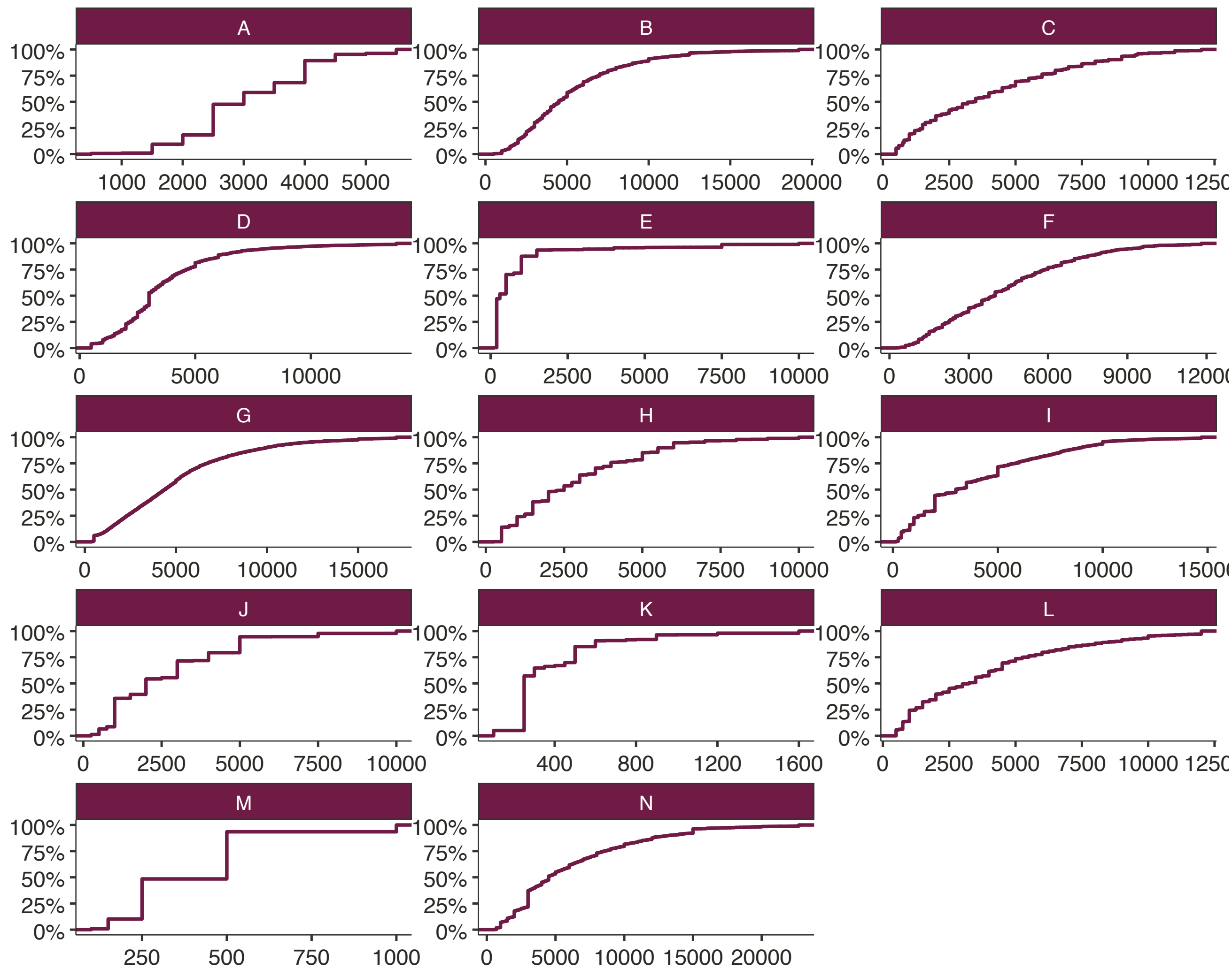
Notes: The solid line includes all lenders; the dashed line removes the two subprime lenders discussed in text. The proportion did not change in February 2011 when the regulation on the proportion required to obtain the advertised APR or below fell from 66% to 51%.

Figure A.6. Coefficient of variation and proportion of within-card variation in credit scores, interest rates, and credit limits



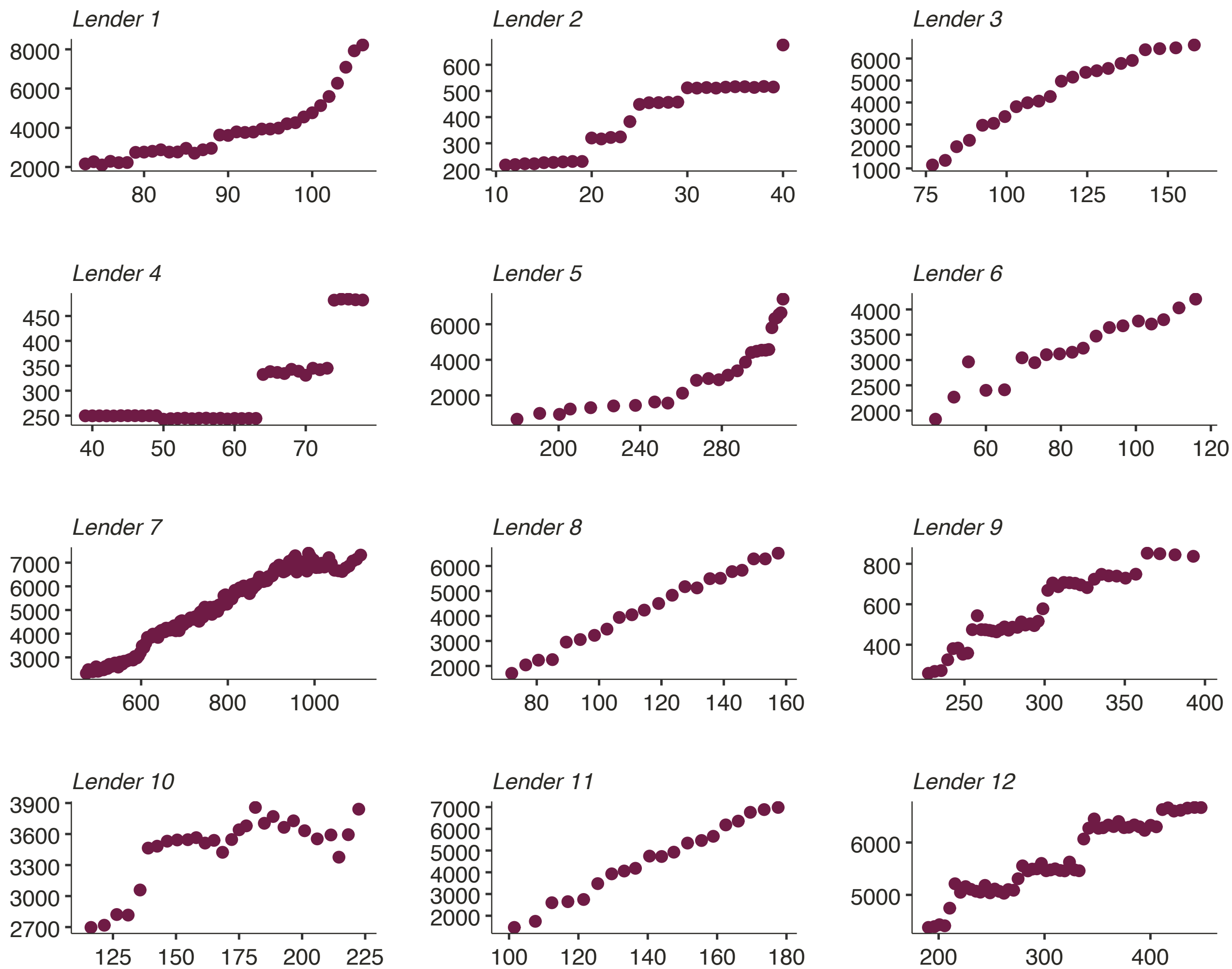
Notes: To construct each bar, I calculate the average of the statistic over the months within a lender to create a lender-specific value. Each bar in this plot is a weighted average (weighting by origination share) of the lender-specific averages for the prime and superprime lenders.

Figure A.7. Empirical CDFs of credit limits at all lenders



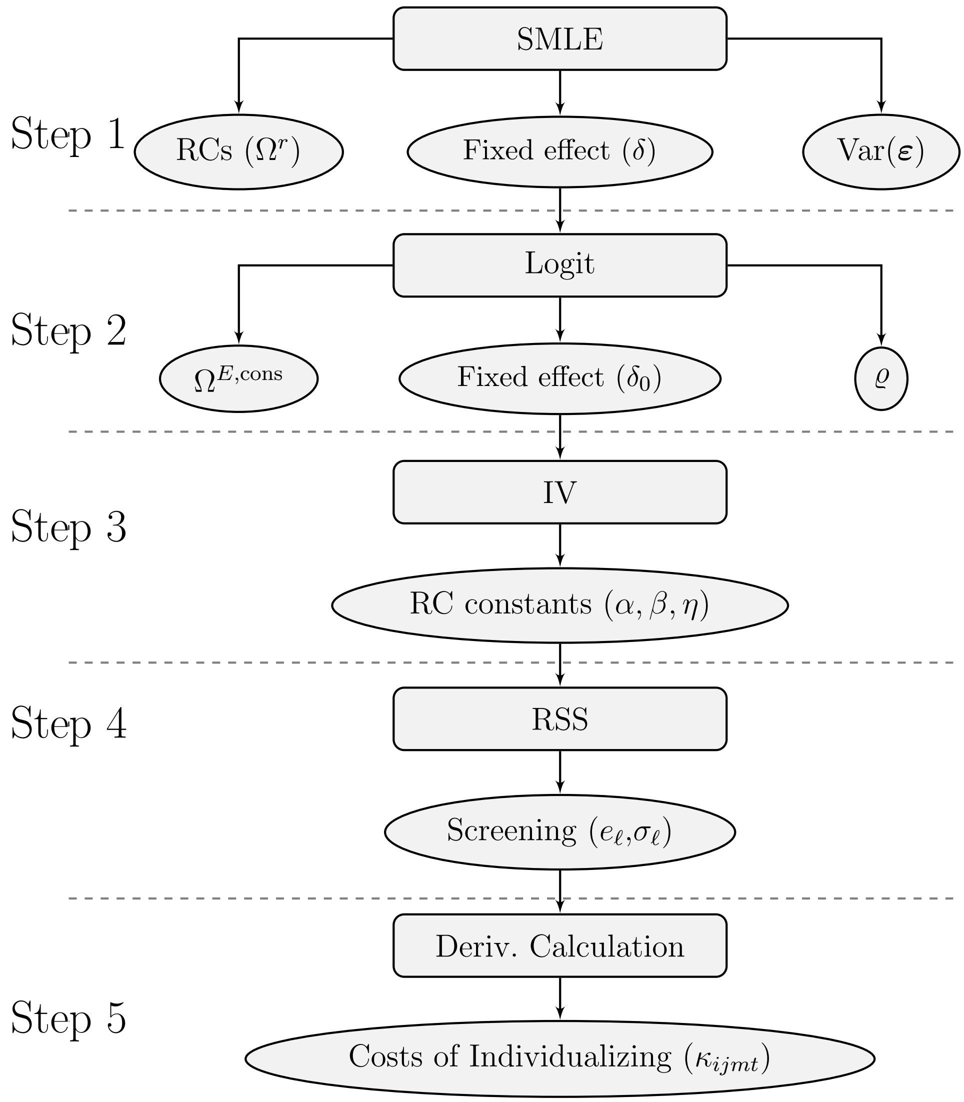
Notes: I scramble lenders' identities to preserve anonymity, so labels do not necessarily match the identities in other tables and figures. I include store cards as well as 13 lenders here.

Figure A.8. Mean credit limits across lenders' credit scores



Notes: Plots are for the year 2013. I scramble lenders' identities to preserve anonymity, so labels do not necessarily match the identities in other tables and figures. Credit score scales differ across lenders so cannot be compared. Credit scores are not available at one lender in this year.

Figure A.9. Steps of model estimation



Notes: Step 1 refers to simulated maximum likelihood estimation of the demand parameters, for those who revolve. Next, 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 the fixed effects δ_{jmt}. Step 4 refers to screening technology estimation. Finally, step 5 refers to estimating the costs of individualizing interest rates

FIGURE A.10. DISTRIBUTIONS OF SHARES AND REVOLVING IN THE DATA AND MODEL

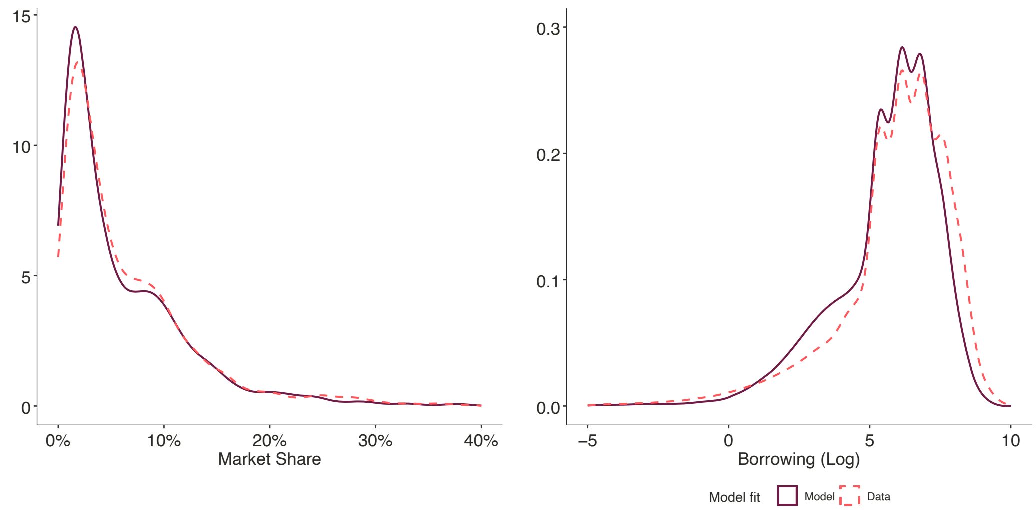
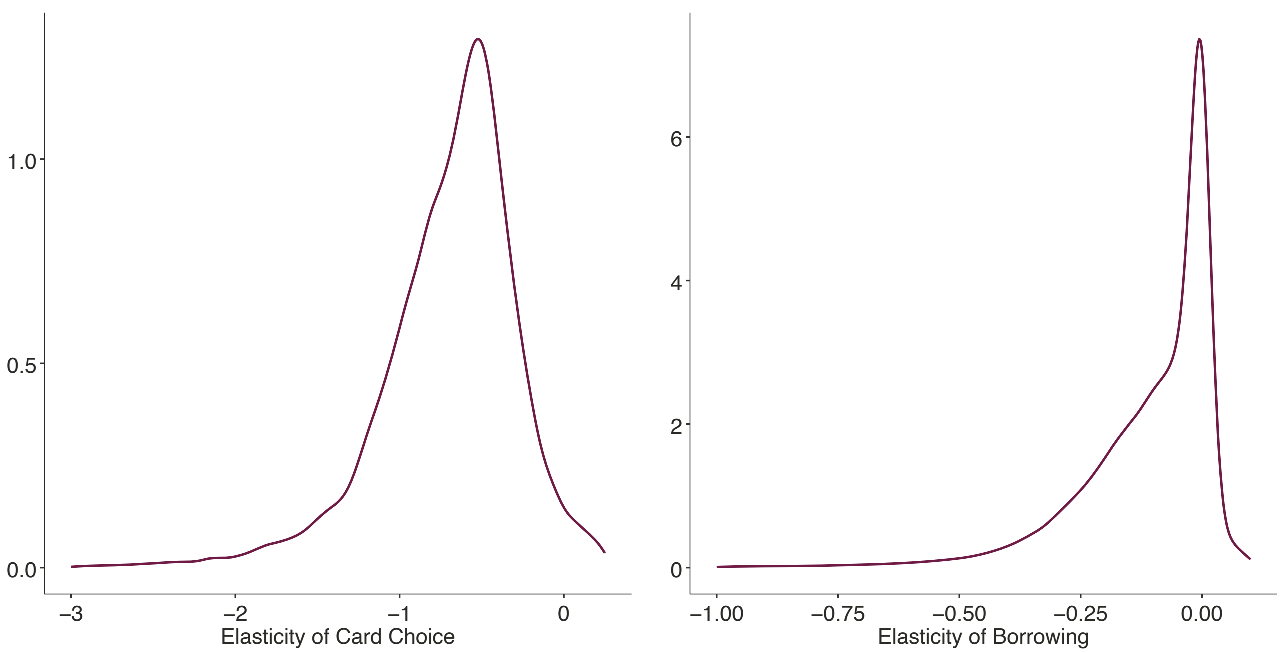
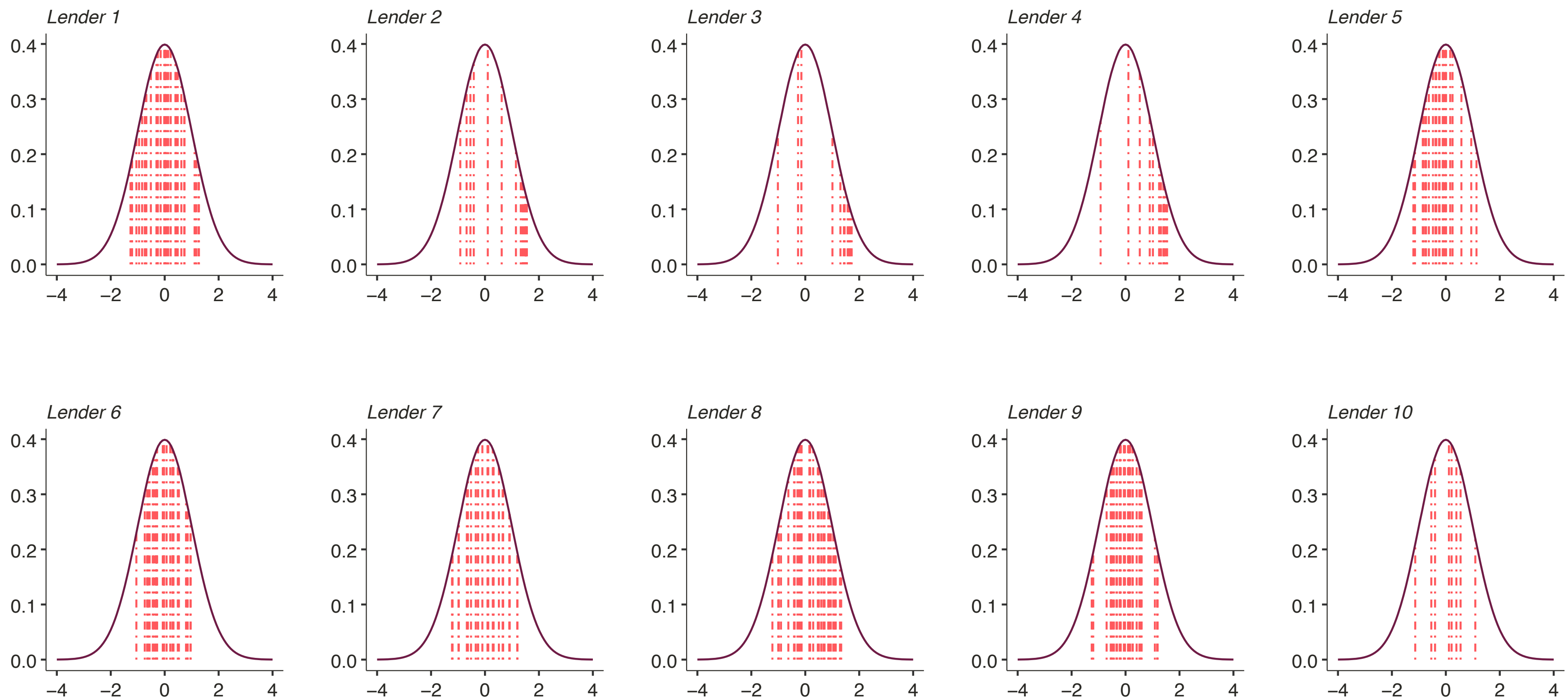


FIGURE A.11. DISTRIBUTION OF INTEREST RATE ELASTICITY



Notes: Equations (18) and (21) define borrowing and card choice elasticity of demand respectively.

Figure A.12. Screening technologies at all lenders



Notes: I scramble lenders' identities to preserve anonymity, so labels do not necessarily match the identities in other tables and figures. Two subprime lenders and store cards are not included in the model.

Figure A.13. Distribution of marginal costs of individualizing interest rates

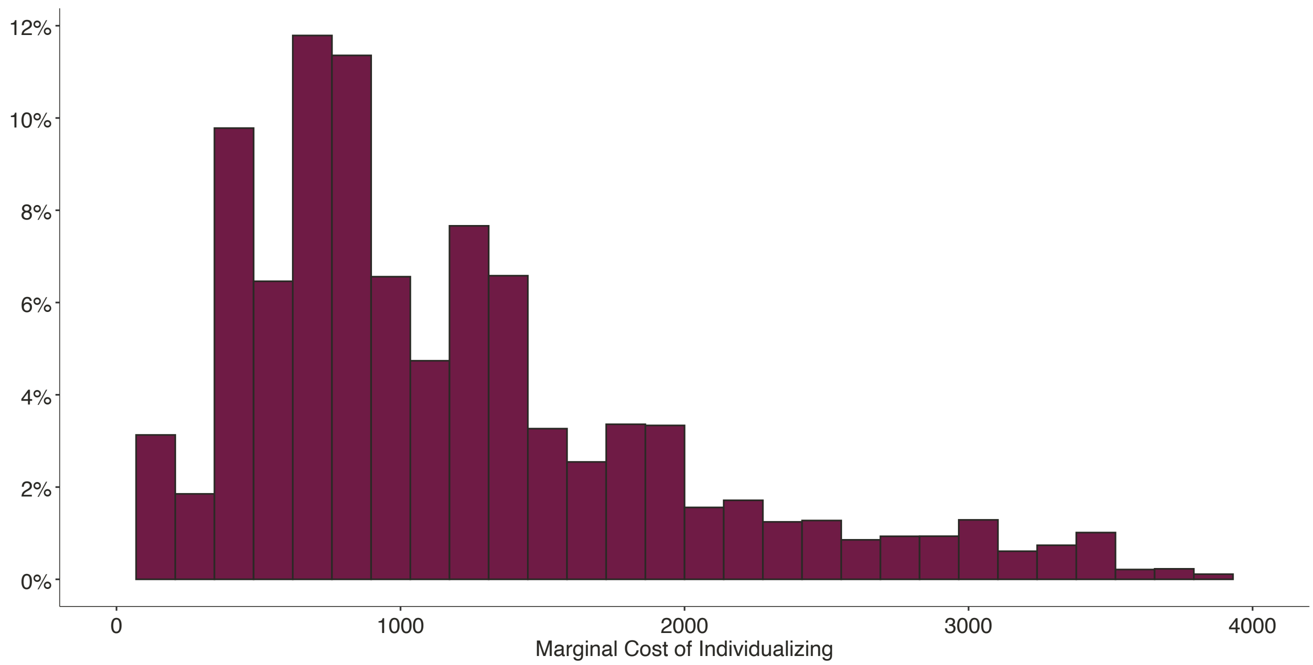


Figure A.14. Distributions of credit limits in baseline and counterfactual

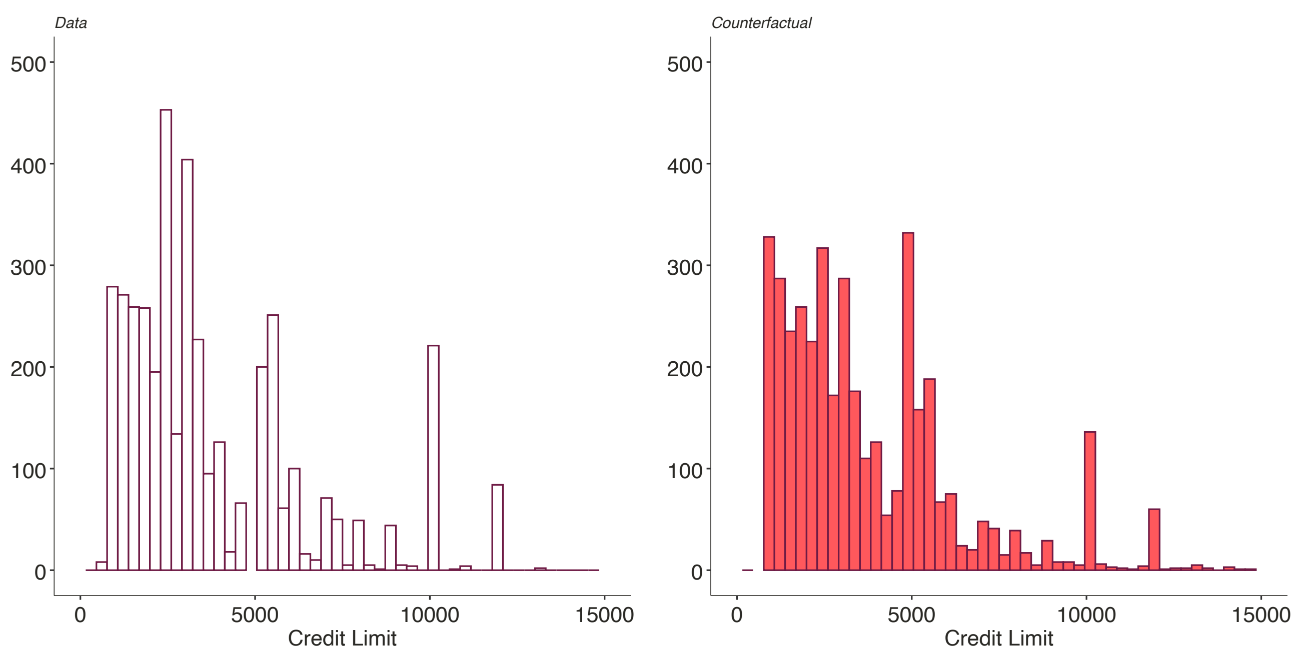
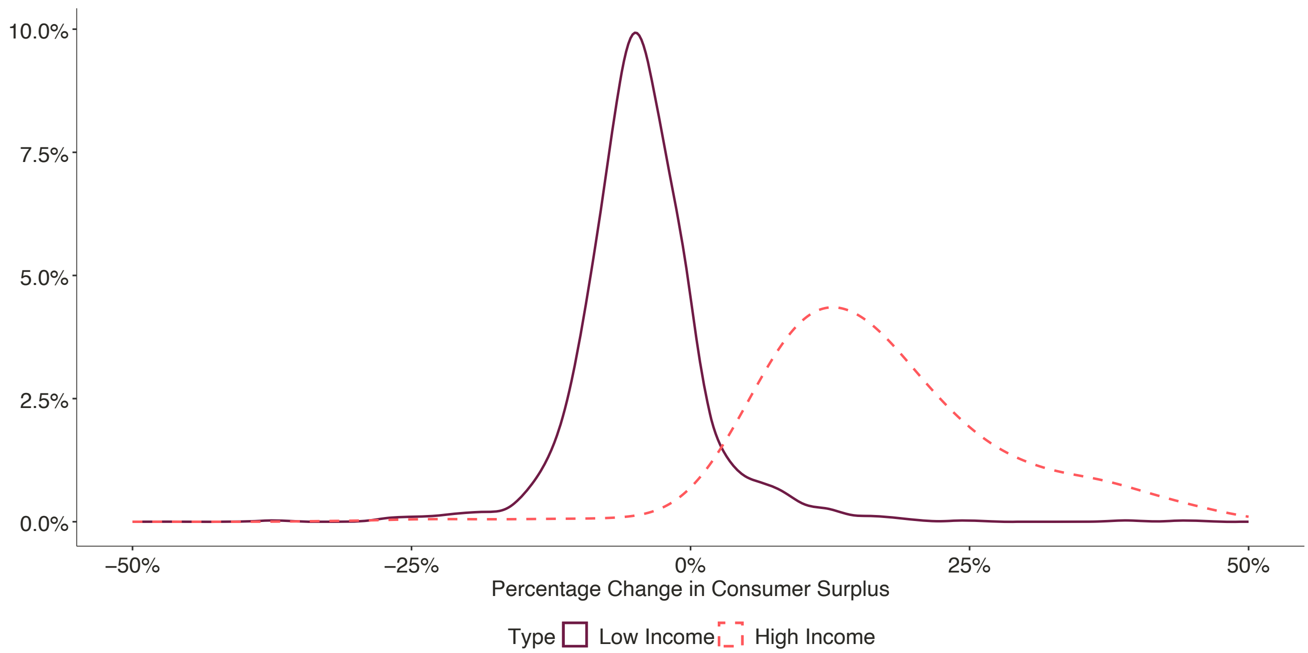


Figure A.15. Distributions of consumer surplus changes by type



A.2 Tables

Table A.1. Summary statistics

Variable	Mean	SD	25%	50%	75%
Panel A: Cardholder features At Origination					
Net Monthly Income (£)	2011.50	4875.90	1049.33	1517.33	2229.56
Age	42.87	14.83	31.00	41.00	53.00
Female	0.52	0.50			
Employed	0.76	0.43			
Homeowner	0.57	0.50			
Existing Customer	0.40	0.50			
Multiple Users	0.08	0.26			
Distribution: Branch	0.32	0.46			
Distribution: Online	0.53	0.50			
Distribution: Post or Telephone	0.15	0.36			
Panel B: Card Features At Origination					
Credit Limit (£)	3378.36	3138.53	1000.00	2500.00	5000.00
Purchase APR (%)	21.56	7.66	16.90	18.90	23.95
Purchase Promo Length	3.55	4.70	0.00	3.00	6.00
Balance Transfer Promo Length	9.23	8.73	0.00	9.00	15.00
Balance Transfer	0.28	0.45			
Get Advertised APR	0.83	0.37			
Panel C: Statement					
Credit Limit (£)	3849.30	3325.63	1250.00	3000.00	5200.00
Purchase APR (%)	18.30	9.54	15.80	17.90	21.90
Closing Balance (£)	1139.33	1864.64	0.00	357.12	1456.70
Repayment (£)	203.66	595.52	0.00	26.59	129.05
Total Interest (£)	8.54	20.15	0.00	0.00	7.57
Direct Debit	0.34	0.47			
Up-to-Date	0.95	0.22			
Panel D: Card-Month Characteristics					
Yearly Minimum Income Threshold (£)	5967.27	10798.66	0.00	3000.00	7500.00
Annual Fee (£)	9.25	34.95	0.00	0.00	0.00
Advertised APR (%)	23.39	11.35	16.90	18.90	29.80
Grace Period	28.78	11.96	25.00	25.00	26.00
Yearly Funding Rate (%)	2.28	0.98	1.59	2.29	2.81
Per-Origination Operational Cost (£)	2.66	1.93	1.69	2.39	3.38
Per-Origination Overhead Cost (£)	3.03	1.36	2.22	2.66	4.18
Cashback	0.11	0.32			
Airmiles	0.06	0.23			

Notes: Any variable with (£) is in 2015 Pounds Sterling (GBP). Any variable without percentiles is a categorical (dummy) variable. Categorical variables' means may not add to 1 because of rounding.

Panel A Notes: Unit of observation is the credit card origination (it_0). "Net Monthly Income" is net of all tax. "Homeowner" is equal to one if the individual owns a house (with a mortgage or without) at origination. "Existing customer" is equal to one if the individual had any other financial product with the lender at the point of origination. "Employed" does not include self-employment. "Multiple users" is equal to one if the individual created multiple instances of the card at origination.

Panel B Notes: Unit of observation is the credit card origination (it_0). Promotional deal lengths are measured in months. "Balance Transfer" is equal to one if the originator transferred a balance from another card onto this newly originated card at origination. "Get Advertised APR" is a dummy equal to one if the individual obtains the APR advertised in the promotional materials.

Panel C Notes: Unit of observation is the statement-month (it). "Closing Balance" includes purchase, cash advance, money transfer, and balance transfer balances. "Total Interest" includes purchase, cash advance, money transfer, and balance transfer interest. "Direct Debit" is equal to one if some form of direct debit was used to pay this statement-month. "Up-to-Date" equals one if the individual repays at least the minimum payment this statement-month.

Panel D Notes: Unit of observation is the card-month (jt). "Yearly Minimum Income" is gross of tax. "Grace Period" is the number of days between the end of a billing cycle and the payment deadline. "Operational" and "Overhead" costs are per-origination. Reward variables are all equal to one if the card-month offers the reward.

Table A.2. Credit Score, interest rate, and credit limit variation by lender

	Credit Score	Interest Rate				Credit Limit				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Bank	**Within**	**C. of V.**	**75/25**	**90/10**	**Within**	**C. of V.**	**75/25**	**90/10**	**Within**	**Share**
A	97.66	0.11	1.19	1.32	20.45	0.78	3.28	8.98	88.53	2.21
B	89.41	0.15	1.25	1.39	45.61	0.79	4.57	11.74	77.89	8.33
C	51.88	0.22	1.29	1.59	18.62	0.84	4.45	16.18	71.09	21.96
D	95.41	0.14	1.02	1.66	23.13	0.74	3.87	9.76	73.92	3.18
E	95.79	0.10	1.09	1.27	49.50	0.76	3.16	10.82	81.23	7.77
F	-	0.12	1.11	1.21	-	0.59	2.65	6.08	-	6.02
G	46.22	0.12	1.06	1.32	2.06	1.64	4.71	9.98	25.13	8.54
H	93.87	0.07	1.11	1.15	0.00	0.66	2.07	5.18	99.48	11.44
I	96.77	0.23	1.53	1.77	67.33	0.76	4.44	10.83	95.07	5.15
J	95.76	0.08	1.03	1.15	24.72	0.66	2.42	5.36	92.76	9.22
K	-	0.07	1.01	1.17	-	0.32	1.51	2.40	-	4.34
Subprime 1	94.81	0.19	1.41	1.42	83.68	0.51	2.00	2.68	88.62	8.85
Subprime 2	96.93	0.10	1.20	1.33	96.48	0.59	1.75	2.95	97.38	2.98
Mean	86.77	0.13	1.18	1.36	39.23	0.74	3.14	7.92	81.01	-
Weighted Mean	79.51	0.14	1.19	1.38	32.51	0.78	3.34	9.18	78.58	-
NS Mean	84.75	0.13	1.15	1.36	27.93	0.78	3.38	8.85	78.34	-
NS Weight Mean	77.08	0.14	1.17	1.37	24.22	0.81	3.53	10.04	76.72	-

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

Table A.3. Summary statistics for lender number of cards

Variable	**Mean**	**Median**
Share Top 2 Cards	86.11	90.65
Share Top 3 Cards	93.44	97.87
Herfindahl-Hirschman Index	5769.38	5326.35
Effective Number of Cards	2.15	1.88

Notes: Let $\chi_{j\ell t}$ denote the proportion of originations at lender ℓ in month t that choose card j, and order j such that $\chi_{j\ell t}$ are decreasing. Then in month t and at lender ℓ, "Share Top Y Cards" is equal to $\sum_{j=1}^{Y} \chi_{j\ell t}$, the "Herfindahl-Hirschman Index" is equal to $HHI_{\ell t} = \sum_{j \in J_{\ell t}} \chi_{j\ell t}^2$, and the "Effective Number of Cards" is the reciprocal of the HHI, which represents the number of cards there would be if every card had equal share within the lender-month. In the table, values of χ are expressed as percentages. Values in the table are means and medians over lender-months. One lender was removed as they did not provide appropriate card identifiers.

Table A.4. Third step demand estimates

	(1)	(2)	(3)	(4)
Dependent Variable	δ^B	δ^B	δ^E	δ^E
Price Sensitivity (α)	6.05	-0.76	1.25	-0.65
	(0.55)	(4.11)	(0.13)	(0.98)
Airmiles (β_{airmiles})			0.02	0.05
			(0.05)	(0.04)
Cashback (β_{cashback})			0.01	-0.04
			(0.03)	(0.05)
Purchase Protection (β_{pp})			0.06	0.03
			(0.04)	(0.06)
Estimation	OLS	IV	OLS	IV
First-stage F	-	32.23	-	36.14

Notes: This table provides the estimates and standard errors (in parentheses) of the demand parameters recovered in the third stage of demand estimation. In IV specifications I use a cost shifter as excluded instrument for interest rate. I include bank and month fixed effects in both regressions, along with network and distribution fixed effects in δ^E regressions.

TABLE A.5. MARGINAL COSTS OF INDIVIDUALIZING RATE REGRESSION

	(1)
Dependent Variable	κ
Log of Income (y)	320.2
	(16.7)
Risk Signal (e)	-338.0
	(55.7)
Lender Dummies	Yes
Distribution-Month Dummies	Yes
F Statistic	218.2

Notes: This table provides the estimates and standard errors (in parentheses) from a regression of the individual-specific marginal costs of individualizing interest rates against income (logged), and risk signal. The regression includes lender (ℓ) and distribution-month (mt) dummies. Standard errors are clustered at the distribution-month level.

B Details on Descriptives

B.1 ANOVA Formulas

In this subsection, I formally describe the ANOVAs conducted in Section 4. I decompose the variation in lenders' credit scores, interest rates, and credit limits into within-card and between-card terms. For each lender ℓ and month t, I split the total variation $V_{\ell t}^{TOT}$ in outcome $y_{ij\ell t}$ for cards $j \in J_{\ell t}$ and originations $i \in I_{j\ell t}$ into within-card variation $V_{\ell t}^{W}$ and between-card variation $V_{\ell t}^{B}$ as follows:

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

where $I_{\ell t}$ is the total number of originations at lender ℓ in month t, $\bar{y}_{\ell t}$ is the grand mean of outcome y, $\bar{y}_{j\ell t}$ is the card-j-specific mean, and $s_{j\ell t} = \frac{I_{j\ell t}}{I_{\ell t}}$ is the share of originations on card j at lender ℓ in month t. Intuitively, the decomposition separates the grand variance into an average of within-card variances ($V_{\ell t}^{W}$) and a weighted variance of card averages ($V_{\ell t}^{B}$). The R-squared from a regression of $y_{ij\ell t}$ on dummies for cards j in a given lender-month pair ℓt provides the ratio $V_{\ell t}^{B}/V_{\ell t}^{TOT}$.

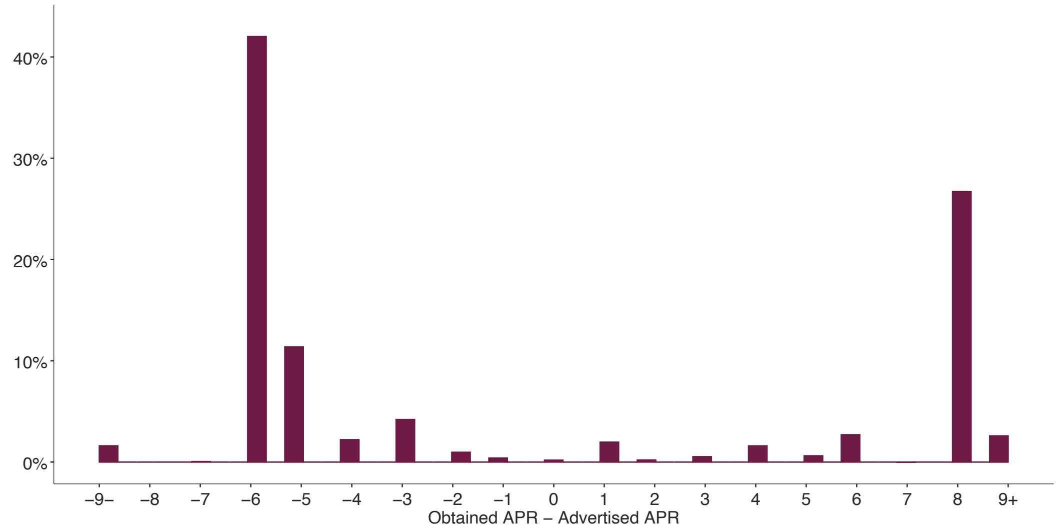
B.2 Pricing by Subprime Lenders

I identify two particular subprime lenders in the sample. These lenders (removed from the solid line to create the higher dashed line in Figure A.5) price differently, giving many customers a rate different from the advertised APR. As Table A.2 reveals, in contrast to prime and superprime lenders, most variation in interest rates for these two lenders is within rather than between cards. I investigate these two lenders' pricing strategies in Figure B.16 by plotting the distribution of percentage point differences (rounded to the nearest integer) between advertised APRs and those customers actually received. The differences are minor and often favorable to consumers. In the most common case, 42% of customers received an interest rate six percentage points *lower* than advertised. Very few customers (around 2.6%) received interest rates more than eight percentage points above the advertised APR. These lenders often engage in "low and grow" strategies: they start consumers on low credit limits and high interest rates and improve contractual terms once the individual improves their credit history through sensible card use.

B.3 Descriptive Findings Relating to Collusion

In the CCMS data, I find that price deviations across lenders are serially uncorrelated, and instances of significant price decreases by one lender are not followed by price decreases by other lenders. These findings are consistent with no collusion among lenders. However, these findings are neither

FIGURE B.16. HISTOGRAM OF PERCENTAGE POINT DIFFERENCES BETWEEN OBTAINED APR AND ADVERTISED APR AT TWO SUBPRIME LENDERS



Notes: Only those with interest rates differing from advertised are shown, and the distribution is winsorized at 3%.

necessary nor sufficient to rule out collusive activities completely since the timing of price changes may be intentionally manipulated to disguise collusive activity, and lenders may punish deviations through alternative mechanisms (Green and Porter, 1984). Formally ruling out collusion in credit markets is left for further research.

C Details on the Model

C.1 Relationship Between Credit Limit and Default in UK Data

In the main text, I cite existing works on credit card markets that have ruled out a causal effect of credit limits on default. Now, I provide evidence using the UK data that corroborates the conclusions of the cited work.

To examine the association between credit limits and default in the data, I regress a dummy for cardholder default 18 months after origination on (logged) origination credit limit and income. In all models (linear probability models, probit, and logit), the coefficient on credit limit is *negative* and strongly statistically and economically significant. Of course, this correlation alone does not preclude a positive causal effect of credit limit on default. Instead, it reveals that the selection effect coming from lenders endogenously choosing lower credit limits for risky customers (the supply-side effect) empirically dominates any positive demand-side causal effect. This selection effect is an essential feature of the supply-side model I estimate.[1] Finally, if credit limit does affect default, then insofar as market fixed effects, income, and the lenders' signal on a customer's risk explain individuals' credit limits, my default model accounts for the effect of credit limits on default, and my parameter estimates (e.g., Ω^D) are lower, rather than upper, bounds.

C.2 Focus on Interest Revenue

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

The first is **interchange revenue**, which accounts for 15% of US lenders' revenues on average. Interchange revenues are the funds lenders receive from merchants and their banks when individuals use their cards for purchases. Interchange fees were significantly lower in the UK than in the US between 2010 and 2015, likely resulting in a smaller proportion of UK lenders' revenue coming from interchange fees.[2]

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

The final source of revenue is **fee revenue**. Around 88% of cards have no annual fee in the UK, so I focus on other fees. All other fees were drastically lowered due to a UK policy investigation between 2003 and 2006. In 2003, the Office of Fair Trading (OFT) began an inquiry into the 'default charges' levied by credit card companies when, for example, a cardholder exceeded their credit limit or was late making the minimum monthly payment.[3] In 2006, the OFT stated that many of the charges were "unlawful," saying it would act upon receiving notice of any fee over £12 (Office of Fair Trading, 2006). In 2010–2015, all fees apart from annual fees (including late, dormancy, over-limit, and foreign transaction) were £12, around 50% lower than in 2003 (House of Commons Treasury Committee, 2003). Fees in the US are levied more frequently and are usually

[1] In ongoing work, I estimate default rates either side of the credit limit discontinuities I described in Section 4. Preliminary results generally show minor differences in default rates on either side of a credit limit threshold. This provides further empirical support to the assumption of no direct effect from credit limits, at least at discontinuities.

[2] The European Parliament and the Council of the European Union adopted the Interchange Fee Regulation (IFR), which set the default interchange fee cap at 0.3% of the transaction for credit cards.

[3] https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/284445/oft842.pdf, last accessed 9 March 2025.

larger than £12, once more suggesting that fees accounted for a smaller proportion of UK lenders' revenues.

These arguments imply that interest revenue accounts for the vast majority of UK credit card lenders' revenue. Consequently, my model focuses solely on interest revenue.

C.3 Credit Limit First Order Condition Derivation

In this subsection, I derive equation (9) from the first order condition of the lender's profit maximization problem. The first step is to replace ε_i with $e_{i\ell t} + w_{i\ell t}$. The second step is to note that for every $\bar{b}$, there exists a threshold signal error $\omega_{i\ell t}(\bar{b})$ such that if the signal error $w_{i\ell t}$ is larger (respectively smaller) than $\omega_{i\ell t}$, the individual's desired borrowing will be larger (respectively smaller) than $\bar{b}$.[4] The value of $\omega_{i\ell t}$ sets $\log(b^*_{ijmt})$ equal to $\log(\bar{b}_{ijmt})$ and is therefore given by

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

From this, I split Π into

$$\int_{-\infty}^{\omega_{i\ell t}} b^*_{ijmt}\pi_{ijmt}(e_{i\ell t}, w_{i\ell t})\phi\left(\frac{w_{i\ell t}}{\sigma_{\ell t}}\right) dw_{i\ell t} + \bar{b}_{ijmt}\int_{\omega_{i\ell t}}^{\infty} \pi_{ijmt}(e_{i\ell t}, w_{i\ell t})\phi\left(\frac{w_{i\ell t}}{\sigma_{\ell t}}\right) dw_{i\ell t}. \tag{17}$$

By the Leibniz integral rule, the first derivative with respect to $\bar{b}_{ijmt}$ is equal to

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

and the second derivative

$$-\frac{d\omega_{i\ell t}}{d\bar{b}_{ijmt}}\pi(e_{i\ell t}, \omega_{i\ell t})\phi\left(\frac{\omega_{i\ell t}}{\sigma_{\ell t}}\right) = -\frac{1}{\sigma^B_{mt}\bar{b}_{ijmt}}\pi(e_{i\ell t}, \omega_{i\ell t})\phi\left(\frac{\omega_{i\ell t}}{\sigma_{\ell t}}\right),$$

which is negative provided that $\pi(e_{i\ell t}, \omega_{i\ell t}) > 0$. In this region, the objective is concave and the first order condition is necessary and sufficient for a maximum. Finally, given that the second order condition requires $\pi(e_{i\ell t}, \omega_{i\ell t}) > 0$ and the integral runs from $\omega_{i\ell t}$ to ∞, for the first derivative to equal zero, π should decrease in $\omega_{i\ell t}$, which requires $\sigma^D_{mt} > 0$. I estimate the parameter $\sigma^D_{mt} > 0$ as part of the demand side estimation, which is completely independent of the supply side estimation. The estimates confirm that the required sign restriction holds in my context.

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

C.4 Elasticities

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

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

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

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

where $\bar{\mathcal{Q}}^B_{ijmt}$ is defined in Section D below. It follows immediately that the elasticity of borrowing is

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

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

$$s^E_{ijmt} = (1 - s^E_{i0mt})s^E_{ijmt|j\in J_{imt}}, \tag{19}$$

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

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

The standard logit derivative for the inside options is

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

and the derivative of the outside option probability is

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

Putting these together yields

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

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

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

D Details on Estimation

D.1 Conditional Log Likelihood

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

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

where

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

with all terms defined as in the main text.[5] The system's endogenous variables are revolving utility V^E_{ijmt}, desired borrowing b^*_{ijmt}, and default net utility V^D_{imt}. Interest rates r_{jmt} correlate with unobserved card characteristics ξ_{jmt}, creating additional endogeneity along with the simultaneity. The exogenous variables are card characteristics X_{jmt} and individual logged income y_i. I never observe utilities V^E_{ijmt} and V^D_{ijmt}. I observe card choice j^*_{imt}, constrained borrowing b_{ijmt}, and default choice for revolvers. Constrained borrowing b_{ijmt} is equal to $\min\{b^*_{ijmt}, \bar{b}_{ijmt}\}$, implying that I only observe desired borrowing b^*_{ijmt} for those who borrow less than their credit limit $\bar{b}_{ijmt}$. Unobservables ε^B_{imt} and ε^D_{imt} satisfy

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

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

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

D.1.1 Expressions for $s_{ijmt}^{(g)}$

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

$$\begin{aligned} s_{ijmt}^{(1)} &= \mathbb{P}(\text{Default}|\log(b_{ijmt}^*) = \log(b)) \cdot f_{\log(b_{ijmt}^*)}(\log(b)) \\ &= \frac{1}{\sigma_{mt}^B}\mathbb{P}(\varepsilon_{imt}^D > -\mathcal{Q}_{imt}^D|\varepsilon_{imt}^B = \mathcal{Q}_{ijmt}^B(b))\phi\left(\frac{\mathcal{Q}_{ijmt}^B(b)}{\sigma_{mt}^B}\right) \\ &= \frac{1}{\sigma_{mt}^B}\Phi_{ijmt}^{BD,1}\phi\left(\frac{\mathcal{Q}_{ijmt}^B(b)}{\sigma_{mt}^B}\right), \end{aligned}$$

where

$$\begin{aligned} \Phi_{ijmt}^{BD,1} &= \Phi\left(\mathcal{Q}_{imt}^D + \frac{\sigma_{mt}^D}{\sigma_{mt}^B}\mathcal{Q}_{ijmt}^B(b)\right) \\ \mathcal{Q}_{ijmt}^B(b) &= \log(b) - \delta_{jmt}^B - u_{ijmt}^B, \\ \mathcal{Q}_{imt}^D &= \eta_{mt}^D + \Omega_{mt}^D\tilde{y}_{imt}, \end{aligned}$$

By a similar derivation,

$$s_{ijmt}^{(2)} = \frac{1}{\sigma_{mt}^B}\left[1 - \Phi_{ijmt}^{BD,1}\right]\phi\left(\frac{\mathcal{Q}_{ijmt}^B(b)}{\sigma_{mt}^B}\right).$$

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

$$\begin{aligned} s_{ijmt}^{(3)} &= \mathbb{P}\left(\log(b_{ijmt}^*) > \log(\bar{b}_{ijmt})\right)\mathbb{P}\left(V_{imt}^D > 0|\log(b_{ijmt}^*) > \log(\bar{b}_{ijmt})\right) \\ &= \mathbb{P}\left(\varepsilon_{imt}^B > \bar{\mathcal{Q}}_{ijmt}^B\right)\mathbb{P}(\varepsilon_{imt}^D > -\mathcal{Q}_{imt}^D|\varepsilon_{imt}^B > \bar{\mathcal{Q}}_{ijmt}^B) \\ &= \mathbb{P}\left(\varepsilon_{imt}^B > \bar{\mathcal{Q}}_{ijmt}^B\right)\int_{\bar{\mathcal{Q}}_{ijmt}^B}^{\infty}\mathbb{P}(\varepsilon_{imt}^D > -\mathcal{Q}_{imt}^D|\varepsilon_{imt}^B = a)f_{\varepsilon_{imt}^B|\varepsilon_{imt}^B > \bar{\mathcal{Q}}_{ijmt}^B}(a|\varepsilon_{imt}^B > \bar{\mathcal{Q}}_{ijmt}^B)da \\ &= \frac{1}{\sigma_{mt}^B}\int_{\bar{\mathcal{Q}}_{ijmt}^B}^{\infty}\Phi\left(\mathcal{Q}_{imt}^D + \frac{\sigma_{mt}^D}{\sigma_{mt}^B}a\right)\phi\left(\frac{a}{\sigma_{mt}^B}\right)da \\ &= \int_{\bar{\mathcal{Q}}_{ijmt}^B/\sigma_{mt}^B}^{\infty}\Phi\left(\mathcal{Q}_{imt}^D + \sigma_{mt}^D\tilde{a}\right)\phi\left(\tilde{a}\right)d\tilde{a}, \end{aligned}$$

where

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

Similarly,

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

D.1.2 Expressions for $s_{ijmt|j\in J_{imt}}^E$

Now I write out the expression for $s_{ijmt|j\in J_{imt}}^E$ in equation (13). It is

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

where scaled indirect utility $\bar{U}^E_{ijmt}$ is

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

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

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

The first step yields estimates of the following parameters

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

D.2 Log Likelihood For Transacting

An individual transacts if the utility from transacting V^E_{i0mt} exceeds the maximal utility from revolving a balance. Based on the type-1 extreme value assumption, the probability that this occurs for individual i is

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

where F_{imt} is the inclusive value given by

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

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

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

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

D.3 Marginal Costs of Individualizing Interest Rates

I derive the expression for $\dfrac{\partial \Pi_{ijmt}}{\partial z_{ijmt}}$, which equals the individual-specific marginal costs of individualizing interest rates, κ_{ijmt}, for those not receiving the advertised rate in equilibrium. I take equation (17) and differentiate with respect to z_{ijmt}. By the Leibniz integral rule, this derivative is given by

$$\int_{-\infty}^{\omega_{i\ell}} b^*_{ij}(1 - \Delta_i)\phi\left(\frac{w_{i\ell}}{\sigma_\ell}\right) dw_{i\ell} + \bar{b}_{ij} \int_{\omega_{i\ell}}^{\infty} (1 - \Delta_i)\phi\left(\frac{w_{i\ell}}{\sigma_{\ell t}}\right) dw_{i\ell}. \tag{22}$$

As in the case of screening technologies, these integrals can be simulated using Halton draws, and thus the derivative can be computed. Note that if it were possible to estimate the demand side with initial borrowing depending on deviations from the advertised rate, the first term in the first integrand would change to $b^*_{ij}(1 - \Delta_i) + \alpha^B_i b^*_{ij} \pi_{ij}$, implying that the estimated κ values are lower bounds.

E Details on Counterfactuals

E.1 Counterfactual Optimization Problem

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

$$\mathcal{E}_{ij} = \mathbb{E}\left[\min\{b^*_{ij}, \bar{b}_{ij}\}\pi_{ij}\right]$$

and rewrite the objective function by separating out the term for card j as

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

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

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

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

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

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

Equation (20) provides an expression for $\frac{\partial s^E_{ij}}{\partial r_{ij}}$. It remains to provide expressions for $\frac{\partial \mathcal{E}_{ij}}{\partial r_{ij}}$ and $\frac{\partial s^E_{ik}}{\partial r_{ij}}$ when $k \neq j$. The former of these two terms is

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

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

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

Then

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

and

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

Putting these together yields

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

E.2 Potential Reasons for Lack of Risk-Based Pricing

My counterfactual results suggest that profit-maximizing lenders would tailor interest rates and credit limits in the absence of any costs or constraints involved in individualizing interest rates. However, interest rates are set at the card level and not individualized to a large extent in the data. The non-trivial marginal costs of individualizing interest rates I estimate rationalize these findings. Identifying the exact sources of these costs is beyond the current scope of this paper. Nevertheless, in what follows, I discuss two possibilities that may contribute.

First, as described in Section 3, EU regulations require that at least 51% of customers originating a card must obtain the advertised APR or lower. This constraint directly impedes lenders in fully individualizing prices. If there is a sufficiently large fixed cost in individualizing *any* interest rate, which can only be recovered if the majority of interest rates are set above the advertised APR, it may have been optimal not to individualize *any* interest rates, even if the regulatory constraint allows 49% to be tailored individually. These fixed costs could include the administrative expenses of constructing the infrastructure and software to set optimal individualized prices.[6] Given that restrictions on the ability to individualize interest rates already existed, lenders might have focused their investments on individualized credit limits.

Second, and arguably more importantly, lenders may encounter significant reputational costs if they advertise a particular APR but then provide customers with a differing, individualized APR, especially since the individualized rate is set after the individual signs the contract. In fact, members of the UK Government expressed their disapproval of such practices (House of Commons Treasury Committee, 2003).

This issue is a focal point for lenders, as they recognize that negative attention arising from unpopular business practices generates reputational risk. A substantial body of literature discusses the importance of reputational risk in the banking sector (see, e.g., Fiordelisi, Soana, and Schwizer, 2013 and Scandizzo, 2011). My dataset spans the years immediately following the global financial crisis—an event that significantly impaired the public's attitude towards the banking industry (Bennett and Rita, 2012). Therefore, in the short term, avoiding further reputational damage was likely to have been a primary objective of credit card lenders.

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The numbers at the end of every reference link to the pages citing the reference.

[6] In conversations with industry and policy experts, significant infrastructure investments were frequently listed as the reason why lenders did not individualize interest rates.

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