Online Appendices: Not for Publication

OA Additional Tables

Table OA.1: Summary statistics of the Homescan sample

	N	Mean	P25	Median	P75
Years per Household	118537	4.07	1.00	3.00	6.00
Transactions	118537	680.07	147.00	373.00	917.00
Average Tx Size	118537	59.02	37.01	51.60	72.01

Notes: NielsenIQ Homescan panel, 2013–2023. Each observation is a household-year.

Table OA.2: Comparing Homescan payment shares to aggregate shares

Payment Method	Homescan	Nilson
AmEx	0.04	0.10
Cash	0.24	0.20
Debit	0.37	0.36
MC	0.11	0.11
Visa	0.24	0.24

Notes: Homescan payment shares are each method's dollar volume divided by total spending. Aggregate shares are from Nilson (2020).

Table OA.3: Event study estimates for the effects of card acceptance on sales to credit-card consumers

	Trips	Spending
Credit Share at Treated Retailer, t=-4	-0.009	-0.015
	(0.034)	(0.046)
Credit Share at Treated Retailer, t=-3	-0.013	-0.054
	(0.027)	(0.035)
Credit Share at Treated Retailer, t=-2	0.007	-0.017
	(0.019)	(0.025)
Credit Share at Treated Retailer, t=0	0.078***	0.066*
	(0.022)	(0.028)
Credit Share at Treated Retailer, t=1	0.079**	0.089**
	(0.026)	(0.034)
Credit Share at Treated Retailer, t=2	0.124***	0.143***
	(0.033)	(0.042)
Credit Share at Treated Retailer, t=3	0.140***	0.194***
	(0.034)	(0.043)
N	333954	333954
Event × Period × Retailer × Income × Zip3 FE	X	X
Event-specific credit-share slopes	X	X

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Regression coefficients from the triple-difference Poisson specification described in Section III.B. The dependent variables are the number of shopping trips by household h at retailer j in period t (column 1) and total spending in dollars (column 2). Periods are six months. Standard errors clustered at the household level.

Table OA.4: Average share of card spending on consumers' top two cards, by primary card

Primary Card	Primary Share	Secondary Share	Top Two Total
AmEx	0.73	0.19	0.93
Discover	0.76	0.18	0.94
MC	0.74	0.20	0.94
Visa	0.78	0.17	0.95
Debit	0.81	0.14	0.96

Notes: Homescan panel, 2017–2019. The primary card has the most trips. The secondary card has the second-most. Each cell reports the average share of total card spending on the primary or secondary card for households with the indicated primary type.

Table OA.5: Credit card multi-homing rates: usage-based vs. ownership-based measurement

Dataset	Measure	Years	Rate	CI	N
DCPC	Ownership	2017-2019	57.7%	[57.0%, 58.4%]	20,772
Homescan	Usage	2017-2019	56.7%	[56.3%, 57.1%]	53,714

Notes: Share of primary credit card users who hold (DCPC) or use (Homescan) cards from two or more of {Visa, MC, AmEx}. DCPC counts are from the Diary of Consumer Payment Choice survey, which asks respondents directly which cards they own. Homescan rates are computed from observed primary and secondary card usage, with a consumer classified as multi-homing if both their primary and secondary card are credit cards. Both samples restrict to 2017–2019.

Table OA.6: Multi-homing rate by income: data vs. model

	Data	Model
Below Median Income	53.6%	54.0%
Above Median Income	57.9%	58.2%
Gradient (High - Low)	+4.3 ppts	+4.3 ppts

Notes: Homescan panel, 2017–2019. Multi-homing rate is the share of households whose primary and secondary payment methods are both credit cards. Income split at the median. The reported gradient is computed from the unrounded values. Displayed cells are rounded to one decimal, so subtracting them may give a slightly different number.

Table OA.7: Data sources and parameters identified

Data Source	Years	Moments	Parameters Identified
Panel A: Identification			
Second-choice survey	2024	Substitution patterns when card types unavailable	Random coefficient distribution (Σ)
		Switching probability when rewards cut in half	Income gradient of reward sensitivity (α_y)
Durbin event study (Nilson Report)	2007–2014	Change in debit spending following fee cap	Reward sensitivity (α_0)
DCPC	2017–2019	Log income differences by primary payment method	Income gradients in base preferences (β_y)
Homescan	2017–2019	Conditional probabilities of carrying card pairs	Multi-homing complementarity (χ^{lm}, χ^{lm}_y), weights (ω, π)
Nilson Report	2019	Dollar spending shares by payment network	Mean unobserved characteristics ($\bar{\xi}$)
Merchant event study	2013–2023	Sales effect of credit card acceptance at grocer	CES elasticity (σ)
Aggregate pricing	2019	Merchant fee/acceptance FOCs	Merchant benefit distribution ($\bar{\gamma}$, ν_γ)
Panel B: Validation			
MRI-Simmons	2009–2022	Payment shares across merchants; bank switching after Durbin	Merchant sorting (Appendix OE)
Yelp Reviews	2010–2018	Merchant card acceptance by sector	Acceptance rate cross-check

Table OA.8: Summary statistics of Financial Institutions in the Nilson Panel in 2010

	N	Mean	P25	P50	P75
Assets	40	28739.45	4192.63	9962.90	28654.60
Credit	40	1503.06	389.51	617.90	1462.50
Debit	40	4778.79	1201.72	2402.00	4631.39
Signature Debit	40	2914.35	775.00	1187.80	2591.56
Sig Debit Ratio	40	0.64	0.62	0.68	0.77
Treated	40	0.47	0.00	0.00	1.00

Notes: Treated indicates the institution had more than $10 billion in assets in 2010. Institution-year observations are averaged to the institution level. Assets are in millions. Credit, Debit, and Signature Debit are card volumes in millions.

Table OA.9: Correlation between top card by trip count and top card by spending share

		Top Card by Spend				
Top Card by Trips		AmEx	Debit	Discover	MC	Visa
AmEx	N	17524	150	107	324	500
	% row	94.2	0.8	0.6	1.7	2.7
Debit	N	586	213679	531	2736	3814
	% row	0.3	96.5	0.2	1.2	1.7
Discover	N	114	114	21036	457	428
	% row	0.5	0.5	95.0	2.1	1.9
MC	N	308	653	342	50153	1314
	% row	0.6	1.2	0.6	95.0	2.5
Visa	N	693	1234	587	2082	104907
	% row	0.6	1.1	0.5	1.9	95.8

Notes: Homescan panel, 2017–2019. Rows classify households by the card with the most trips. Columns classify by the card with the highest spending share. Each cell reports the share of households in that row–column combination.

Table OA.10: Second-choice survey summary statistics

Variable	Mean (SD)	N
Primary Debit	0.52	740
Primary Credit	0.48	740
Switch Rewards	0.71	347
Bank Removed Other Debit	0.76	383
Bank Removed Other Credit	0.87	357
Card Removed Debit	0.41	740
Card Removed Credit	0.24	740
Card Removed Cash	0.35	740
Female	0.51	740
Wave 1	0.50	740
Wave 2	0.50	740
Additional Cards Used	0.79 (0.93)	740
Age	33.09 (7.89)	740
Income	88,572 (64,705)	740

Notes: Credit and debit card users from the second-choice survey (Online Appendix OC.3). *Primary Debit/Primary Credit*: primary payment method is debit/credit card. *Switch Rewards*: would switch from primary credit card if rewards were halved. *Bank Removed Other Debit/Credit*: respondent would switch to another bank if their own bank dropped that payment type (defined only for primary debit/credit users). *Card Removed Debit/Credit/Cash*: respondent would switch to debit, credit, or cash if their primary payment type were no longer available. *Female*: customer is female. *Wave 1/Wave 2*: survey wave. *Additional Cards Used*: number of credit or debit cards beyond the primary card. *Age*: customer's age. *Income*: household annual income, made continuous using the geometric mean of each category's bounds.

Table OA.11: Log income regression on primary payment method

	DCPC
Prefers Debit	0.23***
	(0.04)
Prefers Credit	0.57***
	(0.04)
Num.Obs.	5986
R2 Adj.	0.091
R2 Within	0.090

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Data from the 2017–2019 waves of the DCPC. The dependent variable is log household income. The omitted category is primary cash users.

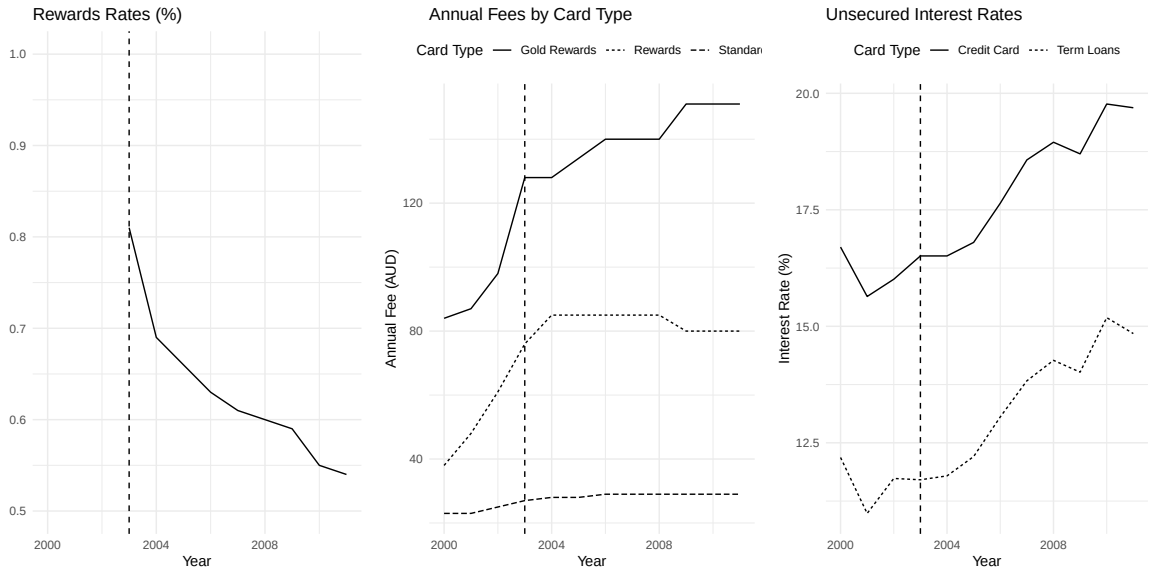
Table OA.12: Baseline Equilibrium

	Cash	Debit	Credit
Market Share (%)	26	41	33
Share of Spending (%)	20	36	44
Merchant Fees (bps)	30	72	225
Rewards (bps)	0	0	145

Notes: The market share of a card type is the fraction of consumers whose primary card is that type. The reward rate is the lump-sum reward divided by the dollars spent on that card, for a consumer who single-homes on it.

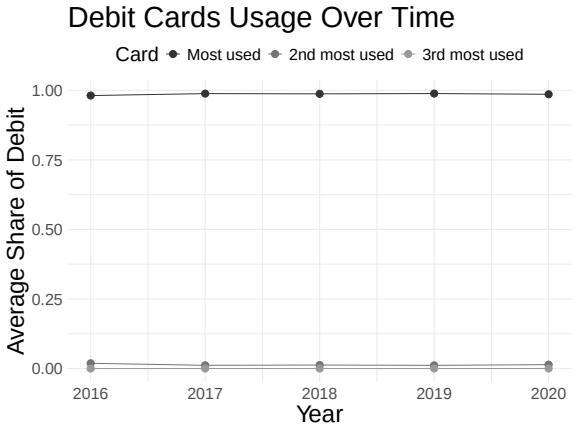
OB Descriptive Figures

Figure OB.1: Australian credit card market after interchange regulation



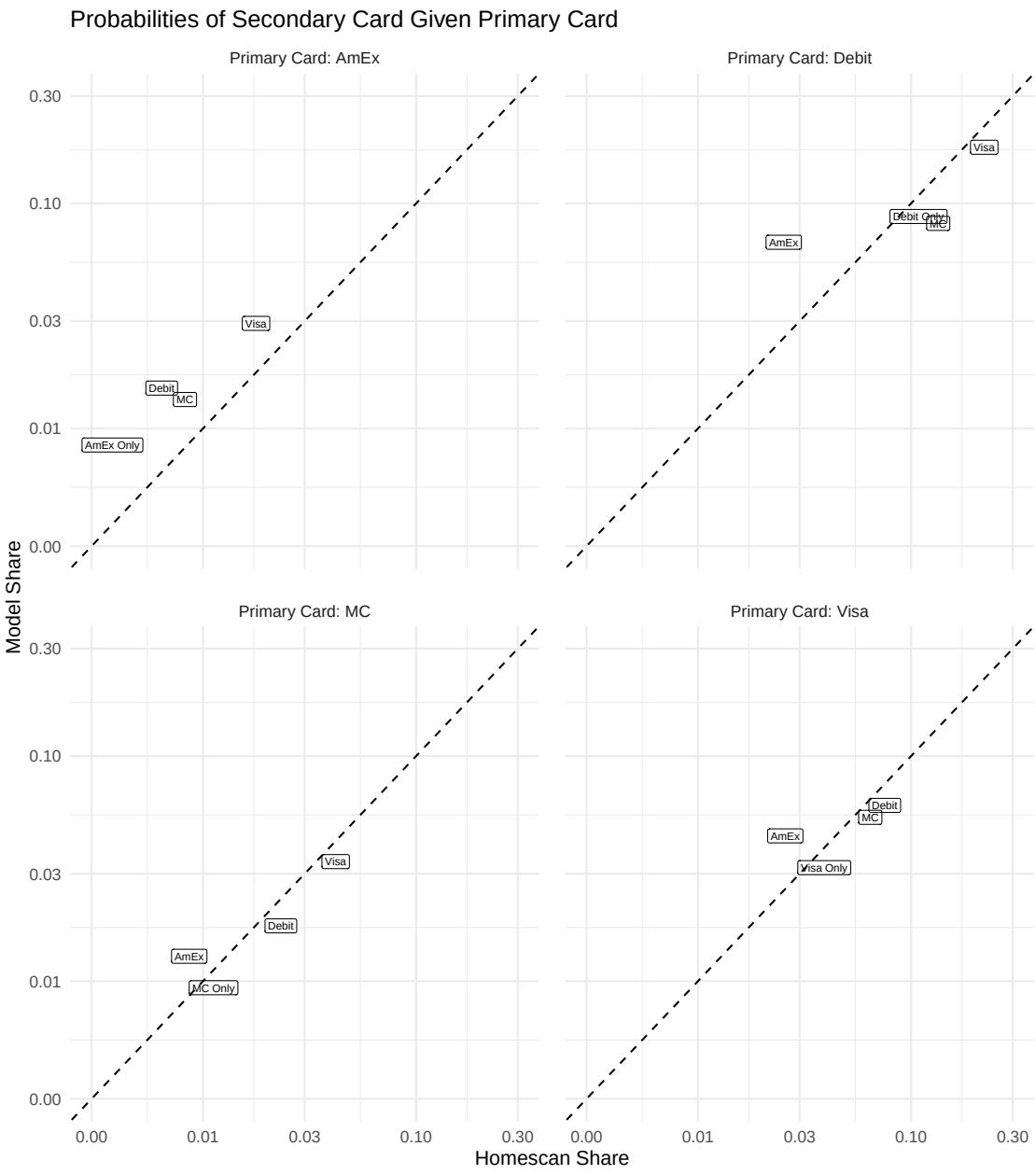
Notes: Vertical line marks 2003, when interchange regulation began. 'Gold Rewards': highest-tier rewards cards. 'Rewards': basic-tier rewards cards. 'Standard': cards without rewards. Rewards data are from Chan et al. (2012), annual fees are from "Banking Fees in Australia" reports, and interest rates are from the Reserve Bank of Australia's F05 publication.

Figure OB.2: Share of debit card spending on primary debit card



Notes: DCPC data, 2017–2019. The primary debit card is the one a consumer uses for the most debit transactions by count.

Figure OB.3: Model fit of market shares by primary–secondary card combination



Notes: Each point plots a card combination's model share against the data share. Facets correspond to primary card choices. Points are labeled by secondary card. The dashed 45-degree line marks perfect fit.

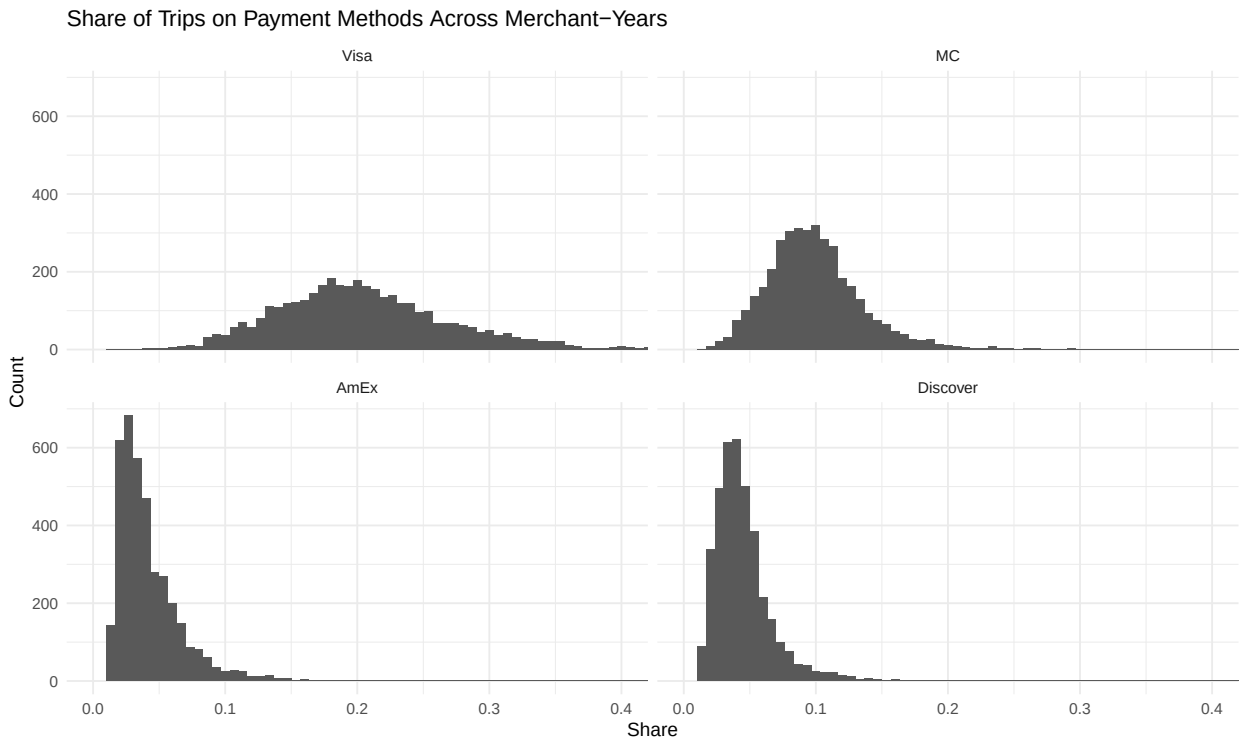


Figure OB.4: Payment mix distribution across merchants in the Homescan data

Notes: Homescan panel, 2013–2023. Each observation is a merchant-year. The figure shows the distribution of payment shares across merchants for Visa, MC, AmEx, and Discover credit cards.

OC Additional Data Details

OC.1 MRI-Simmons

MRI-Simmons USA is a nationally representative panel that merges MRI's Survey of the American Consumer and Simmons Research's National Consumer Study. The survey covers roughly 25,000 consumers per year from 2009–2020 and 50,000 from 2021 onward. I draw on 2009–2022 data for financial institutions, payment method ownership, income, and bank switching. The 2022 wave adds shopping behavior across 214 merchant chains. These data support robustness checks throughout the online appendices but do not enter the structural estimation. Table OC.1 reports summary statistics.

OC.1.1 Payment method

The data report credit and debit spending by bank and network but not cash spending. The survey asks "Which of the following best describes your attitude toward using cash?" with responses including "I prefer to use cash whenever possible." I classify respondents who choose this answer as cash users. Among the rest, I assign each consumer to credit or debit based on whichever card carries higher spending.

OC.1.2 Bank type

The MRI survey lists each consumer's deposit institutions, which I use to sort consumers into small or large banks. Small bank customers hold deposit accounts only at community banks and credit unions. These institutions are largely exempt from the Durbin Amendment because they hold less than $10 billion in assets. Large bank customers hold deposit accounts only at the four largest banks (Chase, Bank of America, Citibank, Wells Fargo) plus U.S. Bank. Online Appendix OD.1 uses this split to test whether consumers switched banks or gained credit card rewards after Durbin.

OC.1.3 Share of consumers across merchants

The 2022 wave records whether each respondent shopped at 214 merchant chains, which span grocery stores, department stores, restaurants, and other sectors. For each merchant, I compute the survey-weighted share of customers preferring each payment method. The average merchant's customer base is 48% credit, 38% debit, and 14% cash, with standard deviations of 8–10 pp. Table OC.1 reports consumer-level summary statistics from the MRI survey.

Table OC.1: Payment preferences and bank choice in the MRI survey

	2009-2021		2022	
Variable	Mean (SD)	N	Mean (SD)	N
Has Debit Card	0.6	349,546	0.75	51,697
Has Credit Card	0.58	349,546	0.75	51,697
Debit User			0.29	51,697
Credit User			0.34	51,697
Cash User			0.37	51,697
Multiple Credit Cards	0.42	349,546	0.57	51,697
Multiple Networks	0.25	349,546	0.34	51,697
Rewards	0.41	349,546	0.63	51,697
Factor Rewards	0.09	323,343	0.16	51,697
Small Banks	0.27	349,546	0.35	51,697
Big Banks	0.37	349,546	0.46	51,697
Switch Banks	0.04	323,343	0.04	51,697
Share of Debit Exp			0.4 (0.37)	43,136
Share of Credit Exp			0.6 (0.37)	43,136
Income	80,749 (60,890)	349,546	99,336 (69,037)	51,697

Notes: Has Debit Card and *Has Credit Card* indicate ownership of each card type. *Debit User*: non-cash user who either holds only debit or whose debit expenditure share exceeds credit. *Credit User*: non-cash user who either holds only credit or whose credit expenditure share exceeds debit. *Cash User*: agrees completely with "I prefer to pay cash for things I buy, whenever I can." *Multiple Networks*: owns credit cards from multiple networks. *Multiple Credit Cards*: owns more than one credit card. *Factor Rewards*: rated rewards as very important when choosing a bank. *Rewards*: receives credit card rewards. *Big Banks*: uses Chase, Citibank, Wells Fargo, Bank of America, or U.S. Bank. *Small Banks*: uses community banks or credit unions. *Switch Banks*: changed banks in the last 12 months (not defined for 2009). *Share of Debit Exp* and *Share of Credit Exp*: debit and credit shares of card expenditure. *Income*: household income in dollars, made continuous using the geometric mean of each category's bounds.

OC.2 Yelp Open Dataset

I use the Yelp Open Dataset (reviews mainly from 2010–2018) to document which payment methods merchants accept and which they refuse. I identify cash-only mentions with regular expressions ("cash only" or "only...cash"), then flag discussions of card acceptance using keywords such as "accept," "take," "took," and "bring." Among these, I search for specific payment methods (Visa, MC, AmEx, Discover, credit, debit).

I classify acceptance reviews with the ChatGPT-4o API. The prompt asks the model which payment methods each review reports as accepted, keeping networks separate (accepting Visa does not imply MC) and keeping types separate (accepting credit does not imply debit). Table OC.2 shows representative review snippets for each acceptance category.

Yelp business profiles also report whether merchants accept credit cards. Table OC.3 compares DCPC acceptance rates to Yelp business attributes by sector. The two sources match in aggregate (95.8% vs. 96.3%).

Table OC.2: Examples of Yelp reviews

Classification	Review (relevant snippet)
Debit, no Credit	You won't be disappointed Keep In Mind: -They only accept debit and cash -Weekends are super busy so be prepared for a crowd
Debit + Credit	Street parking, accept credit/debit cards
Visa and MC	They flat out charge you more if you don't pay with cash, now they do accept debit and consider it the same as cash so its really negligible but honestly they even label everything with two prices the cash price and non cash price. I seldom carry cash, and I seldom use debit and they see fit to penalize me for this. The cashier naturally refused to take my card as it didn't have my name on it and they always require a photo ID to make a credit purchase
Visa, no AmEx	The have complementary water and take all major credit cards except for AMEX.
Credit, no Debit	DEB'S NOW TAKES CREDIT CARDS. No Amex tho and no debit cards, but you can now pay for your delicious and cheap breakfast with Visa, Mastercard, or Discover
Only one: Visa or MC	When I went inside to pay the cashier said they do not take Mastercard. Who doesn't take mastercard. I had to pay with a credit card and with tax I was charged $45.78
AmEx, no Visa	One item that might concern some - American Express is the only credit card they accept.

OC.3 Second-Choice Survey Design Details

Appendix A describes the sample and summary statistics. This section provides additional design details.

The survey included an attention check. I drop 47 respondents who failed it and 12 who completed the survey outside the collection window. Household income was collected in eight brackets and made continuous with geometric means of bracket bounds.

The survey instrument first asked respondents to identify their primary payment method for in-person transactions. Respondents then answered three hypothetical questions. (i) Which method they would use if their primary payment type (credit or debit) did not exist? (ii) Which method they would use if their bank stopped offering their primary card? (iii) Whether they would switch cards if rewards changed (halving for credit users, doubling for debit users)? For question (ii), the survey also asked respondents

Table OC.3: DCPC and Yelp acceptance rates by sector

Sector	DCPC Accept	N (DCPC)	Yelp (raw)	Yelp (wtd)	N (Yelp)
Grocery	97.7%	5,397	98.5%	98.2%	3,087
Shopping	98.1%	4,756	96.4%	96.8%	16,739
Fast Food	95.7%	4,214	98.1%	97.3%	11,552
Gas Station	98.9%	3,366	99.2%	99.6%	896
Restaurant	96.4%	2,165	97.4%	98.2%	23,840
General Services	82.3%	926	93.5%	95.7%	14,146
Entertainment	74.6%	789	91.0%	89.2%	3,201
Medical	94.2%	525	97.5%	98.4%	8,758
Other	91.9%	320	92.3%	96.7%	4,061
Total	95.8%	22,458	96.3%	97.6%	86,280

Notes: DCPC Accept is the share of transactions at merchants accepting cards, from the 2017–2019 Diary of Consumer Payment Choice. Because respondents record acceptance at each transaction, DCPC rates are sales-weighted across merchants visited. Yelp (raw) is the unweighted share of Yelp business profiles reporting credit card acceptance. Yelp (wtd) reweights Yelp businesses by estimated transaction volume within each sector. *N* columns report the number of transactions (DCPC) or businesses (Yelp) in each sector.

to name the banks they would consider switching to, which I use to construct network diversion ratios (Online Appendix OD.5.3).

OD Additional Reduced Form Results

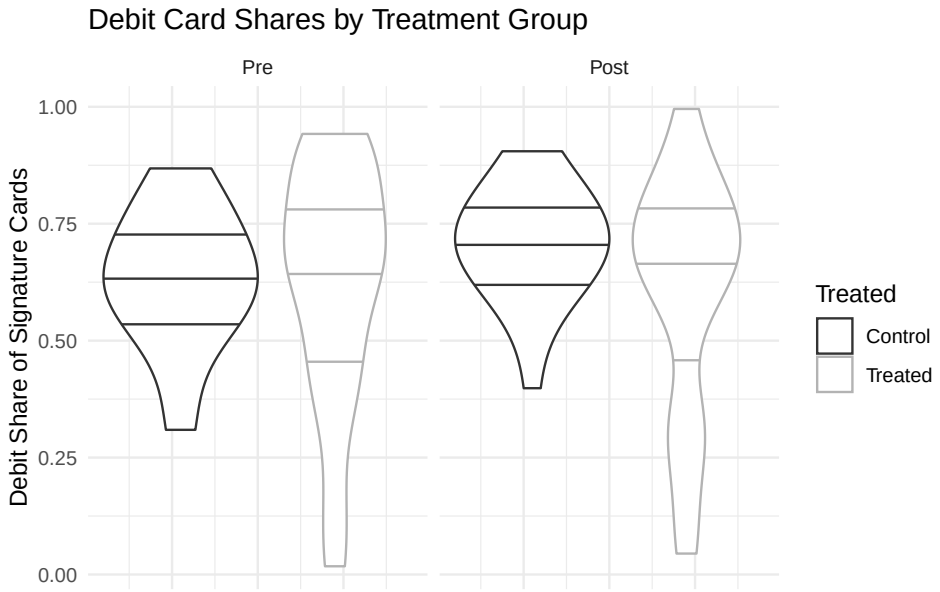
OD.1 Durbin Amendment Robustness Checks

This section checks sensitivity of the main specification and identifies the mechanism behind the debit volume decline.

OD.1.1 Sensitivity of the Main Specification

Treatment and control issuers had similar pre-policy payment mixes. The percentage decline estimate is sensitive to functional form only if treatment and control issuers have different baseline mixes of debit and credit. Figure OD.1 shows the pre-policy distributions of signature debit shares overlap closely across treatment and control banks.

Figure OD.1: Comparing debit versus credit shares at treatment and control banks



Notes: Each panel shows the distribution of signature debit as a share of signature debit plus credit card volumes by value for control (<$10 billion in assets in 2010) and treatment banks (>$10 billion) in the pre- and post-periods. Dashed lines mark the 25th, 50th, and 75th percentiles.

Plausibility of the effect of Durbin on interchange revenue. The estimated interchange decline (Table OD.1) matches Durbin's expected effect. Debit interchange at regulated issuers fell by roughly half while credit interchange was unaffected. Given

Table OD.1: Event study estimates for the effect of the Durbin Amendment on interchange fees, signature debit payment volumes, and deposits

	Interchange	Signature Debit	Deposits	Total Debit	Credit
Treat, t=-4	-0.023	0.009	0.064		-0.040
	(0.087)	(0.050)	(0.052)		(0.121)
Treat, t=-3	0.091	-0.002	0.009	-0.050	0.033
	(0.090)	(0.039)	(0.035)	(0.073)	(0.113)
Treat, t=-2	-0.073	-0.014	0.006	-0.002	0.009
	(0.073)	(0.024)	(0.018)	(0.043)	(0.067)
Treat, t=0	0.004	-0.072+	-0.021	-0.043	0.153*
	(0.054)	(0.037)	(0.020)	(0.072)	(0.066)
Treat, t=1	-0.426***	-0.099*	-0.040	-0.060	0.138
	(0.098)	(0.047)	(0.028)	(0.078)	(0.087)
Treat, t=2	-0.336**	-0.220***	-0.058	-0.143	0.239*
	(0.119)	(0.047)	(0.035)	(0.089)	(0.090)
Treat, t=3	-0.345**	-0.288***	-0.062	-0.244*	0.283*
	(0.108)	(0.062)	(0.038)	(0.092)	(0.105)
N	296	288	317	259	298
Bank FE	X	X	X	X	X
Year FE	X	X	X	X	X

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Difference-in-differences estimates comparing financial institutions above and below the $10 billion Durbin asset threshold. The dependent variable in each column is stated in the column header. Institutions involved in large mergers or divestitures are excluded. Standard errors clustered at the issuer level.

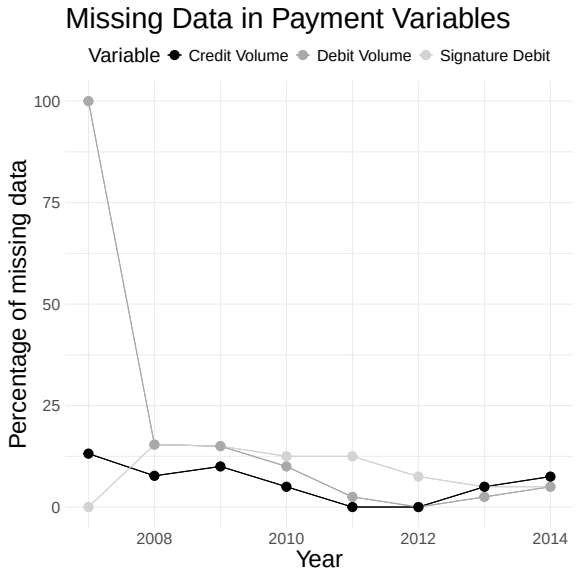
that debit accounted for about two-thirds of total interchange revenue before the policy, this reduction in debit interchange is consistent with the policy (CU Today 2016).

The estimates are somewhat sensitive to whether I use total debit or signature debit volumes. I focus on signature debit because of better data coverage in the early sample (Figure OD.2), which is essential for evaluating pre-trends. Total debit volumes also fall after Durbin, albeit by a smaller amount (22% versus 25% for signature debit, Table OD.1).

The estimates are not driven by outliers or the asset size cutoff. The Nilson sample contains 40 institutions (19 treated, 21 control). Figure OD.3 shows the treatment group distribution shifted left throughout its support, not just at a few outliers. Figure OD.4 shows stable estimates as asset size cutoffs vary toward the $10 billion threshold.

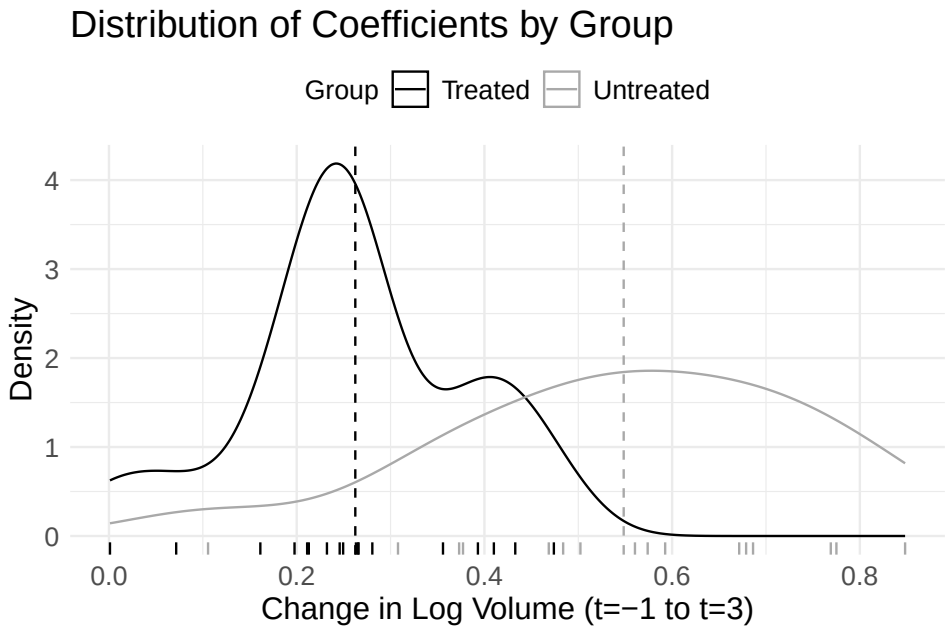
Results are robust to including mergers. The baseline excludes issuers with large acquisitions or divestitures (target assets exceeding half the acquirer's), whose volume changes reflect portfolio transactions rather than consumer payment choices. Including

Figure OD.2: Share of panel observations with missing data by year and card type



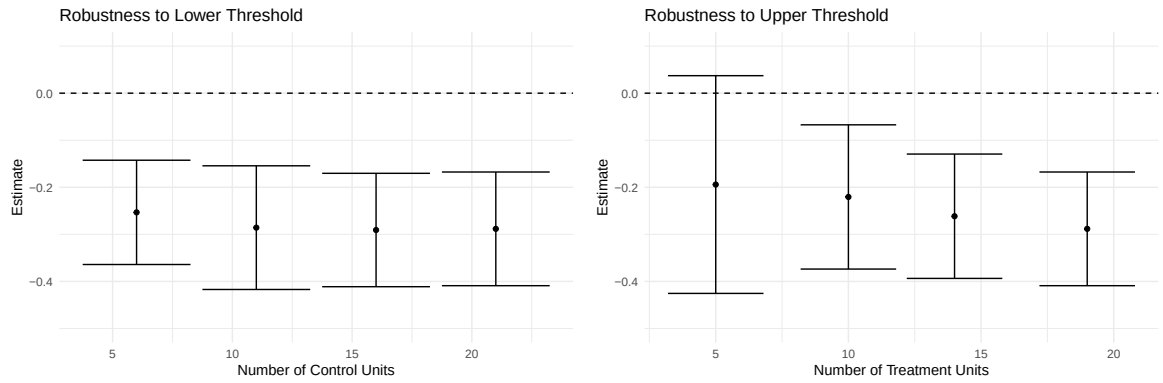
Notes: Data are from the Nilson Report. The figure plots the fraction of issuers in the analysis sample with missing volume data, by year and card type (signature debit, total debit, and credit). The Nilson Report reported the signature debit volumes for the top 200 issuers in earlier years, which improved data coverage for signature debit early on.

Figure OD.3: Distribution of institution-level estimates in the Nilson analysis



Notes: Density plots of institution-level pre-post changes in signature debit volumes for treated and control groups, from which the difference-in-differences estimate of Durbin's effect is derived. Each observation is a financial institution. The main text coefficient roughly equals the difference between the treated and control group means.

Figure OD.4: Robustness of the effect of the Durbin Amendment on debit card volumes to varying asset size cutoffs



Notes: Difference-in-differences estimates of Durbin's effect on signature debit volumes as the minimum asset requirement increases toward $10 billion (control group) or the maximum decreases toward $10 billion (treatment group). The x-axis reports the number of remaining units in the sample, so tighter asset cutoffs correspond to fewer units. Tighter cutoffs therefore move right to left on the graph. Dots are point estimates. Error bars are 95% confidence intervals.

these issuers does not change the estimates (Figures OD.5 and OD.6).

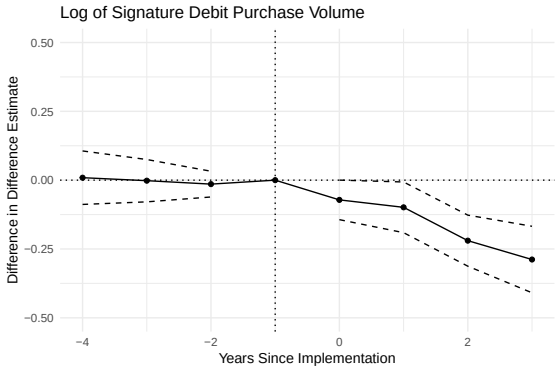
Results extend to total debit and credit card volumes. The main text focuses on signature debit because coverage in the Nilson Report is most complete. Figures OD.7 and OD.8 apply the same design to total debit volumes, credit card volumes, and signature debit's share of total debit. The panel conditions on banks with pre- and post-Durbin observations for both signature debit and credit, but not for the PIN-inclusive total, so the total-debit and compositional panels reflect a different and smaller set of reporting banks (Figure OD.2). Total debit volumes decline after Durbin, although by less than signature debit and with noisier estimates. Among banks that report both signature and total debit, the compositional panel shows little shift between signature and PIN debit, suggesting the decline was broad-based rather than driven by substitution across debit types. Credit card volumes at large banks appear to rise relative to small banks after Durbin (Table OD.1, Figure OD.8), although pre-trends in the credit column are not cleanly zero, so this result should be interpreted with caution.

OD.1.2 Mechanism

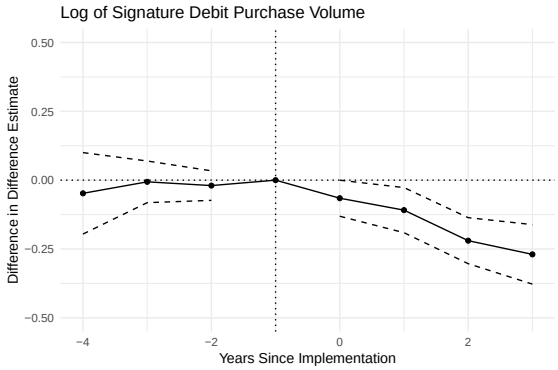
The debit volume decline could reflect three mechanisms. The first is bank switching by consumers fleeing Durbin-exposed institutions. The second is a pull toward credit from improved large-bank rewards. The third is within-bank substitution driven by loss of debit rewards. Banks that ended debit rewards lost volumes comparable to the full treatment effect. Deposits did not shift from large to small banks, ruling out bank

Figure OD.5: Robustness of signature debit volume estimates to including merger banks

(a) Restricted sample



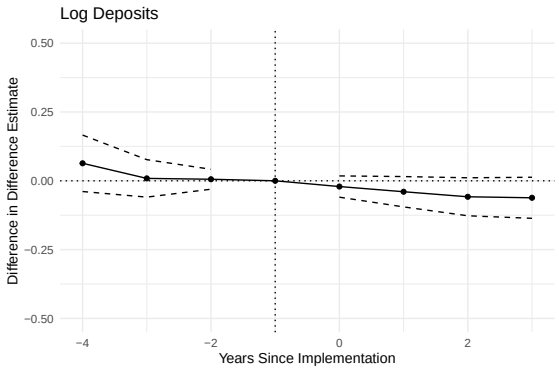
(b) Full sample



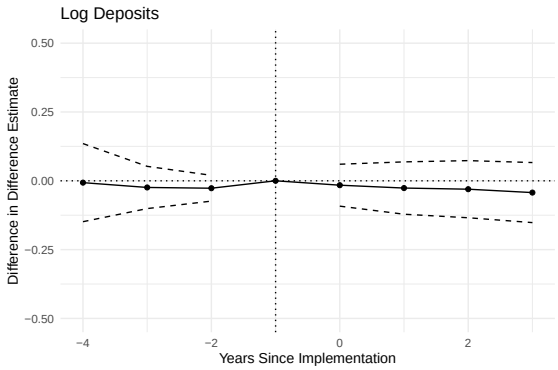
Notes: Same difference-in-differences design as Figure 3. The restricted sample (left) excludes issuers with acquisitions or divestitures exceeding half the acquirer's assets. The full sample (right) includes all issuers.

Figure OD.6: Robustness of deposit estimates to including merger banks

(a) Restricted sample

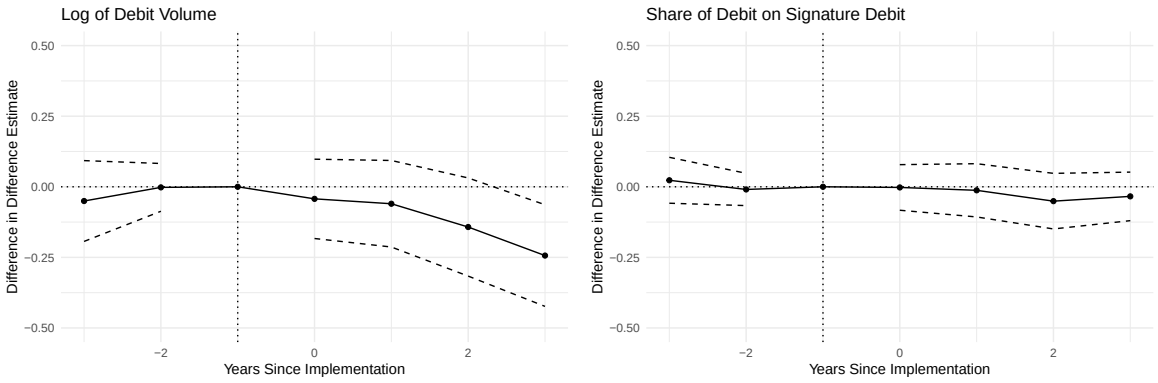


(b) Full sample



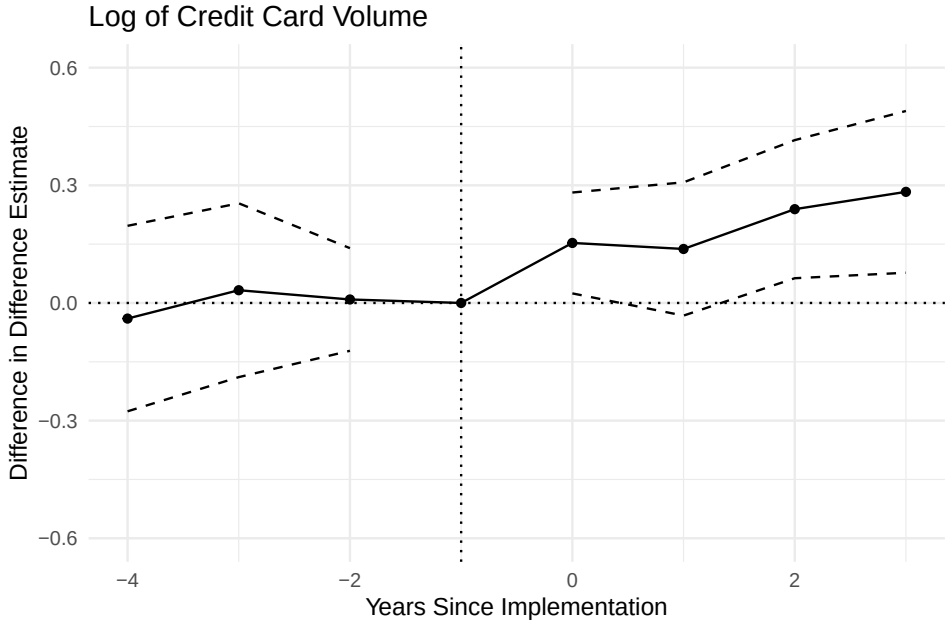
Notes: Same design as Figure OD.5, with log deposits as the dependent variable.

Figure OD.7: The effect of the Durbin Amendment on overall debit volumes



Notes: Data are from the Nilson Report. Both panels use the same difference-in-differences design as Figure 3, comparing issuers above and below the $10 billion Durbin threshold. Left: log total debit volumes (signature plus PIN). Right: signature debit as a share of total debit volumes. The vertical line marks 2010, the year before the policy began to be implemented.

Figure OD.8: The effect of the Durbin Amendment on credit card volumes



Notes: Data are from the Nilson Report. The design is identical to Figure 3, comparing issuers above and below the $10 billion Durbin threshold. The vertical line marks 2010, the year before the policy began to be implemented.

switching. And credit card rewards did not differentially improve at large banks, ruling out a pull toward credit at large banks.

Evidence on the rewards channel. Large banks changed multiple debit card program features after Durbin, including rewards, advertising, and employee incentives. To assess how much rewards contributed to the decline, I collect bank-level data on which institutions paid debit rewards before and after Durbin from archived bank websites via the Wayback Machine. Of the 40 institutions in my baseline panel, only 15 paid debit rewards before Durbin. Among these 15 institutions, 7 ended rewards after Durbin while 8 continued. I compare debit volume changes between these groups:

$$y_{jt} = \sum_{k \neq -1} \beta_k I\{t = k\} \times T_j + \delta_j + \delta_t + \epsilon_{jt} \tag{38}$$

where y_{jt} is the log of debit card payment volumes, T_j is an indicator that institution j ended its rewards program after Durbin, β_k are the dynamic difference-in-differences estimates, δ_j are bank fixed effects, and δ_t are time fixed effects.

Figure OD.9 shows the difference-in-differences estimates. On this restricted sample, banks that ended rewards saw debit volumes fall about 25% relative to banks that kept rewards by 2014, a gap that matches the aggregate estimate and motivates the calibration choice in Section V.A.

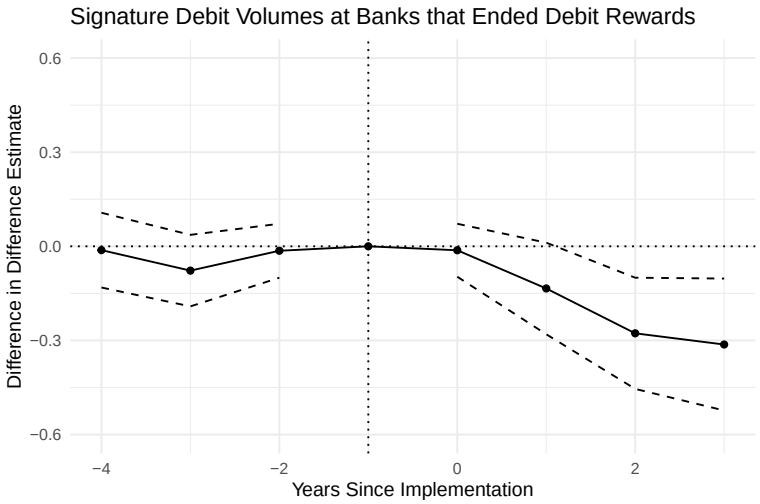
A Roy-model interpretation connects the 25% to the rewards channel specifically. Banks fund debit promotion from interchange revenue, allocating across rewards, advertising, and teller incentives. If banks differ in their productivity across these levers and each chooses the mix that maximizes consumer response per dollar, non-price steering at reward-paying banks would then be small to begin with. The within-subsample comparison then reflects mainly the rewards change.

I do not run a horse race between being above the cutoff and terminating rewards. A regression that controls for rewards and being above or below the cutoff would be misspecified. It assumes equal non-price baselines across banks, whereas the Roy model described above implies the opposite.

The decline reflects within-bank payment switching, not bank switching. An alternative explanation for the debit volume decline is that consumers switched from large banks to small banks after Durbin, taking their debit volumes with them. If this were the case, deposits at large banks should have fallen relative to small banks, and consumers at small banks should report higher rates of recent bank switching.

Figure OD.10 tests both predictions. The left panel uses the same Nilson Report panel and difference-in-differences design as the main specification, with log deposits as the outcome. Deposit growth at large banks tracked deposit growth at small banks

Figure OD.9: Direct effect of rewards on signature debit card volumes



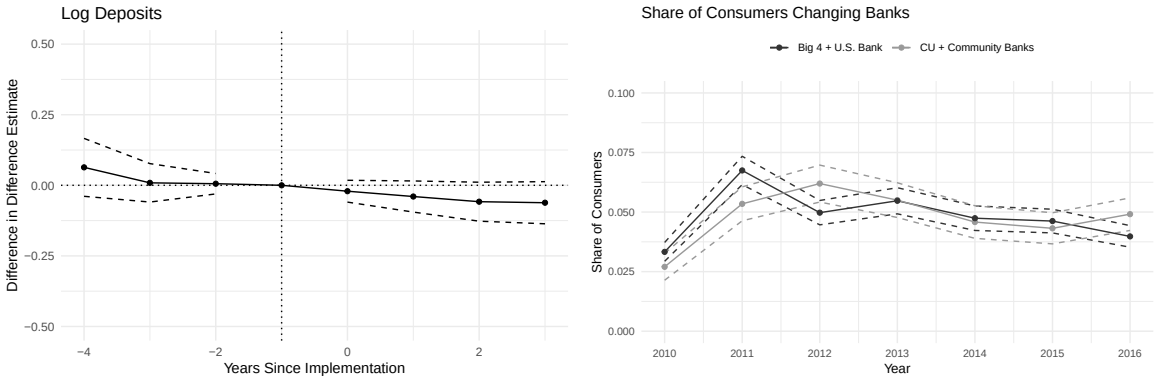
Notes: Point estimates from a regression of log debit volumes on an indicator for not paying rewards, with bank and time fixed effects. Sample: 15 banks and credit unions that paid debit rewards before Durbin. Standard errors clustered at the issuer level.

closely throughout the post-Durbin period, with no evidence of differential outflows. The right panel uses MRI-Simmons survey data, which asks consumers whether they recently changed their primary financial institution. Consumers at small banks did not report higher bank switching rates. The evidence rules out bank switching as the driver. Deposit flows and consumer behavior both stay stable across bank sizes. Debit volumes fall without customers leaving. They must be substituting toward other payment methods within their current banks. The importance of within-issuer substitution is also why I focus on issuers with both debit and credit franchises, which provide a more representative picture of aggregate switching behavior than single-product issuers.

Credit card rewards did not differentially change at large banks. An alternative explanation for why consumers decreased their use of debit cards at large banks is that those banks increased credit card rewards. If so, the debit volume decline could reflect consumers being pulled toward credit by improved rewards rather than being pushed away from debit by the loss of debit rewards. This story predicts that the availability of credit card rewards, or the share of consumers holding credit cards, should have risen differentially at large banks after Durbin.

Figure OD.11 does not support this alternative. Around 40% of small-bank customers also hold credit cards from large issuers (left panel), so even if large banks did improve rewards differentially, small-bank customers would benefit too and the cross-bank gap in debit usage would be dampened. More directly, the rate at which consumers receive credit card rewards did not differentially increase at large banks after Durbin (right

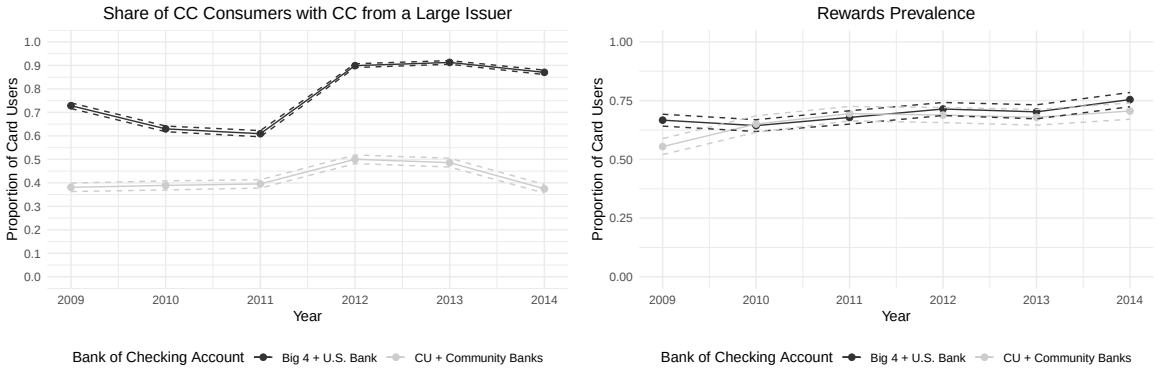
Figure OD.10: The effect of the Durbin Amendment on deposits and bank switching behavior



Notes: Left: estimated effect of Durbin on deposits at large banks, using the Nilson Report panel and the same difference-in-differences design as Figure 3. The vertical line marks 2010, the year before implementation. Right: MRI-Simmons data (2009–2022) showing consumers at small banks (credit unions or community banks, largely exempt from Durbin) did not report higher rates of recent bank switching compared to consumers at large banks.

panel), so the predicted reward differential is not in the data. The debit volume decline at large banks thus reflects the loss of debit promotion, not a pull toward improved credit rewards.

Figure OD.11: Credit card rewards for consumers who use large and small deposit institutions after the Durbin Amendment



Notes: Left: probability of holding a credit card from a large issuer, by deposit institution size. Right: probability of receiving credit card rewards, by deposit institution size. Small deposit institutions: credit unions or community banks only. Large deposit institutions: Chase, Bank of America, Citibank, Wells Fargo, or U.S. Bank. Large credit card issuers: Chase, Bank of America, Citibank, Wells Fargo, Capital One, Discover, and AmEx.

OD.2 Evidence on Whether Rewards Shift Shopping Behavior

Discover's 5% Cashback Bonus program provides a natural experiment for whether rewards affect store choice. The rewards apply at grocery stores but not discount or warehouse stores. Consumers do not change where they shop during reward quarters, but they do shift payments toward Discover. Most of the Discover gain comes from other credit cards. The remaining gain comes from debit and cash in equal amounts (-0.7 pp. each, Table OD.3), so debit and cash appear equally good substitutes for credit at the point of sale.[26] Rewards thus affect payment choice but not shopping location, even when consumers are aware of the rewards.

The Discover program rotates reward categories quarterly. Grocery stores have appeared once a year since 2018 (Table OD.2). I compare shopping and payment behavior at grocery versus discount and warehouse stores during quarters with and without Discover grocery cashback. I focus on these store categories because they are substitutes for consumers (Ellickson et al. 2020).

For the graphical evidence, I restrict to households whose primary or secondary card is Discover.[27] The triple-difference regressions below use the full panel of Homescan households, with Discover cardholders as the treated group, so that the Discover treatment indicator is not absorbed by the store-type-by-time fixed effects. I exclude merchants not accepting Discover and household-years without trips to both store categories.

OD.2.1 Graphical Evidence

Figure OD.12 shows the effects on payment and shopping behavior. The top panel shows grocery spending shares are flat for Discover cardholders during reward quarters (grey shaded areas). The bottom left panel shows Discover cardholders shift their spending share toward Discover during reward quarters, roughly a 7.6 pp. increase (Table OD.3). Consumers respond to rewards without changing where they shop. The bottom right panel shows no change in payment composition at discount and warehouse stores, so time-varying confounds are unlikely to explain the pattern.

OD.2.2 Regression Evidence

Regression estimates test the same patterns. I first confirm that consumers do not shift between grocery and discount/warehouse stores during reward quarters. Column

[26] For analysis of credit-debit substitution margins, see Online Appendix OF.

[27] Primary and secondary cards are defined by trip counts, with spending as a tiebreaker. See Appendix A.

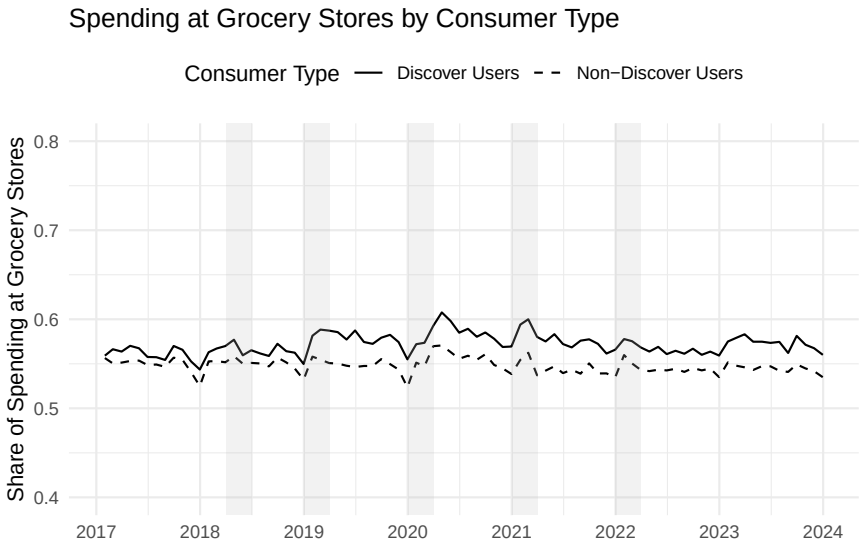
Table OD.2: Discover 5% Cashback Bonus Categories (2017–2022)

Year	Quarter	Reward category
2017	Q1	Gas stations, ground transportation, wholesale clubs.
	Q2	Home improvement stores, wholesale clubs.
	Q3	Restaurants.
	Q4	[redacted], [redacted].
2018	Q1	Gas stations and wholesale clubs.
	Q2	**Grocery stores**.
	Q3	Restaurants.
	Q4	[redacted] and wholesale clubs.
2019	Q1	**Grocery stores**.
	Q2	Gas stations; Uber and Lyft.
	Q3	Restaurants; PayPal.
	Q4	[redacted]; [redacted] (in-store and online); [redacted].
2020	Q1	**Grocery stores**; [redacted] and [redacted].
	Q2	Gas stations; Uber and Lyft; wholesale clubs; [redacted].
	Q3	Restaurants; PayPal.
	Q4	[redacted], [redacted] & [redacted].
2021	Q1	**Grocery stores**, [redacted] & [redacted].
	Q2	Gas stations, wholesale clubs & select streaming services.
	Q3	Restaurants & PayPal.
	Q4	[redacted], [redacted] & [redacted].
2022	Q1	**Grocery stores**; fitness clubs; gym memberships.
	Q2	Gas stations; [redacted].
	Q3	Restaurants; PayPal.
	Q4	[redacted]; digital wallets.

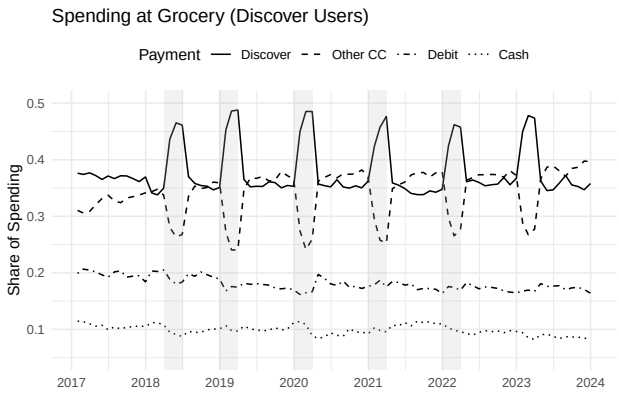
Note: Retailer names have been redacted. General retailer types include a major e-commerce platform, a large online store, a large discount store, two large drugstores, and a home improvement store.

Figure OD.12: Effects of Discover's quarterly reward program at grocery stores on consumer spending on different payment methods across retailer types

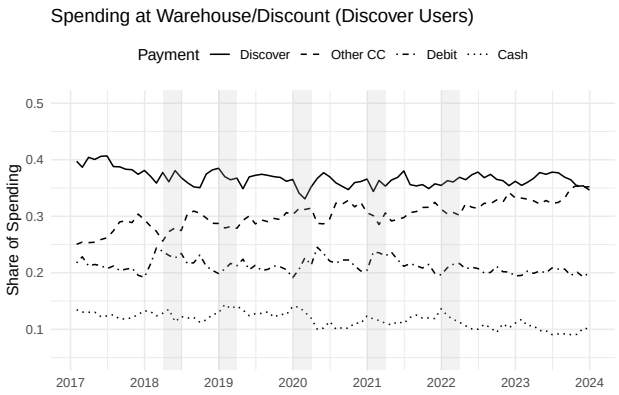
(a) Share of dollars spent at grocery stores



(b) Payment mix at grocery stores



(c) Payment mix at warehouse/discount stores



Notes: Grey areas mark quarters when Discover offers 5% cash back at grocery stores but not discount, warehouse, or other retailers. The first panel shows shopping decisions across retailer types. The second and third panels show payment composition at grocery stores (treated) and discount/warehouse stores (control). All samples condition on Discover cardholders.

1 of Table OD.3 reports a difference-in-differences specification:

$$y_{it} = \alpha \cdot \mathbf{1}\{\text{Reward Qtr}\}_t \times \mathbf{1}\{\text{Discover HH}\}_i + \delta_i + \delta_t + \epsilon_{it} \tag{39}$$

where y_{it} is the grocery spending share for household i in month t, and δ_i and δ_t are household and time fixed effects. The grocery spending share coefficient is noisy and economically marginal, confirming that consumers do not systematically change where they shop.

I then show that these same consumers do respond to rewards on the payment margin, ruling out inattention. Using a triple-difference design, I estimate for each payment method m (columns 2–5):

$$y^m_{igt} = \beta \cdot \mathbf{1}\{\text{Reward Qtr}\}_t \times \mathbf{1}\{\text{Discover HH}\}_i \times \mathbf{1}\{\text{Grocery}\}_g + \delta_{ig} + \delta_{it} + \delta_{gt} + \epsilon_{igt} \tag{40}$$

where y^m_{igt} is the spending share of payment method m for household i at store type g (grocery or discount/warehouse) in month t. The specification includes three sets of two-way fixed effects. Household-by-store-type (δ_{ig}) absorbs time-invariant differences in a household's payment mix across store types. Household-by-time (δ_{it}) absorbs household-level trends in payment behavior common to both store types. Store-type-by-time (δ_{gt}) absorbs aggregate shocks to payment composition at grocery versus discount/warehouse stores. Standard errors are clustered at the household level throughout.

The Discover spending share at grocery stores rises by 7.6 pp. during reward quarters ($p < 0.001$), offset by declines in other credit (-6.0 pp), debit (-0.7 pp), and cash (-0.7 pp). Consumers are aware of reward timing and shift which card they use, yet they do not change where they shop.

The relative magnitudes of the credit, debit, and cash responses are informative about how consumers substitute between different payment methods at the point of sale. The strong response for other credit cards suggests that credit cards are good substitutes for each other. The fact that both cash and debit respond also indicates that, contrary to the segmentation assumption made in the baseline model, consumers are willing to substitute between credit and debit at the point of sale. In Online Appendix OF I discuss how to incorporate this information on credit-debit substitution into the model estimates.

Table OD.3: Effect of Discover cashback rewards on payment composition

	Grocery	Cash	Debit	Other Credit	Discover
Discover HH × Grocery × Reward Month		-0.007***	-0.007***	-0.060***	0.076***
		(0.002)	(0.001)	(0.003)	(0.003)
Discover HH × Reward Month	0.002+				
	(0.001)				
Observations	5152886	8580301	8580301	8580301	8580301
R^2	0.586	0.863	0.911	0.913	0.902
HH × Grocery FE		Yes	Yes	Yes	Yes
HH × Time FE		Yes	Yes	Yes	Yes
Grocery × Time FE		Yes	Yes	Yes	Yes
Household FE	Yes				
Time FE	Yes				
Clustered SE	HH	HH	HH	HH	HH

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Column 1: grocery spending share (difference-in-differences with household and time FE). Columns 2–5: spending share by payment method at grocery versus discount/warehouse stores (triple-difference with household × store-type, household × time, and store-type × time FE). Standard errors clustered at the household level.

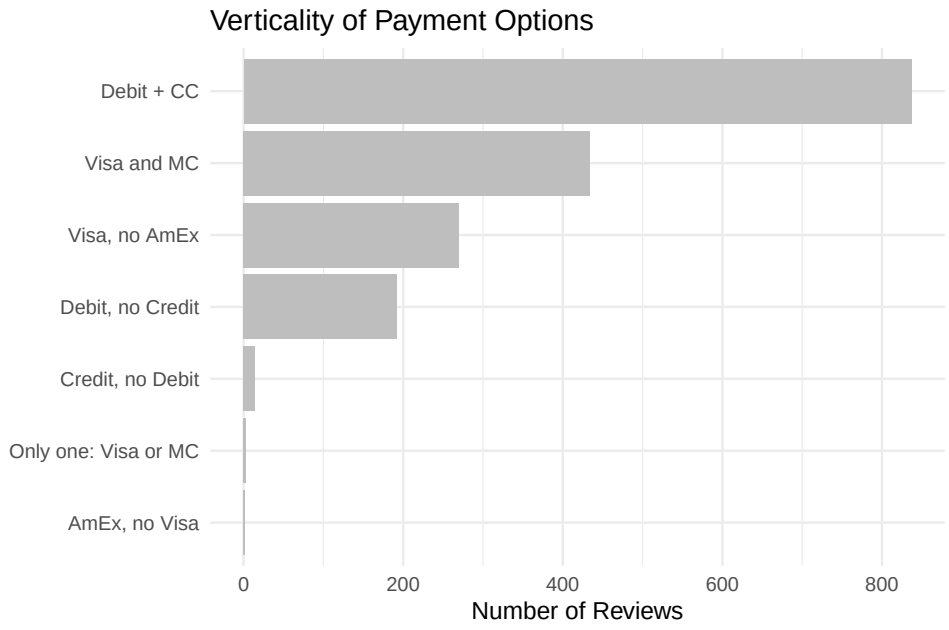
OD.3 Hierarchical Card Acceptance

In the main text, I show that AmEx and Visa are accepted by similar numbers of merchants. However, aggregate acceptance counts alone cannot prove that merchants maintain relationships with multiple networks. This section uses Yelp reviews to show that when AmEx and Visa charged different fees, acceptance patterns were hierarchical. Merchants add payment methods sequentially, in the order cash, debit, Visa/MC, and AmEx. They do not specialize in one network at the expense of another. This provides evidence of multi-homing behavior.

I collect around 1,500 Yelp reviews that mention at least two payment methods by name (see Online Appendix OC.2 for details on the sample construction). The reviews come primarily from the period 2010–2018, before AmEx's acceptance gap with Visa had fully closed, so they capture merchant acceptance decisions during a period of meaningful variation across networks.

Figure OD.13 shows a clear hierarchy in which payment methods co-occur in reviews. The most common combinations are debit and credit together, Visa with MC, Visa without AmEx, and debit without credit. Almost no reviews mention credit without debit, AmEx without Visa, or only one of Visa or MC. This pattern matches the sequential order described above.

Figure OD.13: Hierarchical card acceptance patterns in Yelp reviews



Notes: Each bar shows the frequency of a particular combination of payment methods mentioned in Yelp reviews. The sample contains around 1,500 reviews that mention at least two payment methods by name, primarily from 2010–2018. The bars exclude reviews that reference credit cards generically (e.g., "all major credit cards") without naming individual networks. See Online Appendix OC.2 for sample construction details.

The pattern differs from platform markets such as food delivery, where merchants often operate on one platform but not another (Sullivan 2025). In payment networks, multi-homing is nearly universal among merchants who accept cards at all.

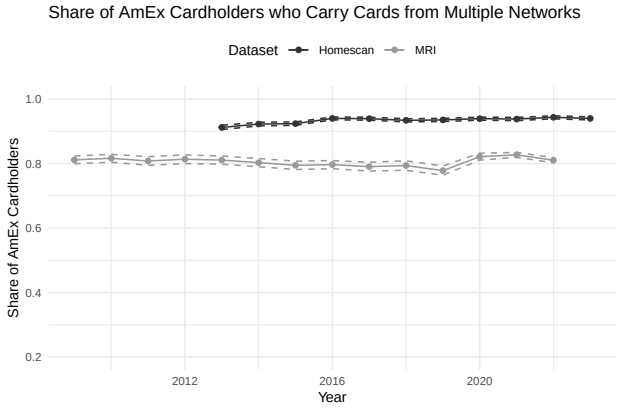
OD.4 Consumer Multi-homing Behavior

Consumer multi-homing across credit card networks reflects differences in rewards and card features, not insurance against acceptance gaps. This section tests whether AmEx cardholders reduced multi-homing as AmEx's acceptance gap with Visa closed. AmEx provides the sharpest test because it historically had the largest gap among major networks, so acceptance-driven multi-homing should be most visible there. If consumers held multiple credit cards mainly as insurance against acceptance gaps, the share of AmEx cardholders who also hold cards from other networks should have fallen as AmEx became accepted nearly everywhere.

Figure OD.14 plots the share of AmEx cardholders who also hold a credit card from another network, using data from MRI-Simmons (2009–2022) and NielsenIQ Homescan. Despite the closing of the AmEx–Visa acceptance gap documented in Figure 5b, the AmEx multi-homing rate has been flat throughout the sample period. The flat multi-

homing rate suggests that consumers multi-home because cards differ in rewards and features, not to hedge acceptance risk. This finding supports the model's treatment of consumer card choice as driven by card attributes rather than acceptance coverage.

Figure OD.14: AmEx Consumer Multi-homing Over Time



Notes: Data from MRI-Simmons (2009–2022) and NielsenIQ Homescan. The figure plots the share of AmEx cardholders who also hold a credit card from another network over time.

OD.5 Consumer Substitution Patterns from a Second Choice Survey

A second-choice survey supports the view that credit and debit are distinct product categories and that higher-income consumers are more reward-sensitive.

OD.5.1 Distinct Product Categories

Debit cards are closer substitutes for cash than credit cards are, but credit and debit remain distinct product categories. Table OD.4 shows the results. When asked what they would use if credit cards did not exist, most credit users would switch to debit. Only 15% would switch to cash. Among primary debit users, 53% would switch to cash, which is consistent with cash and debit being closer substitutes. When asked how they would pay if their bank stopped offering their primary card type, 81% of credit users and 63% of debit users would switch to the same card type on a different network. These shares exclude bank switches that likely keep the consumer on the same network (Section OD.5.3). These high same-type diversion rates support modeling credit and debit as distinct categories.

OD.5.2 Heterogeneity in Reward Sensitivity by Income

High-income individuals are more reward-sensitive. The elasticity of switching propensity with respect to income is 0.19, equivalent to a 0.14 pp increase in switching probability from a baseline of 0.71 (Table OD.5). MRI data from 2009–2022 show the same

Table OD.4: Substitution patterns from a second choice survey

Current Card	Choice Set	Share
Credit	{Cash, DC}	P(Cash) = 0.15
Debit	{Cash, CC}	P(Cash) = 0.53
Credit	{Cash, DC, Other Banks' CC}	P(Other Network's CC) = 0.81
Debit	{Cash, Other Banks' DC, CC}	P(Other Network's DC) = 0.63

Notes: How consumers would pay under counterfactual choice sets. The first column is the consumer's current primary payment method, the second is a hypothetical choice set, and the third is the probability of adopting a given method. The sample contains 357 primary credit and 383 primary debit users. See Online Appendix OC.3 for survey design details.

Table OD.5: Income heterogeneity in rewards sensitivity

	P(Switch)	P(Rewards Important)
Log Income	0.14***	0.02***
	(0.04)	(0.00)
DV Mean:	0.71	0.11
N	347	375040
Dataset:	2nd Choice	MRI
Year FE:		X

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Model 1 uses second-choice survey data. The dependent variable indicates willingness to switch if current credit card rewards were halved. Model 2 uses MRI-Simmons data. The dependent variable indicates the consumer cites rewards as important for financial institution choice. Both regressions use log household income as the independent variable.

pattern. Higher-income individuals are more likely to cite rewards as important for financial services choice.

OD.5.3 Technical Details of Constructing Network Diversion

The survey asks how consumers would switch if their bank stopped offering their preferred payment type. The model requires diversion between networks (e.g., Visa to MC), but the survey measures diversion between banks (e.g., Chase to Bank of America). I designed the question this way because consumers often do not know which cards are Visa or MC. The survey therefore overstates true network switching. A Visa consumer switching from Chase to Bank of America might stay on Visa if both banks offer it.

To correct this, I adjust responses by removing the expected "within-network" bank switches:

1. From the Nilson Report, I collect the share of Visa and MC cards at each major bank.

2. For each respondent, I define a choice set of alternative banks. The set includes banks where they already hold cards and banks they researched when last shopping for a card.

3. For each alternative bank, I calculate the probability a switch keeps the consumer on the same network, using network composition at the current and alternative banks.

4. I reduce the reported diversion ratio by subtracting the expected fraction of bank switches that keep consumers on the same network.

Formally, let $r_i \in \{\text{CC}, \text{DC}\}$ denote the primary card of survey respondent i. Let $N_c = \sum_i I\{r_i = \text{CC}\}$ be the number of primary credit card consumers, $N_d = \sum_i I\{r_i = \text{DC}\}$ be the number of debit card consumers, and $N = N_d + N_c$. I have already dropped primary cash consumers from the sample.

Let $S_{i,1}$ indicate switching to cash if credit cards did not exist. Let $S_{i,2}$ indicate switching to cash if debit cards did not exist. Let $S_{i,3}$ indicate switching to the same card type if the consumer's bank stopped offering their primary payment type.

For survey respondent i, let the imputed choice set of alternative banks be $\mathcal{C}_i$, the current bank be b_i, and the customer's card type be t_i (credit or debit). For each bank j and network $k \in \{\text{Visa}, \text{MC}\}$, let $n_j^{k,t}$ denote the share of type-t cards (credit/debit) on network k offered by bank j.

The adjustment term ι is the expected number of respondents who report switching to the same card type but remain on the same network:

$$\iota = \sum_{i=1}^{N} S_{i,3} \times \sum_{k \in \{\text{Visa},\text{MC}\}} n_{b_i}^{k,t_i} \times \left(\frac{1}{|\mathcal{C}_i|} \sum_{j \in \mathcal{C}_i} n_j^{k,t_i} \right)$$

The inner sum is the probability that the consumer's current network and a randomly drawn alternative bank's network coincide, treating both as independent draws from their respective bank-level network mixes. The sum of products of shares takes the same form as a Herfindahl index for two independent draws.

The data moments for the second-choice survey are then:

$$\hat{g}_1 = \begin{pmatrix} N_c^{-1} \sum_{i, r_i = \text{CC}} S_{i,1} \\ N_d^{-1} \sum_{i, r_i = \text{DC}} S_{i,2} \\ \frac{\sum_i S_{i,3} - \iota}{N - \iota} \end{pmatrix} \tag{41}$$

Table OD.6: Share switching to the same card type on a different network, under alternative assumptions about whether a bank switch (e.g., Chase to Bank of America) also changes the network (Visa to MC)

Assumption on Diversion	Credit Card	Debit Card
Consideration	0.81	0.63
All Divert	0.87	0.76
Half	0.76	0.62

In practice, diversion to credit cards does not depend on how within-network moves are modeled. Table OD.6 shows diversion to the same type under varying assumptions about the share of between-bank moves that also involve network switching. The estimation uses the Consideration row.

OD.6 Survey Evidence on Credit Aversion

SCPC and marketing surveys show that many consumers actively prefer debit over credit for substantive reasons, not because they are unaware of credit card rewards. Debit-preferring consumers cite budget control and debt aversion as their primary motivations. The model captures these motivations as higher non-pecuniary utility for debit.

Table OD.7: Most important characteristic of preferred payment instrument, by payment preference

	Cash	Debit	Credit
Budget control	0.14	0.06	0.01
Convenience	0.46	0.61	0.34
Rewards	0.00	0.00	0.39

Notes: Three consumer groups defined by preferred non-bill payment instrument (cash, debit, or credit). Each cell reports the share of consumers in that group who cite the row feature as the "most important characteristic" of their preferred payment instrument. Source: SCPC 2017–2019. All statistics use individual-level sampling weights.

Table OD.7 shows 14% and 6% of cash and debit users in the SCPC cite budget control as most important, versus 1% of credit users. Debit consumers are about 27 pp. more likely to cite convenience (Table OD.7), perhaps because debit cards come bundled with checking accounts and require no monthly bill. By contrast, 39% of credit card consumers say rewards are the most important reason they pay with credit. Among card owners who hold both products, 79% nonetheless make debit their primary instrument, showing that budget control and debt aversion keep many consumers on debit even

when credit would pay them more.

These results are consistent with findings from marketing surveys. About a quarter of consumers feel "impulsive," "anxious," or "overwhelmed" with credit cards, twice the rate for debit (Issa 2017). Among consumers without credit cards, 37% cite debt aversion ("prefer not to carry any debt"), versus only 26% who do not qualify (Boehm 2018).

Behavioral research finds some consumers prefer immediate payment to avoid carrying balances (Prelec and Loewenstein 1998). Zinman (2009) finds that around 30% of debit card users show spending-control motives. Australia banned unsolicited credit limit increases in 2018 after finding they caused "significant consumer detriment" (International 2018).

OE Additional Model Details

OE.1 Consumer Payment Probabilities

This section derives the payment probabilities $\pi^w_{M,j}$ from Section IV.B.2 for a model with two credit cards and one debit card, with results collected in Table OE.1.

Single-homers are straightforward. A consumer uses her card if the merchant accepts it and pays cash otherwise. For multi-homers carrying two credit cards, substitution is also simple. Both cards serve the same function, so if only one is accepted the consumer switches to it with probability 1 (middle panel of Table OE.1).

For a multi-homer carrying one credit and one debit card, credit and debit are segmented. Each card is used only for its intended transaction type. When both are accepted, the consumer uses credit with probability π and debit with probability $1-\pi$. When only one card is accepted, the consumer uses it for the share of transactions assigned to that type and pays cash for the rest. A consumer whose credit card is accepted but whose debit card is not still uses credit with probability π. She does not redirect debit transactions to the credit card.

Table OE.1: Consumer Payment Probabilities π^w_M (Baseline)

Primary Card	**Secondary Card**	**Merchant Accepts**	π^w_{M,w_1}	π^w_{M,w_2}
Any Card	None	Primary card accepted	1	0
Any Card	None	Primary card not accepted	0	0
Visa	MC	Both Visa and MC	π	$1-\pi$
Visa	MC	Only Visa	1	0
Visa	MC	Only MC	0	1
Visa	MC	Neither	0	0
Credit	Debit	Both Credit and Debit	π	$1-\pi$
Credit	Debit	Only Credit	π	0
Credit	Debit	Only Debit	0	$1-\pi$
Credit	Debit	Neither	0	0

OE.2 Acceptance Thresholds

Every acceptance decision hinges on the same two forces, which are consumer multi-homing patterns and the fee spread across networks. Consider two cards with fees $\tau_1 \leq \tau_2$. Every payment method generates the same incremental sales per dollar. A merchant already accepting card 1 decides whether to also accept card 2. The incremental quasi-profit (Theorem 1) depends on two consumer groups:

- **New transactions** (N): single-homers on card 2 who would otherwise pay cash, generating incremental fees and sales.
- **Diverted transactions** (D): multi-homers who switch from card 1 to card 2, changing the fee without generating new card transactions.

Both N and D are weighted sums of wallet shares $\mu^{(\cdot)}$, with weights depending on π and card holdings. The incremental quasi-profit coefficients are:

$$\Delta a = N\tau_2 + D(\tau_2 - \tau_1) \tag{42}$$

$$\Delta b = \tfrac{1}{\sigma}\big[N(1-\sigma\tau_2) - D\sigma(\tau_2 - \tau_1)\big] \tag{43}$$

The merchant accepts card 2 if and only if $\gamma \geq \underline{\gamma}_2$, where

$$\underline{\gamma}_2 = \frac{\sigma\big[N\tau_2 + D(\tau_2 - \tau_1)\big]}{N(1-\sigma\tau_2) - D\sigma(\tau_2 - \tau_1)} \tag{44}$$

This threshold rule applies whenever $\Delta b > 0$, i.e., the incremental sales gain from accepting card 2 is positive. In the empirical setting, $\Delta b > 0$ holds for all observed networks at baseline parameters. When $\Delta b \leq 0$, accepting the card destroys value for every type and the merchant declines unconditionally.

OE.2.1 Two Credit Cards

Multi-homing across credit cards affects acceptance, and relative fees matter. Since both are credit cards, multi-homers switch to whichever is accepted (Table OE.1, middle panel), so all divert, giving $D = (1-\pi)\mu^{(1,2)} + \pi\mu^{(2,1)}$. The new-transaction mass is $N = \mu^{(2,0)}$ (single-homers on card 2). Substituting into (44) gives

$$\underline{\gamma}_2 = \frac{\sigma\mu^{(2,0)}\tau_2 + \sigma\left[(1-\pi)\mu^{(1,2)} + \pi\mu^{(2,1)}\right](\tau_2 - \tau_1)}{\mu^{(2,0)}(1-\sigma\tau_2) - \sigma\left[(1-\pi)\mu^{(1,2)} + \pi\mu^{(2,1)}\right](\tau_2 - \tau_1)} \tag{45}$$

By inspection, cutting τ_1 raises $\underline{\gamma}_2$ by widening $\tau_2 - \tau_1$, which increases diversion drag without changing incremental sales. Three special cases follow. With $D = 0$ (no multi-homers), $\underline{\gamma}_2 = \sigma\tau_2/(1-\sigma\tau_2)$. As $N \to 0$ (no single-homers), $\underline{\gamma}_2 \to \infty$. When $\tau_2 = \tau_1$, the threshold collapses to $\underline{\gamma}_1$. This is consistent with Figures 5a and 5b, which show that AmEx acceptance responded sharply to its fee relative to Visa.

OE.2.2 Credit and Debit (Baseline)

Multi-homing across credit and debit does not affect credit acceptance, and relative fees do not matter. Credit and debit are segmented at the point of sale (Table OE.1,

bottom panel). Adding credit does not divert any spending from debit, so $D = 0$. The threshold reduces to

$$\underline{\gamma}_c = \frac{\sigma\tau_c}{1 - \sigma\tau_c}$$

independent of the debit fee. Segmentation ensures Δa and Δb share the same wallet-share weights, so the threshold depends only on credit's own fee. This is consistent with the Durbin evidence. After debit interchange fees fell by roughly half, credit interchange fees did not change (Figure 5) and yet credit card acceptance was unchanged (Figure OF.1).

OE.3 CES Price Index and Multi-Homing Pecuniary Utility

A more natural pecuniary utility for multi-homers would use the CES price index directly:

$$\log U^w = \pi f^{w_1} + (1 - \pi) f^{w_2} - \log P^{(w_1, w_2)}.$$

I do not use the CES-index definition because it counterfactually predicts that Visa-AmEx multi-homing rates fall as AmEx acceptance rises (Appendix OD.4).

When w_1 and w_2 are different types (credit and debit), the card-payment probability decomposes linearly as $v_M^w = \pi \cdot \mathbf{1}[w_1 \in M] + (1 - \pi) \cdot \mathbf{1}[w_2 \in M]$, and $(P^w)^{1-\sigma} = \pi (P^{(w_1,0)})^{1-\sigma} + (1 - \pi)(P^{(w_2,0)})^{1-\sigma}$. The only remaining gap is a Jensen correction in the log price index, second-order in the difference between credit and debit price indices.

For same-type multi-homers (e.g., two credit cards), there is an additional first-order gap from union acceptance. The consumer pays by card whenever *either* card is accepted, so $\pi \log P^{(w_1,0)} + (1 - \pi) \log P^{(w_2,0)} \geq \log P^{(w_1,w_2)}$, with equality when w_1 and w_2 have identical acceptance sets. Since credit card acceptance is symmetric across networks in the estimated model and all counterfactuals, the same-type multi-homer first-order gap vanishes. For different-type multi-homers, the second-order Jensen wedge above remains.

OE.4 Details on the Conduct Assumption

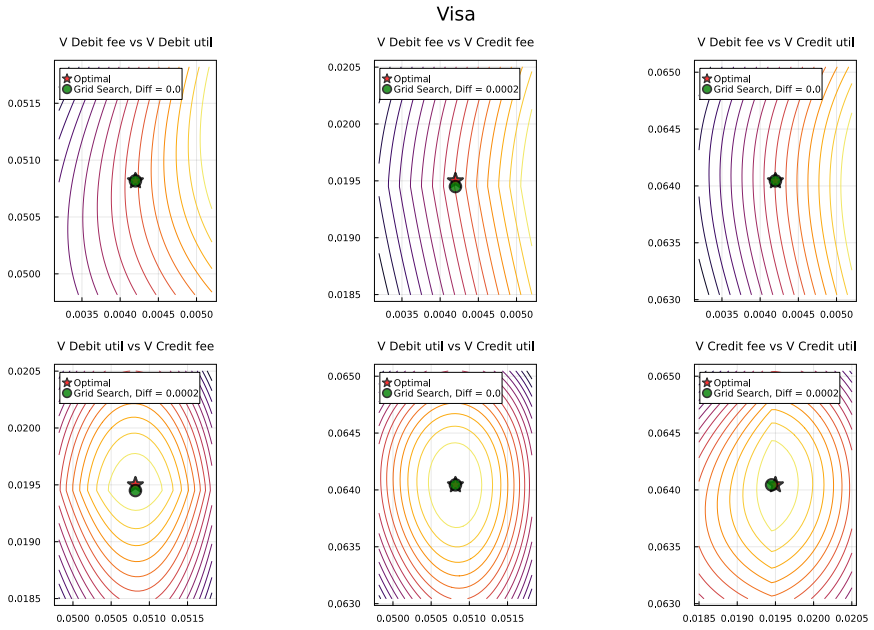
Why networks compete in gains A_j rather than utilities or rewards. Weyl (2010) shows that guaranteeing utility gains captures penetration pricing when merchant acceptance is low, giving consumers a dominant adoption strategy and pinning down a unique subgame equilibrium.

Non-differentiability with multiple networks. Network profits are non-differentiable in merchant fees when more than two networks compete. A network raising its fee competes with acceptance of all other networks, while a network cutting its fee competes

with cash. These regions have different marginal revenues, creating non-differentiability at the symmetric equilibrium. Rochet and Tirole (2003)'s two-network model avoids this issue. Teh et al. (2023) show the problem arises with three or more networks.

Trembles for equilibrium selection. To select a unique equilibrium, I introduce small trembles ν_x in networks' fee choices, smoothing the profit function and ensuring equal profit loss from marginal fee increases or decreases (following Bilal and Lhuillier (2025)). This convolution smooths the profit function, making Ψ differentiable, and as the perturbation vanishes, the smoothed objective converges uniformly to the original. To assess approximation error, Figure OE.1 plots pairwise heatmaps of Visa's profit (without trembles) across all control-variable pairs, comparing the perturbed-FOC solution with a grid search over the original profit function. The match is almost exact.

Figure OE.1: Comparing the maximum from solving the FOCs of the perturbed profit function with the maximum of the original profit function



OE.5 Model Solution Algorithm

The algorithm has two layers. An inner fixed point solves for the allocation (consumer wallet shares and merchant acceptance) given network fees A_j and τ_j. An outer loop then jointly solves networks' first-order conditions over fees, taking the inner equilibrium as given.

OE.5.1 Fixed Point Iteration

The inner fixed point iterates on wallet-specific price indices P^w. Given a conjecture for these price indices, the algorithm recovers the implied uniform reward rates by inversion and proceeds through the following steps:

1. Compute consumer wallet shares $\tilde{\mu}_y^w$ for each income level.
2. Solve merchant acceptance. Each merchant type γ maximizes quasi-profit to determine the optimal card bundle $M^*(\gamma)$.
3. Update price indices P^w by integrating the price-index integrand over the merchant type distribution.
4. Check convergence. If $\max_{w,s} |P^{w,\text{new}} - P^{w,\text{old}}| < \epsilon$, stop. Otherwise, apply damping and return to step 1.

Profits for each network follow from Equations 24 and 26. Demand integration uses 2,000 Monte Carlo draws jointly over unobserved preference heterogeneity and log-normal income.

The outer loop solves networks' first-order conditions jointly, respecting the ownership matrix that accounts for Visa's co-ownership of credit and debit products. Capped fees (e.g., under Durbin or counterfactual caps) bypass the first-order condition and are instead confirmed binding via Lagrange multiplier checks. For the normal expectations in the trembles, N-dimensional Gauss-Hermite quadrature with 2 points per dimension ensures equal profit loss from raising or lowering fees. Second-order conditions for local maxima are verified numerically at every solution.

OE.6 Numerical Validation of the Quasi-Profit Approximation

The quasi-profit functions match true profits closely. Figure OE.2 compares exact and approximate profits for all 32 potential payment bundles in the baseline equilibrium. The fit holds across all values of γ. Figure OE.3 plots the upper envelopes of true and approximate profit functions. Slope changes in the envelope mark where the merchant's optimal acceptance strategy shifts. The close fit confirms that the approximation accurately captures how optimal acceptance varies with merchant type.

OE.7 Mechanical Welfare Adjustment for Dual Routing

The dual routing counterfactual in Section VI.D differs from the other counterfactuals because it changes the consumer's choice set and preferences rather than fees, ownership, or the set of products. For a covered consumer, the choice set $\widetilde{\mathcal{W}}$ drops every wallet

Figure OE.2: Comparison of exact profits (which factor in price changes) and quasi-profits (which do not) in the baseline equilibrium for every possible subset of accepted cards.

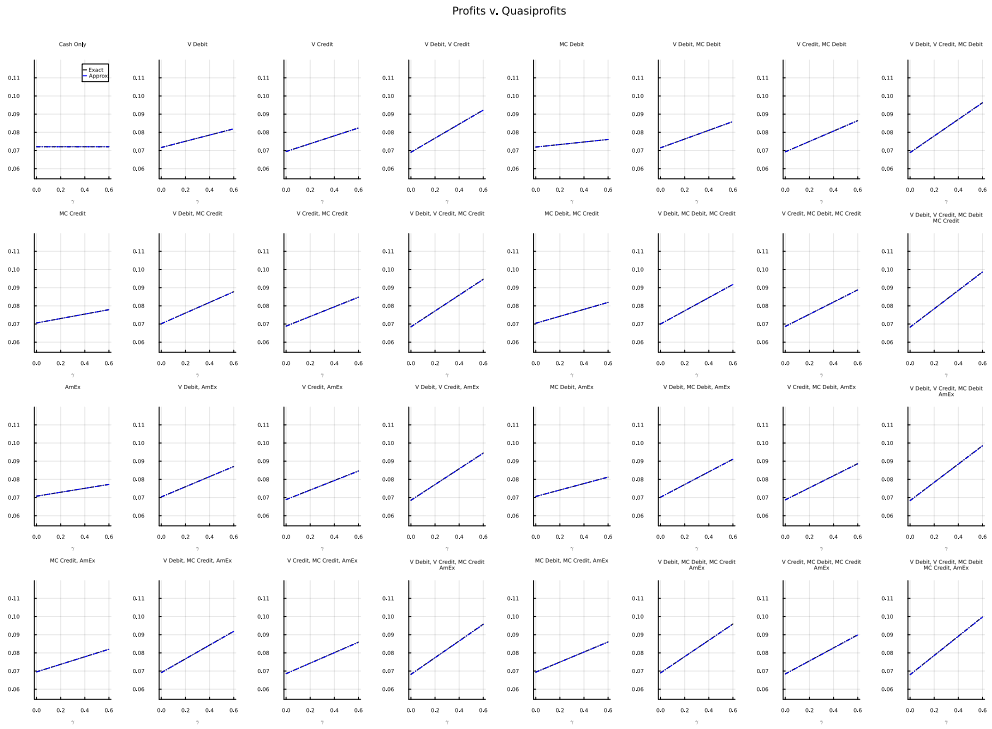
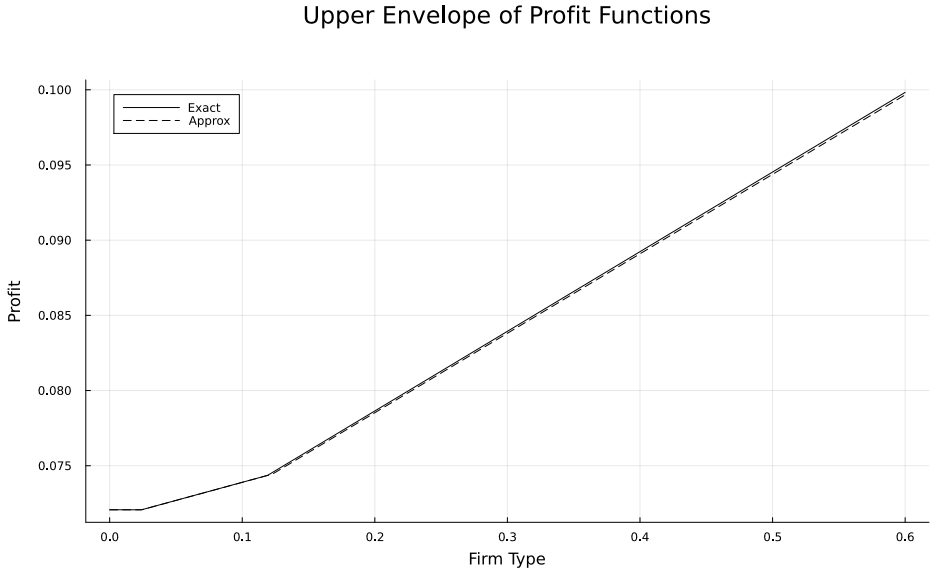


Figure OE.3: Comparison of the upper envelope of profits computed with the exact profit formula versus the quasi-profit approximation.



whose primary card is a credit card and whose secondary is cash, debit, or a credit card on the same network. The credit-credit complementarity rises from χ^{22} to $\widetilde{\chi}^{22}$. The

new value holds the share of consumers with a credit primary at its baseline level, at baseline prices. Both changes move consumer surplus in Equation 30 through the logit log-sum even if fees, rewards, and merchant acceptance were held fixed. They also move merchant and network profits, because consumers re-sort across wallets at those fixed prices. The restriction lowers surplus by removing wallets, and the higher complementarity raises it. To keep the dual routing results comparable with the other counterfactuals in the welfare tables, I subtract this mechanical component from consumer surplus, merchant profit, and network profit, so that each reported welfare change reflects only the equilibrium response.

Income-specific adjustment. Let u_i^w denote consumer i's utility from wallet w at baseline fees, rewards, merchant acceptance, and price index, and let $\tilde{u}_i^w$ denote the same utility with $\widetilde{\chi}^{22}$ in place of χ^{22}. For a consumer with reward sensitivity α_i, the mechanical change in consumption-equivalent welfare is

$$w_i^{\text{mech}} = \frac{1}{\alpha_i}\left[\log \sum_{w \in \mathcal{W}_i} \exp\left(\tilde{u}_i^w\right) - \log \sum_{w \in \mathcal{W}} \exp\left(u_i^w\right)\right], \tag{46}$$

where $\mathcal{W}_i = \widetilde{\mathcal{W}}$ for covered consumers and $\mathcal{W}_i = \mathcal{W}$ otherwise. Consumers re-choose wallets under the new choice set and preferences, but fees, rewards, merchant acceptance, and the price index stay at their baseline values.

The adjustment rises with income. In the baseline specification it averages 4.0 bps at low income, 8.7 bps at median income, and 13 bps at high income. High-income consumers hold more credit cards, so the restriction and the higher complementarity reach more of them.

Aggregate adjustment. The aggregate dollar gain scales the income-specific term (46) by income y and integrates against the baseline income distribution F, mirroring Equation 30:

$$W^{\text{mech}} = \int \mathbb{E}\left[w_i^{\text{mech}} \mid y\right] \cdot y \, dF(y). \tag{47}$$

Both integrals are computed by Monte Carlo over 500 joint draws of income, preference shocks, and coverage per bootstrap sample. The mechanical changes in merchant and network profits use the same fixed-price benchmark, with profits evaluated at the wallet choices implied by $\widetilde{\mathcal{W}}$ and $\widetilde{\chi}^{22}$. The welfare tables subtract the mechanical effects before reporting, so the \$9 billion consumer-surplus figure and the \$12 billion total in Section VI.D are net of this adjustment. The consumer-surplus component is roughly

$11 billion in the baseline specification.

OE.8 A Microfoundation for Segmentation Between Credit and Debit at the Point of Sale

Payment methods can be substitutes at adoption yet poor substitutes at the point of sale. A microfoundation building on Koulayev et al. (2016) and Huynh et al. (2022) separates usage from adoption to show that the two stages are independent. It also gives a natural origin for the complementarity parameters χ^{lm} in the main text. Carrying two different card types generates option value, while carrying two cards of the same type generates diminishing returns. Rewards shift consumers between debit and credit at adoption even when the two are segmented at usage.

OE.8.1 Utility at the Point of Sale

At the point of sale, the consumer picks one card from her wallet. Let $\mathcal{J} = \{0, 1, 2, \ldots, J\}$ denote the set of payment methods, where $j = 0$ is cash, and let W denote the cards in consumer i's wallet. Let $X_j \in \mathbb{R}^k$ be the characteristics of method j (e.g., whether j is a credit card), and f_j the reward for using j. For transaction t, the utility of method j is:

$$\begin{aligned} u_{ijt} &= \alpha f_j + \gamma_{it}' X_j + \epsilon_{ijt} \\ \gamma_{it} &\sim \mathcal{N}(\gamma_i, \Sigma) \\ \epsilon_{ijt} &\sim \text{T1EV} \end{aligned}$$

The random shocks $\gamma_{it} \in \mathbb{R}^k$ capture transaction-specific preferences over card types. For a given transaction, a consumer may strongly prefer credit over debit, or cards over cash. The mean $\gamma_i \in \mathbb{R}^k$ is consumer-specific, so some consumers prefer credit cards in general. The idiosyncratic shocks ϵ_{ijt} capture why different cards of the same type (e.g., different credit cards) vary in value across transactions. Because ϵ_{ijt} has full support, every card in a wallet is used with positive probability at merchants that accept it. A wallet therefore contains only cards the consumer uses, and a card held but never used, such as a debit card kept as a backup, lies outside it.

These assumptions yield the expected utility from wallet W_i:

$$V_i(W_i) = \int \log\left(\sum_{j \in W_i} \exp\left(\alpha f_j + \gamma_{it}' X_j\right) \right) dH(\gamma_{it})$$

where H captures the distribution of γ_{it}.

OE.8.2 Utility at Adoption

At adoption, consumers choose a wallet to maximize expected point-of-sale utility less adoption costs:

$$W_i^* = \underset{W \subseteq \mathcal{J}}{\operatorname{argmax}} \, V_i(W) - \sum_{j \in W} c' X_j + \phi a_i^W$$
$$a_i^W \sim \mathcal{N}(0, \nu^2)$$

where $c \in \mathbb{R}^k$ captures adoption costs by payment-method characteristics.

OE.8.3 Mapping to the Model in the Main Text

The microfounded model clarifies how segmentation at the point of sale differs from segmentation at adoption. It also clarifies how payment methods can complement or substitute for each other in a wallet.

Usage-stage vs. adoption-stage segmentation. The main text assumes consumers use credit and debit for distinct transaction types, yet those carrying two credit cards freely substitute between them. This is consistent with strong transaction-level preferences over credit versus debit but low heterogeneity in adoption costs across cards. Strong usage-stage preferences arise when Σ is large. A consumer wanting a credit feature for a given transaction then gets little utility from a debit card. This corresponds to certain transactions (e.g., large purchases) being better suited to credit than debit.

Strong adoption-stage substitution is compatible with $\nu^2 \to 0$. Large Σ does not induce segmentation at adoption because the consumer values the expected utility V_i, which integrates over the transaction-specific shocks γ_{it}. If adoption costs are similar across instruments, consumers remain sensitive to rewards in choosing what to adopt.

As an extreme example, suppose a consumer has 50 large-ticket and 50 small-ticket transactions, strongly preferring credit for the former and debit for the latter. At adoption, credit and debit offer similar expected utilities because each covers half of transactions. Her adoption choice is therefore sensitive to rewards even though her transaction-level preferences are sharply bifurcated.

Complements and substitutes at adoption. The microfounded model also explains why debit holders may want to adopt credit cards. At adoption, consumers know their mean preferences γ_i but have not yet drawn the transaction shocks γ_{it}. Those shocks are

realized only at the point of sale. A consumer with high Σ faces uncertainty over which card type she will prefer for each future transaction. Adopting both types lets her use credit when $\gamma_{it}' X_j$ favors credit and debit when it favors debit, raising V_i. This option value is positive even though the consumer knows her transaction-level preferences will be sharply bifurcated.

The model also captures incremental adoption costs. If all cards of a given type pay the same rewards f_j, then V_i is concave in the number of same-type cards, but costs are linear. This explains why consumers do not adopt every card on the market, captured in the main text by $\chi^{22} < 0$ for wallets with two credit cards from different networks.

A consumer who highly values credit cards may still want a credit card alongside a debit card to capture more transaction-specific shocks γ_{it}, which occurs when $\gamma_i' X_j$ is large for credit. The main text captures this through $\chi^{12} > 0$ and $\chi^{21} > 0$ for wallets that combine credit and debit.

OF Credit-Debit Segmentation

The baseline model assumes consumers do not substitute between credit and debit at the point of sale. Incorporating substitution would make the model more realistic in some dimensions, but it generates predictions about merchant acceptance behavior that are at odds with the empirical evidence. This Appendix presents the case for segmentation and two alternative specifications.

Section OF.1 weighs the direct evidence. Antitrust testimony and consumer surveys describe credit and debit as distinct products at the point of sale, while the Discover rewards experiment shows some substitution at the margin.

Section OF.2 generalizes the model to allow substitution and derives two equilibrium predictions. The first is that credit acceptance depends on credit-debit multi-homing rates. The second is that debit fee caps discipline credit fees. *Ohio v. AmEx* testimony contradicts the first, and the lack of an effect of the Durbin Amendment on credit interchange contradicts the second.

Section OF.3.1 estimates a specification that allows point-of-sale substitution and incremental debit sales relative to cash. This matches the consumer-side substitution evidence most closely at the cost of contradicting the merchant-side patterns from *Ohio v. AmEx* and Durbin. Section OF.3.2 estimates a specification that treats debit as generating no incremental sales relative to cash. This gives up some fidelity to the consumer-side substitution evidence but matches the merchant-side acceptance pattern in *Ohio v. AmEx*. It is also silent on Durbin pricing because debit fees are zero by construction. The welfare effect of repealing the Durbin Amendment flips sign across the specifications that can evaluate it. Total welfare effects are similar across the three counterfactuals that regulate credit card competition (the credit fee cap, the merger, and dual routing).

OF.1 Empirical Evidence on Credit-Debit Substitution at the Point of Sale

Antitrust testimony and consumer surveys describe credit and debit as distinct products on many transactions. But the Discover rewards experiment finds substitution between credit and debit in response to rewards at the point of sale.

Testimony and surveys consistent with segmentation. Antitrust testimony in *Ohio v. American Express* identifies the credit facility as the primary reason credit and debit are not close substitutes at the transaction level (Conrath 2014). Credit cards let consumers defer payment and carry balances. Debit payments are drawn immediately from a checking account. Large-ticket merchants rely on this distinction. Sears, Southwest Airlines, and Home Depot each testified that their customers expect or require access to a line

of credit. Hotels and car rental companies use the credit card as a security deposit. Hilton described debit at check-in as "atrocious" because holds can take six weeks to clear. Alaska Airlines, Crate & Barrel, and Best Buy called credit and debit "totally different products that cannot substitute for each other" and never considered debit-only acceptance.

Consumer-side evidence describes similar compartmentalization. AmEx's own analysis finds customers using debit for everyday purchases below a personal threshold of $20–$200, with Official Payments putting the switching point closer to $300. An internal AmEx note describes credit and debit as "not substitutes in the consumer's (or Durbin's) mind."

Credit and debit are not substitutes at the transaction level. That does not imply rewards cannot influence the decision to adopt credit or debit. Online Appendix OE.8 provides a microfoundation in which payment methods substitute at adoption but segment at usage.

Reward experiments consistent with some substitution. The Discover quarterly rewards program (Online Appendix OD.2) shifts grocery spending onto Discover from both cash and debit when Discover pays higher rewards, not from cash alone. Under the segmentation assumption, only the use of cash and other credit cards should decline. The fact that debit card volumes also decline suggests that credit and debit are at least partial substitutes for consumers.

Summarizing the evidence. The direct evidence does not cleanly resolve the question. Most antitrust testimony and survey responses describe segmentation, but the Discover experiment shows some limited substitution in routine grocery purchases. Below, I relax the no-substitution assumption and derive how it changes the model.

OF.2 Generalizing Credit-Debit Substitution

The alternative specifications below differ in how much consumers substitute between credit and debit at the point of sale. The model therefore treats segmentation as a continuous parameter. The parameter $\zeta \in [0, 1]$ governs how often a consumer holding both card types reaches for the secondary card when a merchant accepts only one. The parameter $\kappa_d \in [0, 1]$ governs the demand boost from debit relative to credit.

Generalized payment probabilities. When a consumer multi-homing across credit and debit visits a merchant that accepts only one, she redirects a fraction ζ of her intended

transactions to the accepted type. When only the primary card is accepted, the consumer uses it with probability $\pi + \zeta(1-\pi)$. The first term, π, comes from intended usage. The second term is a fraction ζ of what would have gone to the secondary type. Table OF.1 reports the general probabilities. Setting $\zeta = 0$ recovers Table OE.1.

Table OF.1: Consumer Payment Probabilities π^w_M (General)

Primary Card	**Secondary Card**	**Merchant Accepts**	π^w_{M,w_1}	π^w_{M,w_2}
Credit	Debit	Both Credit and Debit	π	$1-\pi$
Credit	Debit	Only Credit	$\pi+\zeta(1-\pi)$	0
Credit	Debit	Only Debit	0	$(1-\pi)+\zeta\pi$
Credit	Debit	Neither	0	0

Generalized payment surplus. When debit generates fewer incremental sales than credit, I parameterize each payment method with κ_j to weight its sales boost relative to credit cards. The baseline sets $\kappa_j = 1$ for all payment methods. With heterogeneous sales benefits $\kappa_j \leq 1$, payment surplus generalizes to

$$v^w_M = \sum_{j=1}^{J} \pi^w_{M,j}\kappa_j \tag{48}$$

where $\kappa_j \in [0,1]$ governs the demand boost from accepting card j.

Merchant problem with heterogeneous κ_j. Taking the generalized payment surplus v^w_M from Equation (48), the merchant's per-unit margin becomes

$$L^w_M(p) = \underbrace{\frac{1-\pi^w_{M,w_1}-\pi^w_{M,w_2}}{1+\gamma v^w_M}}_{\text{share on cash}} \times (p-1) + \sum_{j=1}^{2} \underbrace{\frac{\pi^w_{M,w_j}\left(1+\gamma\kappa_{w_j}\right)}{1+\gamma v^w_M}}_{\text{share on card } w_j} \times \left(p\left(1-\tau_{w_j}\right)-1\right) \tag{49}$$

Collecting terms yields

$$L^w_M(p) = p\left(1 - \frac{\tau^w_M + \gamma\tilde{\tau}^w_M}{1+\gamma v^w_M}\right) - 1 \tag{50}$$

where the wallet-average fees are $\tau^w_M = \sum_j \pi^w_{M,w_j}\tau_{w_j}$ and $\tilde{\tau}^w_M = \sum_j \pi^w_{M,w_j}\tau_{w_j}\kappa_{w_j}$. The κ-weighted fee $\tilde{\tau}^w_M$ equals τ^w_M in the baseline.

Profits become

$$\Pi(\gamma, p, M) = C \times \sum_{w \in \mathcal{W}} \mu^w (1 + \gamma v_M^w) p^{-\sigma} \times \left[p \left(1 - \frac{\tau_M^w + \gamma \tilde{\tau}_M^w}{1 + \gamma v_M^w} \right) - 1 \right] \tag{51}$$

and the optimal price is $p^* = \frac{\sigma}{\sigma - 1} \times \frac{1}{1 - \hat{\tau}}$, with effective fee $\hat{\tau} = \frac{\sum_w \mu^w (\tau_M^w + \gamma \tilde{\tau}_M^w)}{\sum_w \mu^w (1 + \gamma v_M^w)}$. Dollar volume on card j generalizes to

$$d_j = \sum_{w \in \mathcal{W}} \tilde{\mu}^w \times \int \frac{(1 + \gamma \kappa_j) \pi_{M^*(\gamma), j}^w}{1 + \gamma v_M^w} q^{w*}(\gamma) p^*(\gamma) \, \mathrm{d}G(\gamma) \tag{52}$$

where the numerator $(1 + \gamma \kappa_j)$ reflects the demand boost specific to card type j. In the baseline ($\kappa_j = 1$), the numerator reduces to $(1 + \gamma)$, matching the main-text expression.

The quasi-profit coefficients (Appendix B.2) generalize to

$$a_M = \sum_{w \in \mathcal{W}} \mu^w \tau_M^w, \qquad b_M = \frac{1}{\sigma} \sum_{w \in \mathcal{W}} \mu^w \left(v_M^w - \sigma \tilde{\tau}_M^w \right) \tag{53}$$

In the baseline, $\tilde{\tau}_M^w = \tau_M^w$, recovering the coefficients in Equation 12.

Two-card credit-debit acceptance threshold. With point-of-sale substitution, merchants' credit acceptance decisions depend on the gap between credit and debit fees and on credit-debit multi-homing rates. A two-card example shows this dependence. Let card 1 denote debit (fee τ_d, sales parameter $\kappa_d \leq 1$) and card 2 denote credit (fee τ_c, sales parameter $\kappa_c = 1$), following Online Appendix OE.2. Let $M \equiv (1 - \pi)\mu^{(1,2)} + \pi \mu^{(2,1)}$ denote the multi-homer mass. The N/D decomposition from Online Appendix OE.2 generalizes to

$$\begin{aligned} N &= \mu^{(2,0)} + (1 - \zeta) M \\ D &= \zeta M \end{aligned}$$

N equals new card transactions. It sums single-homers on credit and multi-homing spending that remains as cash under partial substitution. D captures actual diversion, which is multi-homer spending redirected from debit to credit. When $\zeta = 0$ (baseline), $D = 0$. When $\zeta = 1$, $D = M$, the same expression as for two credit cards (Online Appendix OE.2.1).

The $\Delta a / \Delta b$ formulas from (42)–(43) extend to this setting with one modification. Each diverted transaction was generating debit surplus $\kappa_d(1 - \sigma \tau_d)$ and now generates credit

surplus $(1-\sigma\tau_c)$, so the D component of Δb captures the net sales gain from switching:

$$\begin{aligned}\Delta a &= N\tau_c + D(\tau_c - \tau_d)\\ \Delta b &= \tfrac{1}{\sigma}\big[N(1-\sigma\tau_c) + D\big((1-\sigma\tau_c) - \kappa_d(1-\sigma\tau_d)\big)\big]\end{aligned} \tag{54}$$

The threshold follows immediately:

$$\underline{\gamma}_c = \frac{\sigma\big[N\tau_c + D\,(\tau_c - \tau_d)\big]}{N(1-\sigma\tau_c) + D\big[(1-\sigma\tau_c) - \kappa_d(1-\sigma\tau_d)\big]} \tag{55}$$

Setting $\zeta = 0$ gives $D = 0$, and the threshold reduces to $\sigma\tau_c/(1-\sigma\tau_c)$.

By inspection, the acceptance threshold now depends on the gap between credit and debit fees $\tau_c - \tau_d$ and the share of transactions that substitute between credit and debit (D). The threshold reduces to the standard credit card acceptance threshold from the model in the main text $(\sigma\tau_c/(1-\sigma\tau_c))$ under two situations:

- When $\zeta = 0$, $D = 0$, so both channels are off.
- When $\kappa_d = 0$ and $\tau_d = 0$, the sales channel is off ($\kappa_d = 0$). The fee channel becomes $D\tau_c$, so $(N + D)$ factors out of numerator and denominator.

When $\zeta > 0$ and $\kappa_d > 0$ (intermediate case), both channels are active and the threshold depends on multi-homing shares. Table OF.2 summarizes the three specifications.

Table OF.2: Credit-Debit Acceptance Threshold Across Specifications

Specification	**Assumption**	**Dep. on credit-debit multi-homing?**	**Location**
Segmented baseline	ζ=0, κ_d=1	No	Main text
Incremental debit sales	$\zeta \in (0,1)$, $\kappa_d \in (0,1)$	Yes	Section OF.3.1
Debit as cash	ζ=1, κ_d=0, τ_d=0	No	Section OF.3.2

Notes: "Dep. on credit-debit multi-homing" indicates whether the credit acceptance threshold depends on the rate of credit-debit multi-homing. When it does, credit acceptance is linked to debit pricing, a prediction the Durbin episode does not support (Section OF.3.1).

The generalized threshold yields two testable predictions for the case when there is substitution and debit cards generate incremental sales relative to cash.

Prediction 1: Credit acceptance should depend on credit-debit multi-homing. The threshold (55) contains $D = \zeta M$. When $\zeta > 0$, credit-debit multi-homing rates enter the credit acceptance threshold.

Testimony in *Ohio v. American Express* is hard to reconcile with this prediction. Expert witnesses testified that merchants discipline credit fees by threatening to divert transactions to rival credit cards, not to debit (Conrath 2014). Section OF.1 documents merchants treating credit and debit as distinct products.

Prediction 2: Debit fee caps should discipline credit fees. The $(\tau_c - \tau_d)$ term in the threshold implies equilibrium fee co-movement. When credit and debit are substitutes, a lower debit fee allows less aggressive credit pricing before acceptance breaks down.

The Durbin Amendment cut regulated debit interchange fees by roughly half, yet credit interchange fees did not respond (Figure 5). "Very little, if anything, happened with credit card prices after Durbin was implemented" (Katz, in Conrath (2014)). AmEx and Discover both told merchants that they do not price credit off debit, benchmarking instead against rival credit products. Alaska Airlines, IKEA, Best Buy, and Hilton all testified to seeing no decrease in credit pricing after Durbin. Section OF.3.1 quantifies the implied co-movement by estimating a specification with incremental debit sales and confirms the implied gap is large.

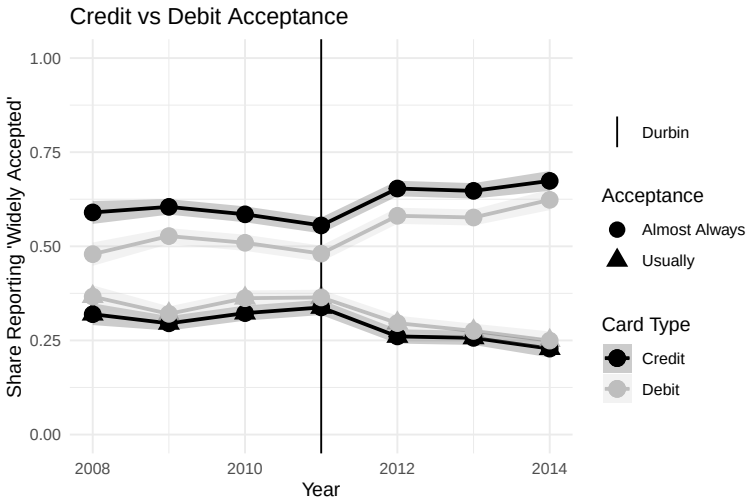
The acceptance threshold also predicts that if credit card merchant fees do not respond to the debit fee cap, credit card acceptance should decline. Survey data show acceptance ratings for both credit and debit did not decline through the Durbin period (Figure OF.1), so a decline in credit acceptance cannot rationalize networks holding credit fees fixed. Bundling cannot explain either pattern. The 2003 settlement had already ended bundling (Constantine 2012). AmEx, which has no bundling with debit, also faced no competitive pressure from cheaper debit despite about a fifth of AmEx consumers also using debit (Figure 6).

OF.3 Alternative Specifications

In the main text, I focus on the baseline model because it most accurately captures the effects of the Durbin Amendment. The goal of the model is to study how regulatory changes to interchange fees shape network competition, consumer rewards, and welfare. Every counterfactual in the paper revisits margins similar to Durbin's debit fee cap, so a credible model must reproduce Durbin's actual response. The two substitution predictions fail this test.

At the same time, the baseline model misses the substitution in response to rewards that the Discover experiment documents. Sections OF.3.1 and OF.3.2 thus estimate two alternatives that weigh the consumer-side substitution evidence and the merchant-side acceptance and pricing evidence differently. The credit-focused counterfactuals

Figure OF.1: Credit and Debit Card Acceptance over Time



Notes: Data from the Survey of Consumer Payment Choice (SCPC). The SCPC asks: "Please rate how likely each payment method is to be accepted for payment by stores, companies, online merchants, and other people or organizations," with separate responses for Credit card and Debit card. The figure plots the distribution of acceptance ratings for each card type over time.

(the credit fee cap, merger, and dual routing) deliver similar welfare across all three specifications.

OF.3.1 Estimating with Incremental Debit Sales

I estimate a specification that allows point-of-sale substitution between credit and debit and incremental debit sales relative to cash, with $\kappa_d = 0.5$ and $\zeta = 0.5$. This is the specification that matches the consumer-side substitution evidence from the Discover rewards shock most closely. Because debit still generates incremental sales, credit acceptance depends on the debit fee through the $(\tau_c - \tau_d)$ term in the threshold (Equation (55)).

Model Modification. Consumers holding both card types substitute between them at the point of sale half the time ($\zeta = 0.5$) rather than never (baseline) or always (debit as cash). Debit acceptance generates half the demand boost of credit ($\kappa_d = 0.5$ in Eq. 48) rather than the full boost ($\kappa_d = 1$) of the baseline or none ($\kappa_d = 0$) of debit as cash.

Two additional adjustments are required. First, I drop AmEx, leaving four products (Visa Debit, Visa Credit, MC Debit, MC Credit). With debit-credit substitution active, each network's debit and credit arms interact in the merchant acceptance decision. A merchant considering Visa Credit must account for diversion from Visa Debit holders who can now substitute across card types. This linkage worsens the non-differentiability problem discussed in Online Appendix OE.4 and is moderated by dropping AmEx.

Similarly, I do not evaluate the CBDC counterfactual as it increases the number of products.

Second, I add a fixed cost of card acceptance F to the merchant's acceptance problem. In the baseline, acceptance solves $\text{argmax}_M -a_M + b_M\gamma$ (Equation 12), which is linear in γ with no fixed cost. The fixed cost modifies this to $\text{argmax}_M -a_M - F\mathbf{1}[|M| > 0] + b_M\gamma$. A merchant that accepts any card pays F, which raises the threshold at which the marginal merchant begins accepting cards. The fixed cost is identified by requiring that the first merchant willing to add Visa Credit is indifferent between the bundle of both debit networks plus MC Credit and the empty bundle. Without the fixed cost parameter, merchants should accept MC Credit before Visa Credit because more consumers multi-home across Visa Credit and debit than across MC Credit and debit. Accepting Visa Credit therefore diverts more transactions from cheap debit to expensive credit, making it costlier at the margin. This acceptance ordering is counterfactual. The fixed cost eliminates it by making the extensive margin (accepting any card) dominate the ordering among credit networks.

Parameter Estimates. Table OF.3 reports estimated parameters under incremental debit sales. Because debit generates incremental sales and consumers substitute between credit and debit at the point of sale, cheap debit becomes a close alternative to expensive credit in the merchant's acceptance decision. The estimator must explain why merchants keep accepting expensive credit anyway. Merchant margins provide the resolution. Higher margins favor the incremental-sales channel over the fee channel, forcing down the CES elasticity to $\sigma = 4.98$ (Table OF.3) from the baseline 5.61 (Table 2). Network costs remain positive and plausible for all networks (30–60 bps).

OF.3.2 Debit as Cash

I estimate a specification that treats debit as generating no incremental sales relative to cash, with $(\zeta, \kappa_d, \tau_d) = (1, 0, 0)$. This admits full point-of-sale substitution between credit and debit. This specification shuts off the multi-homing channel behind Prediction 1. Credit acceptance then depends only on the credit fee and multi-homing across credit cards (Table OF.2). Because fees are measured relative to cash (Section IV.B.1), treating debit as cash raises the implied cost of cash to match debit, so $\tau_d = 0$ and targeted credit fees fall by the same amount. The specification is therefore silent on Durbin pricing because debit fees are zero by construction.

The $\kappa_d = 0$ assumption is itself an imperfect description of the data. Pre-Durbin Visa Debit merchant fees were roughly 160 bps (Figure 5), well above the cost of cash

Table OF.3: Estimated parameters: Incremental debit sales

Panel A: Consumer Preference Parameters

Parameter	Est	SE
Log Price Sensitivity ($\log \alpha_0$)	7.07	0.27
Card-Credit Complement (χ^{12})	5.05	0.45
Credit-Card Complement (χ^{21})	3.42	0.31
Credit-Credit Complement (χ^{22})	-3.71	0.55
Visa Debit Utility (Ξ)	-2.75	0.32
Visa Credit Utility (Ξ)	-6.80	0.39
MC Debit Utility (Ξ)	-2.88	0.35
MC Credit Utility (Ξ)	-7.04	0.44
Primary Weight (ω)	0.61	0.00
P(Use Primary) (π)	0.83	0.00

Panel B: Consumer Heterogeneity Parameters

Parameter	Est	SE
Card Volatility	0.95	0.27
Credit Volatility	2.35	0.67
Correlation of β	-0.84	0.03
Income Volatility (ν_y)	0.75	0.01
Income Elasticity (α_y)	0.20	0.06
Card Income Effect (β_y^C)	-1.01	0.25
Credit Income Effect (β_y^L)	-0.50	0.53
Card-Credit Income (χ_y^{12})	0.66	0.23
Credit-Card Income (χ_y^{21})	0.43	0.15
Credit-Credit Income (χ_y^{22})	-0.26	0.12

Panel C: Merchant Parameters

Parameter	Est	SE
Merchant CES	4.98	0.99
Average γ	0.29	0.06
S.D. of γ	0.13	0.03
Fixed Cost F (pp)	0.43	0.04

Panel D: Network Cost Parameters (bps)

Parameter	Est	SE
Cash	30	10
Visa Debit	46	9
MC Debit	60	4
Visa Credit	37	13
MC Credit	55	7

Notes: S.D. refers to the standard deviation, and R.C. refers to the random coefficients. The Ξ are the unobserved characteristics, and the χ^{lm} is the complementarity parameter. In Panel B, volatility parameters are the standard deviations of the random coefficients. Merchant types γ are distributed according to a Gamma distribution. This specification drops AmEx, leaving four products (Visa Debit, Visa Credit, MC Debit, MC Credit). Standard errors computed by bootstrap.

from Felt et al. (2023). Merchants accepted debit voluntarily at those fees, so revealed preference says debit must generate some incremental sales relative to cash. This is why the appendix imposes universal debit acceptance below. With $\kappa_d = 0$, merchants would not voluntarily accept debit at fees above cash costs, and the imposition is required to match observed acceptance rather than derived from primitives.

Parameter Estimates. Treating debit as cash lowers every credit card's net cost of acceptance because fees are measured relative to cash and cash's implied cost rises to equal debit's. Rationalizing observed acceptance at a lower net cost requires lower merchant margins, which the estimator delivers by raising the CES elasticity to $\sigma = 7.15$ from the baseline 5.61 (Table OF.4).

Table OF.4: Estimated parameters: Debit as cash

Panel A: Consumer Preference Parameters

Parameter	Est	SE
Log Price Sensitivity ($\log \alpha_0$)	6.88	0.26
Card-Credit Complement (χ^{12})	3.17	0.37
Credit-Card Complement (χ^{21})	1.43	0.19
Credit-Credit Complement (χ^{22})	-1.69	0.51
Visa Debit Utility (Ξ)	-0.80	0.26
Visa Credit Utility (Ξ)	-5.10	0.31
MC Debit Utility (Ξ)	-0.98	0.32
MC Credit Utility (Ξ)	-5.30	0.36
Amex Utility (Ξ)	-5.37	0.36
Primary Weight (ω)	0.62	0.01
P(Use Primary) (π)	0.83	0.00

Panel B: Consumer Heterogeneity Parameters

Parameter	Est	SE
Card Volatility	0.91	0.25
Credit Volatility	2.30	0.64
Correlation of β	-0.78	0.04
Income Volatility (ν_y)	0.75	0.01
Income Elasticity (α_y)	0.20	0.06
Card Income Effect (β_y^C)	0.03	0.06
Credit Income Effect (β_y^L)	-0.63	0.59
Card-Credit Income (χ_y^{12})	0.32	0.14
Credit-Card Income (χ_y^{21})	0.05	0.06
Credit-Credit Income (χ_y^{22})	0.11	0.04

Panel C: Merchant Parameters

Parameter	Est	SE
Merchant CES	7.15	1.53
Average γ	0.26	0.06
S.D. of γ	0.11	0.03

Panel D: Network Cost Parameters (bps)

Parameter	Est	SE
Cash	30	10
Visa Debit	38	10
MC Debit	54	5
Visa Credit	45	10
MC Credit	58	6
Amex	56	6

Notes: S.D. refers to the standard deviation, and R.C. refers to the random coefficients. The Ξ are the unobserved characteristics, and the χ^{lm} is the complementarity parameter. In Panel B, volatility parameters are the standard deviations of the random coefficients. Merchant types γ are distributed according to a Gamma distribution. Standard errors computed by bootstrap.

OF.3.3 Counterfactual Results Under Credit-Debit Substitution

Credit-focused counterfactuals. Welfare estimates are similar across the baseline and both alternatives for counterfactuals that primarily change competition between credit networks. The credit fee cap raises total welfare by \$23–28B and the merger raises total welfare by \$8–16B (Tables OF.6 and OF.8). Dual routing reduces credit merchant fees and rewards under all three specifications. Credit-debit substitution amplifies dual routing. Welfare gains rise to \$16B (SE \$3B) under incremental debit sales, versus \$12B at baseline. Point-of-sale substitution makes multi-homing more valuable and moves merchants toward accepting only the cheapest card.[28]

[28]Both figures are reported net of the mechanical adjustment (Online Appendix OE.7), so the comparison isolates the equilibrium response. The gap between \$16B and \$12B comes from the stronger fee-spillover channel under incremental debit sales.

Durbin Amendment: opposite predictions. Uncapping debit fees raises total welfare by $7B under the baseline but lowers it by $10B under incremental debit sales. The debit-as-cash specification cannot evaluate the Durbin counterfactual because debit fees are zero by construction.

The sign reversal follows directly from whether debit disciplines credit pricing. In the baseline, credit and debit are segmented at the point of sale, so uncapping debit fees raises debit rewards and attracts consumers to debit without affecting credit network pricing. Uncapping debit then raises debit rewards relative to credit rewards, thereby reducing credit card use and increasing welfare.

In the incremental-debit-sales specification, debit competes with credit at the point of sale, so regulated debit fees act as a competitive constraint on credit networks. Uncapping debit removes this constraint. Credit networks respond by raising both fees (by 33 bps) and rewards (by 32 bps), an escalation on both sides of the credit market. The fee escalation redistributes surplus toward credit networks and high-spending consumers at the expense of merchants and lower-income consumers who rely on debit. Total welfare also falls because more people use credit cards.

The Durbin episode is inconsistent with the predicted co-movement. Durbin halved regulated debit interchange, yet credit interchange did not respond (Figure 5), and networks, merchants, and expert witnesses all testified to no link between debit and credit pricing. This evidence directly contradicts the 33 bps credit fee response that the incremental-debit-sales model predicts. It is also the primary reason I focus on the baseline specification with segmentation.

The other counterfactuals do not depend on the substitution assumption because they primarily change credit network competition, so the fee spillover channel is less important. The substitution assumption affects how debit competes with credit, so it matters most for counterfactuals that change debit pricing.

Table OF.5: Counterfactual effects on prices and shares: Incremental debit sales

	Price Controls		Change Competition	
	Cap Fees	Uncap Debit	Monopoly	Dual Routing
Δ Prices (bps)				
Credit Fees	-105 (0)	34 (20)	33 (5)	-46 (5)
Credit Rewards	-116 (1)	32 (23)	-74 (20)	-66 (21)
Debit Fees	0.0 (0.0)	25 (0)	0.0 (0.0)	0.0 (0.0)
Debit Rewards	-0.6 (0.7)	24 (0)	-15 (8)	-0.1 (0.9)
Δ Shares of Total Spending (pp.)				
Cash	6 (2)	-1.8 (1.6)	22 (1)	2.1 (2.0)
Debit	16 (2)	2.5 (4.8)	-0.2 (2.0)	8 (1)
Credit	-22 (3)	-0.7 (3.9)	-22 (1)	-10 (3)
Δ Fees, Rewards ($Bn)				
Total Fees	-59 (2)	24 (12)	-34 (3)	-32 (3)
Total Rewards	-59 (1)	22 (12)	-55 (7)	-38 (6)

Notes: Bootstrap standard errors in parentheses. Counterfactual scenarios are defined in Table 4. This specification drops AmEx, leaving four products (Visa Debit, Visa Credit, MC Debit, MC Credit). Dollar values are computed by normalizing to $10 trillion of total consumer purchases (Nilson 2020).

Table OF.6: Counterfactual welfare effects: Incremental debit sales

	Price Controls		Change Competition	
	Cap Fees	Uncap Debit	Monopoly	Dual Routing
Δ Welfare ($Bn)				
Consumers	30 (4)	-11 (8)	-5.0 (12.2)	11 (5)
Merchants	0.1 (0.2)	-0.4 (1.2)	-4.0 (1.9)	-0.6 (0.9)
Networks	-1.4 (0.4)	1.4 (6.1)	24 (6)	6 (3)
Total	28 (5)	-10 (7)	15 (8)	16 (3)
Δ Consumer Surplus by Income (bps consumption)				
Low	49 (3)	-14 (10)	14 (7)	24 (2)
Median	39 (5)	-12 (10)	4.4 (10.8)	17 (4)
High	16 (5)	-10 (7)	-20 (15)	2.7 (7.9)

Notes: Bootstrap standard errors in parentheses. Counterfactual scenarios are defined in Table 5. This specification drops AmEx, leaving four products (Visa Debit, Visa Credit, MC Debit, MC Credit). Dollar values are computed by normalizing to $10 trillion of total consumer purchases (Nilson 2020).

Table OF.7: Counterfactual effects on prices and shares: Debit as cash

	Price Controls	Change Competition	
	Cap Fees	Monopoly	Dual Routing
Δ Prices (bps)			
Credit Fees	-105 (0)	27 (3)	-27 (3)
Credit Rewards	-110 (1)	-112 (41)	-33 (3)
Debit Fees	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)
Debit Rewards	0.9 (0.3)	-29 (8)	0.9 (0.3)
Δ Shares of Total Spending (pp.)			
Cash	9 (2)	29 (1)	1.3 (0.3)
Debit	11 (1)	-3.4 (1.9)	1.6 (0.5)
Credit	-20 (3)	-26 (2)	-3.0 (0.7)
Δ Fees, Rewards ($Bn)			
Total Fees	-56 (1)	-34 (3)	-16 (1)
Total Rewards	-56 (1)	-68 (10)	-17 (1)

Notes: Bootstrap standard errors in parentheses. Counterfactual scenarios are defined in Table 4. Dollar values are computed by normalizing to $10 trillion of total consumer purchases (Nilson 2020).

Table OF.8: Counterfactual welfare effects: Debit as cash

	Price Controls	Change Competition	
	Cap Fees	Monopoly	Dual Routing
Δ Welfare ($Bn)			
Consumers	25 (4)	-15 (12)	6 (1)
Merchants	0.1 (0.1)	-4.7 (1.9)	0.5 (0.2)
Networks	-2.1 (0.3)	28 (7)	2.0 (0.5)
Total	23 (4)	8 (7)	9 (1)
Δ Consumer Surplus by Income (bps consumption)			
Low	45 (2)	10 (6)	12 (1)
Median	34 (4)	-4.0 (9.4)	9 (1)
High	11 (4)	-33 (15)	2.1 (1.6)

Notes: Bootstrap standard errors in parentheses. Counterfactual scenarios are defined in Table 5. Uncap Debit and CBDC counterfactuals are omitted because these scenarios modify debit-specific regulation that interacts with the point-of-sale substitution assumption. Dollar values are computed by normalizing to $10 trillion of total consumer purchases (Nilson 2020).

OG Alternative Specifications and Additional Counterfactuals

Sections OG.1–OG.3 re-estimate under three alternative specifications with no merchant fee pass-through, with credit constraints, and with lower reward sensitivity. Online Appendix OF addresses credit-debit substitution. Section OG.4 compares the 120 bps cap to a tighter cost-of-cash cap and the constrained social optimum.

OG.1 No Merchant Fee Pass-Through

The main counterfactuals assume merchants pass merchant-fee changes into retail prices one-for-one. Without pass-through, fee savings accrue to merchants instead of consumers. Total welfare gains keep their sign under every policy. Small counterfactuals are nearly unchanged, while credit fee cap and monopoly gains shrink by a third or more. The credit fee cap's distributional story also reverses, with merchants gaining at consumers' expense.

Model modification. This specification modifies the merchant pricing equation (Eq. 9). Merchants set the standard CES markup $\hat{p} = \frac{\sigma}{\sigma-1}$ without the $\frac{1}{1-\hat{\tau}}$ pass-through term, so retail prices no longer respond to merchant fees. This applies symmetrically to fee increases and decreases. Under the credit fee cap, all merchant-fee savings accrue to merchants rather than passing to consumers through lower retail prices. The optimal acceptance decision is unchanged because first-order price changes have second-order profit effects. All other equations (consumer demand, merchant acceptance, network conduct) are unchanged.

Results. Estimated parameters change little from the baseline (Table OG.1), as expected since none of the merchant acceptance decisions depend on the pricing strategy. Counterfactuals with small fee and reward changes are robust. Uncapping debit raises total welfare by \$8B (versus \$7B at baseline), and dual routing raises \$8B (versus \$12B, both net of the mechanical adjustment described in Online Appendix OE.7).

Counterfactuals with large net fee changes are the exception. The welfare gain from the credit fee cap falls to \$17B from \$27B, and the monopoly gain falls to \$9B from \$16B. This gap reflects deadweight loss from under-consumption under zero pass-through. Under full pass-through, lower rewards reduce consumption while merchant price cuts stimulate it, so total consumption is roughly unchanged and deadweight loss is essentially flat. The welfare gain comes from the credit-aversion channel and redistribution. Under zero pass-through, merchant prices do not adjust, so the rewards-driven reduction in consumption from a fee cap or monopoly is not offset. Deadweight loss rises,

Table OG.1: Estimated parameters: No merchant fee pass-through

Panel A: Consumer Preference Parameters

Parameter	Est	SE
Log Price Sensitivity ($\log \alpha_0$)	6.76	0.26
Card-Credit Complement (χ^{12})	4.60	0.48
Credit-Card Complement (χ^{21})	3.93	0.42
Credit-Credit Complement (χ^{22})	-4.76	0.65
Visa Debit Utility (Ξ)	-3.96	0.47
Visa Credit Utility (Ξ)	-5.92	0.42
MC Debit Utility (Ξ)	-4.14	0.51
MC Credit Utility (Ξ)	-6.15	0.46
Amex Utility (Ξ)	-6.23	0.47
Primary Weight (ω)	0.62	0.01
P(Use Primary) (π)	0.83	0.00

Panel B: Consumer Heterogeneity Parameters

Parameter	Est	SE
Card Volatility	0.91	0.26
Credit Volatility	2.36	0.66
Correlation of β	-0.78	0.04
Income Volatility (ν_y)	0.75	0.01
Income Elasticity (α_y)	0.20	0.06
Card Income Effect (β_y^C)	-1.52	0.45
Credit Income Effect (β_y^L)	0.61	0.34
Card-Credit Income (χ_y^{12})	0.56	0.22
Credit-Card Income (χ_y^{21})	0.51	0.19
Credit-Credit Income (χ_y^{22})	-0.44	0.18

Panel C: Merchant Parameters

Parameter	Est	SE
Merchant CES	5.61	1.23
Average γ	0.26	0.06
S.D. of γ	0.11	0.03

Panel D: Network Cost Parameters (bps)

Parameter	Est	SE
Cash	30	10
Visa Debit	38	10
MC Debit	55	5
Visa Credit	39	11
MC Credit	52	7
Amex	51	6

Notes: S.D. refers to the standard deviation, and R.C. refers to the random coefficients. The Ξ are the unobserved characteristics, and the χ^{lm} is the complementarity parameter. In Panel B, volatility parameters are the standard deviations of the random coefficients. Merchant types γ are distributed according to a Gamma distribution. Standard errors computed by bootstrap.

and total welfare gains shrink.

The surplus distribution also shifts under the credit fee cap. Merchants retain the fee savings rather than passing them to consumers, so merchant surplus rises by \$49B while consumer surplus falls by \$31B (versus gains for both groups under full pass-through).

Table OG.2: Counterfactual effects on prices and shares: No merchant fee pass-through

	Price Controls		Change Competition	
	Cap Fees	Uncap Debit	Monopoly	Dual Routing
Δ Prices (bps)				
Credit Fees	-105 (0)	-3.7 (0.8)	39 (3)	-38 (3)
Credit Rewards	-110 (0)	-6 (1)	-82 (32)	-44 (4)
Debit Fees	0.0 (0.0)	25 (0)	0.0 (0.0)	0.0 (0.0)
Debit Rewards	1.5 (0.2)	25 (0)	-37 (8)	1.3 (0.3)
Δ Shares of Total Spending (pp.)				
Cash	7 (2)	-7 (1)	29 (1)	1.0 (0.3)
Debit	13 (2)	13 (3)	-7 (1)	3.3 (0.7)
Credit	-20 (3)	-6 (2)	-22 (1)	-4.3 (0.9)
Δ Fees, Rewards ($Bn)				
Total Fees	-59 (2)	4.0 (1.6)	-38 (3)	-22 (1)
Total Rewards	-57 (1)	0.1 (1.9)	-64 (9)	-24 (1)

Notes: Bootstrap standard errors in parentheses. Counterfactual scenarios are defined in Table 4. Dollar values are computed by normalizing to $10 trillion of total consumer purchases (Nilson 2020).

Table OG.3: Counterfactual welfare effects: No merchant fee pass-through

	Price Controls		Change Competition	
	Cap Fees	Uncap Debit	Monopoly	Dual Routing
Δ Welfare ($Bn)				
Consumers	-31 (2)	9 (0)	-49 (12)	-13 (2)
Merchants	49 (3)	-4.0 (1.3)	27 (5)	20 (1)
Networks	-1.5 (0.3)	2.9 (0.3)	31 (7)	1.6 (0.6)
Total	17 (5)	8 (1)	9 (8)	8 (2)
Δ Consumer Surplus by Income (bps consumption)				
Low	-10 (1)	11 (1)	-26 (6)	-4.2 (0.8)
Median	-22 (2)	10 (0)	-38 (10)	-10 (1)
High	-44 (3)	7 (0)	-67 (16)	-18 (2)

Notes: Bootstrap standard errors in parentheses. Counterfactual scenarios are defined in Table 5. Dollar values are computed by normalizing to $10 trillion of total consumer purchases (Nilson 2020). Totals may not sum due to independent rounding.

OG.2 Credit Constraints

The baseline model attributes low-income credit avoidance to preferences. Some of that gap may instead reflect access, since subprime consumers cannot obtain a credit card at all. Both specifications must match the same estimated Durbin Amendment effect, so reclassifying some credit avoidance from preference to access just reallocates reward sensitivity across consumers. The main counterfactual conclusions hold, with larger credit fee cap and monopoly welfare gains than at baseline ($32B versus $27B and $24B versus $16B).

Model modification. This specification modifies the consumer adoption stage. Before evaluating choice probabilities (Eq. 22), some consumers are blocked from holding credit cards. Constrained consumers cannot have a credit card as a primary or secondary card. All other equations are unchanged.

Credit access follows a logistic function of demeaned log income, $P(\text{access} \mid y) = \Lambda(\gamma_0 + \gamma_y \log \tilde{y})$. This function adds two parameters (γ_0, γ_y) estimated from DCPC credit score data and held fixed in the structural step. Table OG.4 reports the logistic regression. Combining these estimates with the structural income distribution ($\nu_y = 0.75$), the access probability is 79% at median income, 93% at the 90th percentile, and 52% at the 10th percentile. On an income-weighted basis, around 15% of consumers are credit-constrained.

Table OG.4: Logistic regression: Credit card access on income

	Credit Score Above 650
Demeaned Log Income	1.30***
	(0.07)
Intercept	1.33***
	(0.05)
Num.Obs.	2783
Log.Lik.	-1234.828

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Notes: Dependent variable is an indicator for credit score above 650. Income is log-transformed and demeaned. Standard errors in parentheses.

Results. Constraints now partly explain low-income consumers' credit avoidance, so the income gradient in credit preference weakens. The coefficient β_y^L falls from 0.62 to 0.14 (Table OG.5). The median consumer's credit aversion also falls. Indifference between Visa debit and credit requires 0.9% in rewards (SE 0.1%), versus 1.2% at baseline.

Table OG.5: Estimated parameters: Credit constraints

Panel A: Consumer Preference Parameters

Parameter	Est	SE
Log Price Sensitivity ($\log \alpha_0$)	6.77	0.26
Card-Credit Complement (χ^{12})	4.74	0.45
Credit-Card Complement (χ^{21})	4.00	0.37
Credit-Credit Complement (χ^{22})	-5.01	0.68
Visa Debit Utility (Ξ)	-4.17	0.46
Visa Credit Utility (Ξ)	-5.67	0.31
MC Debit Utility (Ξ)	-4.33	0.50
MC Credit Utility (Ξ)	-5.90	0.36
Amex Utility (Ξ)	-5.97	0.36
Primary Weight (ω)	0.62	0.01
P(Use Primary) (π)	0.83	0.00

Panel B: Consumer Heterogeneity Parameters

Parameter	Est	SE
Card Volatility	0.91	0.26
Credit Volatility	2.33	0.66
Correlation of β	-0.78	0.04
Income Volatility (ν_y)	0.75	0.01
Income Elasticity (α_y)	0.20	0.06
Card Income Effect (β_y^C)	-1.54	0.43
Credit Income Effect (β_y^L)	0.14	0.25
Card-Credit Income (χ_y^{12})	0.51	0.22
Credit-Card Income (χ_y^{21})	0.52	0.19
Credit-Credit Income (χ_y^{22})	-0.32	0.19
Constraint Intercept	1.33	0.09
Constraint Slope	1.30	0.12

Panel C: Merchant Parameters

Parameter	Est	SE
Merchant CES	5.61	1.16
Average γ	0.26	0.06
S.D. of γ	0.11	0.03

Panel D: Network Cost Parameters (bps)

Parameter	Est	SE
Cash	30	10
Visa Debit	38	10
MC Debit	55	5
Visa Credit	39	11
MC Credit	52	7
Amex	51	7

Notes: S.D. refers to the standard deviation, and R.C. refers to the random coefficients. The Ξ are the unobserved characteristics, and the χ^{lm} is the complementarity parameter. In Panel B, volatility parameters are the standard deviations of the random coefficients. Constraint intercept and slope are the logistic parameters γ_0 and γ_y governing credit card access probability. Merchant types γ are distributed according to a Gamma distribution. Standard errors computed by bootstrap.

Adding the access constraint raises credit fee cap welfare gains to \$32B (SE \$4B) from \$27B at baseline, and monopoly gains to \$24B from \$16B (Table OG.7). Constrained consumers respond less elastically to changes in credit rewards, so the moment-matching constraint forces unconstrained consumers to be more reward-sensitive than in the baseline. The credit fee cap then acts on fewer consumers but provokes a larger response from each. The same logic amplifies the monopoly counterfactual, since more reward-sensitive consumers face bigger distortions from the arms race over rewards, so eliminating competition delivers larger gains. Price and share responses stay close to baseline, because the cap forces similar fee cuts regardless of why consumers avoid credit (Table OG.6). Other counterfactuals are close to baseline.

Table OG.6: Counterfactual effects on prices and shares: Credit constraints

	Price Controls		Change Competition	
	Cap Fees	Uncap Debit	Monopoly	Dual Routing
Δ Prices (bps)				
Credit Fees	-105 (0)	-2.8 (0.6)	35 (3)	-36 (3)
Credit Rewards	-110 (1)	-6 (1)	-90 (31)	-41 (4)
Debit Fees	0.0 (0.0)	25 (0)	0.0 (0.0)	0.0 (0.0)
Debit Rewards	1.4 (0.3)	25 (0)	-33 (8)	1.1 (0.4)
Δ Shares of Total Spending (pp.)				
Cash	8 (2)	-7 (1)	30 (1)	0.8 (0.3)
Debit	12 (2)	13 (3)	-6 (1)	2.6 (0.7)
Credit	-20 (3)	-6 (1)	-24 (1)	-3.4 (0.9)
Δ Fees, Rewards ($Bn)				
Total Fees	-59 (3)	4.9 (1.4)	-41 (3)	-20 (1)
Total Rewards	-49 (2)	1.6 (1.3)	-56 (8)	-19 (1)

Notes: Bootstrap standard errors in parentheses. Counterfactual scenarios are defined in Table 4. Dollar values are computed by normalizing to $10 trillion of total consumer purchases (Nilson 2020).

Table OG.7: Counterfactual welfare effects: Credit constraints

	Price Controls		Change Competition	
	Cap Fees	Uncap Debit	Monopoly	Dual Routing
Δ Welfare ($Bn)				
Consumers	33 (4)	3.4 (1.8)	-0.5 (10.4)	10 (2)
Merchants	0.5 (0.2)	-0.7 (0.2)	-4.2 (1.9)	1.2 (0.3)
Networks	-1.8 (0.4)	3.0 (0.3)	29 (6)	1.7 (0.6)
Total	32 (4)	6 (2)	24 (6)	13 (1)
Δ Consumer Surplus by Income (bps consumption)				
Low	41 (4)	8 (2)	3.0 (10.1)	13 (1)
Median	35 (4)	4.9 (1.5)	0.8 (11.2)	10 (2)
High	20 (5)	2.7 (1.9)	-18 (14)	4.4 (2.2)

Notes: Bootstrap standard errors in parentheses. Counterfactual scenarios are defined in Table 5. Dollar values are computed by normalizing to $10 trillion of total consumer purchases (Nilson 2020).

OG.3 Lower Reward Sensitivity

The Durbin Amendment event-study coefficient identifies reward sensitivity in the estimation. If that coefficient overstates how aggressively consumers switch when rewards change, every counterfactual inherits the error. Halving the target moment leaves the credit fee cap welfare-improving but reverses the sign of the monopoly counterfactual. The fee cap's total welfare gain falls from \$27B to \$15B, and dual routing still raises welfare by \$8B. This specification is not the preferred one, since it also drives Visa Debit and Visa Credit marginal costs to implausibly negative values.

Model modification. No model equations change. Instead, the Durbin regression coefficient that the model targets is halved.

Results. Halving the target lowers estimated reward sensitivity from 6.75 to 5.92 and raises mean unobserved disutility to compensate (Table OG.8). The estimated network costs are less plausible. Visa Debit and Visa Credit both have negative marginal costs (-6 and -8 bps, respectively), well below the baseline estimates that match accounting data (Lowe 2005; Mukharlyamov and Sarin 2025; NACHA 2017; Visa 2020).

The monopoly counterfactual reverses sign, from $+$\$16B at baseline to $-$\$18B (SE \$13B) here (Table OG.10). At baseline, a monopolist raises welfare by eliminating the competitive rewards arms race. With less reward-responsive consumers, that arms race is smaller, so there is less distortion for the monopolist to correct. At the same time, less responsive consumers do not switch away from a merged network, leaving its market power unchecked. The net effect is a large welfare loss.

Fee cap gains are attenuated (\$15B versus \$27B) for the opposite reason. Less responsive consumers face less distortion from the current fee structure, so there is less to correct (Table OG.9). Uncapping debit fees raises welfare by \$3.7B (SE \$0.6B), versus \$7B at baseline, attenuated for the same reason. Dual routing still raises welfare by \$8B (SE \$1B), versus the \$12B baseline gain (both net of the mechanical adjustment), because it operates through merchant-side competition rather than consumer switching.

Table OG.8: Estimated parameters: Lower reward sensitivity

Panel A: Consumer Preference Parameters

Parameter	Est	SE
Log Price Sensitivity ($\log \alpha_0$)	5.92	0.20
Card-Credit Complement (χ^{12})	6.13	0.65
Credit-Card Complement (χ^{21})	5.06	0.55
Credit-Credit Complement (χ^{22})	-7.39	0.99
Visa Debit Utility (Ξ)	-5.39	0.66
Visa Credit Utility (Ξ)	-7.01	0.55
MC Debit Utility (Ξ)	-5.80	0.73
MC Credit Utility (Ξ)	-7.55	0.63
Amex Utility (Ξ)	-7.66	0.64
Primary Weight (ω)	0.61	0.00
P(Use Primary) (π)	0.83	0.00

Panel B: Consumer Heterogeneity Parameters

Parameter	Est	SE
Card Volatility	2.16	0.44
Credit Volatility	5.61	1.12
Correlation of β	-0.81	0.03
Income Volatility (ν_y)	0.75	0.01
Income Elasticity (α_y)	0.20	0.06
Card Income Effect (β_y^C)	-1.64	0.51
Credit Income Effect (β_y^L)	2.06	0.54
Card-Credit Income (χ_y^{12})	0.38	0.25
Credit-Card Income (χ_y^{21})	0.37	0.22
Credit-Credit Income (χ_y^{22})	-0.28	0.22

Panel C: Merchant Parameters

Parameter	Est	SE
Merchant CES	5.61	1.25
Average γ	0.28	0.07
S.D. of γ	0.12	0.04

Panel D: Network Cost Parameters (bps)

Parameter	Est	SE
Cash	30	10
Visa Debit	-6	16
MC Debit	33	8
Visa Credit	-8	18
MC Credit	24	11
Amex	24	10

Notes: S.D. refers to the standard deviation, and R.C. refers to the random coefficients. The Ξ are the unobserved characteristics, and the χ^{lm} is the complementarity parameter. In Panel B, volatility parameters are the standard deviations of the random coefficients. Merchant types γ are distributed according to a Gamma distribution. Standard errors computed by bootstrap.

Table OG.9: Counterfactual effects on prices and shares: Lower reward sensitivity

	Price Controls		Change Competition	
	Cap Fees	Uncap Debit	Monopoly	Dual Routing
Δ Prices (bps)				
Credit Fees	-105 (0)	-1.6 (0.3)	40 (4)	-44 (4)
Credit Rewards	-109 (1)	-4.1 (0.4)	-248 (58)	-55 (5)
Debit Fees	0.0 (0.0)	25 (0)	0.0 (0.0)	0.0 (0.0)
Debit Rewards	1.7 (0.3)	25 (0)	-73 (13)	2.4 (0.5)
Δ Shares of Total Spending (pp.)				
Cash	2.1 (0.7)	-3.1 (0.5)	29 (1)	-0.1 (0.2)
Debit	8 (1)	6 (1)	-5 (1)	1.7 (0.3)
Credit	-10 (2)	-2.6 (0.5)	-24 (1)	-1.5 (0.4)
Δ Fees, Rewards ($Bn)				
Total Fees	-52 (1)	7 (1)	-41 (3)	-21 (1)
Total Rewards	-52 (1)	4.7 (0.7)	-110 (15)	-25 (2)

Notes: Bootstrap standard errors in parentheses. Counterfactual scenarios are defined in Table 4. Dollar values are computed by normalizing to $10 trillion of total consumer purchases (Nilson 2020).

Table OG.10: Counterfactual welfare effects: Lower reward sensitivity

	Price Controls		Change Competition	
	Cap Fees	Uncap Debit	Monopoly	Dual Routing
Δ Welfare ($Bn)				
Consumers	16 (2)	1.1 (0.7)	-71 (21)	2.8 (1.4)
Merchants	0.0 (0.1)	-0.4 (0.1)	-12 (4)	0.5 (0.3)
Networks	-1.1 (0.3)	3.1 (0.2)	65 (11)	4.4 (0.8)
Total	15 (2)	3.7 (0.6)	-18 (13)	8 (1)
Δ Consumer Surplus by Income (bps consumption)				
Low	41 (2)	3.3 (1.0)	-12 (10)	15 (1)
Median	26 (2)	2.4 (0.7)	-47 (17)	7 (1)
High	1.6 (2.6)	-0.8 (0.8)	-107 (27)	-4.1 (2.0)

Notes: Bootstrap standard errors in parentheses. Counterfactual scenarios are defined in Table 5. Dollar values are computed by normalizing to $10 trillion of total consumer purchases (Nilson 2020). Totals may not sum due to independent rounding.

OG.4 Comparison to Other Credit Fee Caps and the Social Optimum

The main text caps credit card merchant fees at 120 bps. This section compares that cap to a tighter cap at the cost of cash and to the constrained social optimum.

The cost-of-cash cap sets fees at 30 bps, matching the Rochet-Tirole tourist test (Rochet and Tirole 2006) and the benchmark behind European interchange regulation (European Commission 2015). At this level, the cap also replicates perfect merchant surcharging (Zenger 2011). It delivers $29 billion in total welfare gains versus $27 billion under the 120 bps cap, roughly 7% more (Table OG.12). The extra gains come from deeper credit card reward cuts. The cost-of-cash cap also requires far greater out-of-sample extrapolation, eliminating roughly 87% of credit card merchant fees versus about half under the 120 bps cap.

The constrained social optimum provides an upper bound. The planner chooses merchant fees τ^l and consumer rewards f^l for each card type l to maximize total welfare subject to non-negative network profits. A break-even constraint is necessary because, under elastic labor supply, an unconstrained planner would subsidize merchants indefinitely to reduce the CES markup distortion. The planner's main lever is eliminating network markups on merchant fees. It also sets negative rewards, though less negative than under the tourist test. The planner jointly optimizes fees and rewards, whereas the tourist test leaves reward-setting to profit-maximizing networks (Table OG.11). Total welfare under the social optimum is $35B, versus $27B under the 120 bps cap (Table OG.12). The 120 bps cap captures roughly 77% of the planner's gains without directly regulating rewards, because the dominant distortion is over-adoption of credit cards rather than network market power.

OG.5 Central Bank Digital Currencies and Public Entry

Proposals for central bank digital currencies (CBDC) and faster payments (Shin 2021; Federal Reserve 2022; Berg et al. 2024) motivate the possibility that government entry could discipline network pricing. I simulate a public debit network with MC debit's demand and cost characteristics that sets merchant fees at cost and offers zero consumer rewards, earning zero profit. Because the entrant offers no consumer-side subsidies, its market share is small. Consumer welfare gains are roughly $3.7 billion and total welfare gains are roughly $1.6 billion, both smaller than repealing Durbin caps and smaller than the $12 billion total welfare gain under dual routing. These results depend on modeling the entrant as a debit product that does not substitute for credit at the point of sale. The segmentation assumption (Section IV.F) limits the competitive pressure a new payment method can exert on incumbent merchant fees. A public product that also displaced

Table OG.11: Effects of Fee Caps on Prices and Shares

	Cap Credit (120 bps)		Tourist Test		Ramsey Planner	
Δ Prices (bps)						
Credit Fees	-105	(0)	-195	(10)	-198	(16)
Credit Rewards	-110	(0)	-199	(9)	-164	(17)
Debit Fees	0.0	(0.0)	-42	(10)	-44	(11)
Debit Rewards	1.3	(0.2)	-38	(9)	-11	(16)
Δ Shares of Total Spending (pp.)						
Cash	6	(2)	35	(10)	18	(13)
Debit	13	(2)	-5	(6)	8	(9)
Credit	-19	(3)	-30	(4)	-26	(5)
Δ Fees, Rewards ($Bn)						
Total Fees	-58	(2)	-101	(8)	-102	(9)
Total Rewards	-57	(1)	-86	(4)	-75	(9)

Notes: Bootstrap standard errors in parentheses. Cap Credit caps credit card merchant fees at 120 bps. Tourist Test caps both credit and debit fees at the estimated cost of cash (30 bps). Ramsey Planner maximizes total welfare over merchant fees and consumer rewards, subject to equilibrium conditions and the network break-even constraint.

Table OG.12: Welfare Effects of Fee Caps

	Cap Credit (120 bps)		Tourist Test		Ramsey Planner	
Δ Welfare ($Bn)						
Consumers	28	(4)	38	(7)	53	(4)
Merchants	0.4	(0.2)	2.8	(1.6)	5.0	(1.7)
Networks	-1.4	(0.3)	-11	(2)	-24	(7)
Total	27	(4)	29	(8)	35	(5)
Δ Consumer Surplus by Income (bps consumption)						
Low	48	(3)	71	(6)	82	(6)
Median	37	(4)	55	(8)	67	(5)
High	15	(5)	13	(8)	35	(4)

Notes: Bootstrap standard errors in parentheses. Columns correspond to the same scenarios as Table OG.11. Low (high) income consumers have log income at -2 ($+2$) standard deviations relative to the median. Dollar values are computed by normalizing to $10 trillion of total consumer purchases (Nilson 2020).

credit could generate larger inroads, but is beyond the scope of most of the current proposals for public options. The estimated welfare gains do not include any fixed costs of setting up the public network. Directly regulating fees or mandating multi-homing is thus likely more effective than introducing a public option. The model omits two forces that push the entrant's equilibrium footprint in opposite directions. Consumer adoption frictions (Nocciola and Zamora-Pérez 2024) would shrink the entrant's footprint. Merchant acceptance cascades (Engert et al. 2024) could enlarge it. The model has no fixed costs of card acceptance, so it rules out cascades in which merchants drop incumbent

cards to save those costs as the entrant grows.

OH Price Coherence

This appendix explains why merchants almost never surcharge despite legal ability to do so, drawing on surcharging law, evidence on differential pricing, and a model of price coherence.

I extend the baseline model to allow merchants to set different prices for card and cash consumers. In this extension, I show that surcharges cannot steer consumers from card to cash. Card-preferring consumers will not switch to cash unless the surcharge exceeds the merchant fee. Because surcharges do not shift payment behavior, the envelope theorem makes the profit loss from uniform pricing second-order in fee dispersion. Returns to surcharging across card networks are even smaller, since fee differences across networks are an order of magnitude below the cash-card gap.

Cash discounts have been legal since 1981 yet remain rare, providing a revealed-preference bound. Menu costs suffice to deter surcharging even at the cash-card margin. Since fee gaps between cards are far smaller, those same menu costs exceed any incentive to price differently across networks.

OH.1 Legal Background

Cash discounts have long been legal in the U.S., but card surcharges became permitted only gradually.[29] The Cash Discount Act of 1981 guarantees merchants' right to offer cash discounts (Chakravorti and Shah 2001; Levitin 2005; Prager et al. 2009). The Durbin Amendment in 2010 granted merchants the right to offer debit discounts (Schuh et al. 2011; Briglevics and Shy 2014). A 2013 settlement between Visa, MC, and the DOJ removed the networks' rules against surcharging, allowing surcharging in 40 states (Blakeley and Fagan 2015).[30] As of 2023, only Massachusetts and Connecticut ban surcharging (CardX 2023), though disclosure rules in New York and Maine make it impractical.[31]

OH.2 Empirical Evidence

Surcharging is rare regardless of legality, which is consistent with menu costs rather than legal bans explaining price coherence. I restrict the sample to cash, check, debit, and credit transactions at retail merchants. In the full DCPC sample (all transaction

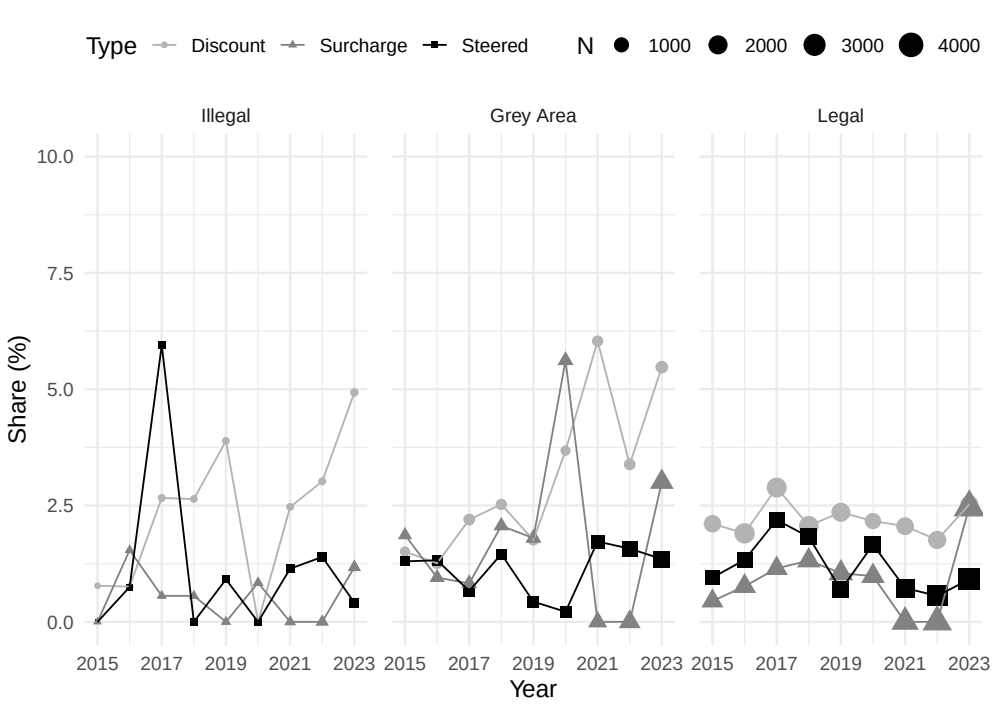
[29] Under full information, discounts and surcharges are the same. But if shrouded, cash discounts are giveaways while surcharges are add-on prices (Bourguignon et al. 2019).

[30] Visa allowed multi-state merchants to surcharge in states that permitted it (Visa 2013). AmEx and Discover relaxed their no-surcharge rules to match (Merchant 2016).

[31] In New York and Maine, retailers must disclose both the credit card price and cash price in dollar amounts. In New York, this rule ensures consumers "should not have to do math to figure out whether they are paying the surcharge." (Westchester 2019).

types, before this restriction), about 5% of transactions involve card surcharges or cash discounts, supporting the price coherence assumption.

I flag violations of price coherence using DCPC variables on discounts, surcharges, and payment steering. The figure below plots three time series. "Discount" is the share of cash/check transactions with a discount. "Surcharge" is the share of credit card transactions with a fee. "Steered" is the share of cash transactions by credit-preferring consumers who switched due to a discount, relative to credit transactions plus those same cash transactions. I group states by surcharging legality into "Legal" (never banned), "Illegal" (still banned as of 2020), and "Grey Area" (repealed bans during 2013–2020).



Rates are low across all groups, and legality does not explain the rarity. Cash discounts, always legal, are still rare. Surcharge rates do not vary with state legal status, ruling out legal bans as the main driver of price coherence. This pattern fits the view that menu costs deter differential pricing even at the cash-card margin, where fee gaps are largest.

OH.3 Private Incentives to Surcharge

OH.3.1 No Steering Between Cash and Card

I show merchants cannot steer consumers from card to cash in a natural extension of the baseline model that permits surcharging. The model assumes card convenience benefits are constant across purchases. A consumer who values cards at merchant type

γ gets the same proportional benefit regardless of the item, which rules out substituting between payment methods within a trip in response to payment-specific prices.

Consumers choose effective consumption $q(\omega)$ of each variety, a linear aggregate of card consumption $c(\omega)$ and cash consumption $a(\omega)$. Merchants charge card consumers a price $1+s(\omega)$ higher. Consumers solve

$$U = \max_{c,a} \left(\int_0^1 q(\omega)^{\frac{\sigma-1}{\sigma}} \, \mathrm{d}\omega \right)^{\frac{\sigma}{\sigma-1}} \tag{56}$$

$$\text{s.t. } q(\omega) = \left(1+\gamma(\omega) v^w_{M(\omega)}\right)^{\frac{1}{\sigma-1}} c(\omega) + a(\omega) \tag{57}$$

$$y \geq \int_0^1 \left(c(\omega)(1+s(\omega)) + a(\omega)\right) p(\omega) \, \mathrm{d}\omega \tag{58}$$

Linear aggregation makes card goods higher quality and perfect substitutes for cash goods. The baseline model corresponds to corner solutions where consumers use only their preferred payment type.

Lemma 1. *At a merchant of type γ that accepts cards, a card consumer will use cash only if $s > (1+\gamma)^{\frac{1}{\sigma-1}} - 1$*

Proof. The first-order conditions for card spending c and cash spending a yield

$$\frac{\partial \mathcal{L}}{\partial c} = I^{\frac{1}{\sigma-1}} \times q^{-\frac{1}{\sigma}} \times (1+\gamma)^{\frac{1}{\sigma-1}} - \lambda(1+s)p$$
$$\frac{\partial \mathcal{L}}{\partial a} = I^{\frac{1}{\sigma-1}} \times q^{-\frac{1}{\sigma}} - \lambda p$$

Both payment methods are used if $(1+\gamma)^{\frac{1}{\sigma-1}} = 1+s$. Since the aggregator is linear, consumers use cash exclusively if $s > (1+\gamma)^{\frac{1}{\sigma-1}} - 1$.

□

Theorem 2. *In a market with a monopoly credit card network that charges a merchant fee of τ, no merchant that accepts the credit card in the baseline model can steer consumers by setting $s = \tau$.*

Proof. The lowest type accepting credit cards satisfies $\gamma^* = \frac{\sigma\tau}{1-\sigma\tau}$. For general $\gamma > 0, \sigma > 1$, the inequality $(1+\gamma)^{\frac{1}{\sigma-1}} \geq 1 + \frac{\gamma}{\gamma+1}\frac{1}{\sigma-1}$ holds. By Lemma 1, the required surcharge to induce switching exceeds $s^* \geq \tau\frac{\sigma}{\sigma-1} > \tau$, so setting $s = \tau$ does not induce steering.

□

The analysis assumes consumers use only their primary card type. Credit users do not switch to debit, and vice versa. This is consistent with empirical evidence (Conrath 2014) and antitrust analysis (Jones 2001).

OH.3.2 Second-Order Losses from Uniform Pricing

Since surcharges do not change the payment method, uniform pricing generates only second-order losses by the envelope theorem. I quantify these with a second-order Taylor approximation.

Suppose merchants charge wallet-specific prices p^w (stacked into a vector). After normalization, total profits are proportional to

$$\begin{aligned}\widehat{\Pi} &\propto \sum_{w \in \mathcal{W}} \mu^w \pi^w \\ \pi^w &= \left(1 + \gamma v_M^w\right) \left(p^w\right)^{-\sigma} \left(p^w \left(1 - \tilde{\tau}^w\right) - 1\right)\end{aligned}$$

where $\tilde{\tau}^w \equiv \frac{(1+\gamma)\tau_M^w}{1+\gamma v_M^w}$ is the wallet-specific effective fee derived from the merchant problem (Section B.2). The notation distinguishes the wallet-specific effective fee from the raw average τ_M^w. Let p^* denote optimal payment-specific prices and $\hat{p}$ denote the optimal uniform price.

Theorem 3. *The percentage loss from uniform pricing is:*

$$\log \widehat{\Pi}\left(p^*\right) - \log \widehat{\Pi}\left(\hat{p}\right) = \sum_w \frac{\mu^w \left(1 + \gamma v_M^w\right)}{\sum_l \mu^l \left(1 + \gamma v_M^l\right)} \times \frac{\sigma\left(\sigma - 1\right)}{2} \left(\tilde{\tau}^w - \hat{\tilde{\tau}}\right)^2 + O\left(\tau^3\right)$$

Proof. The percentage loss is a weighted sum across wallets. By the envelope theorem, the first-order term vanishes. The second derivative $\frac{\partial^2 \log \pi^w}{\partial (\log p)^2}$, evaluated at the optimal price $p^{w*} = \frac{\sigma}{\sigma - 1}\left(1 - \tilde{\tau}^w\right)^{-1}$, equals $-\sigma\left(\sigma - 1\right)$. Since $\log p^{w*} - \log \hat{p} \approx \tilde{\tau}^w - \hat{\tilde{\tau}} + O(\tau^2)$, the second-order Taylor expansion yields the result.

□

High fees alone do not make uniform pricing costly. Fee *dispersion* among accepted payment methods does so. At the estimated σ =5.61, losses from uniform pricing are 13 bp of profit.

OH.3.3 Card-vs-Card Surcharging

Merchants also seek the right to surcharge cards differently, e.g., charge AmEx more than Visa (Conrath 2014). The results above bound the gains. In a type-symmetric equilibrium, fee dispersion across networks of the same type is near zero, so losses from uniform pricing are negligible.

The rarity of cash discounts sharpens this point. Cash discounts have been legal since 1981, yet merchants almost never offer them. The cash-card fee gap is roughly 2–3% (the full merchant discount fee, since cash carries no merchant fee). That merchants do not surcharge even at this margin fits the view that menu costs exceed the gains at a 2–3% fee gap. These costs include maintaining payment-specific prices, communicating them, and absorbing the resulting customer friction (Caddy et al. 2020).

Fee differences across card networks are an order of magnitude smaller. Even away from exact type-symmetry, AmEx-Visa fee gaps are tens of bp, well below the cash-card gap. Since merchants do not price differently at the larger margin, they will not do so at the smaller one.

OH.3.4 Limitations

The results above assume every card transaction generates incremental sales for the merchant. If some card categories do not boost sales, merchants would face stronger incentives to surcharge those categories. In the limit where no card transaction generates incremental sales, surcharging at the full merchant fee would be profitable, and declining the card entirely would yield equivalent profits.

OI Merchant Sorting

OI.1 Sorting Concern and Main Finding

Card fees may not redistribute across consumer types if consumers with different payment preferences shop at different merchants. Under perfect sorting, credit card users shop only at high-end merchants while cash/debit users shop at discount retailers, eliminating cross-consumer redistribution. This would undermine the redistributive channel central to the welfare analysis, since fee changes would affect only consumers who already use the relevant payment method.

I measure payment shares across hundreds of merchants using NielsenIQ Homescan and MRI-Simmons data. Some sorting exists, but no large merchant serves only one payment type. Even merchants at the 90th percentile of credit card use receive 15% of transactions from debit/cash.

I derive a sufficient statistic linking sorting patterns to redistribution magnitude. With no sorting (uniform payment shares across merchants), merchant fees redistribute across consumer types because all consumers face the same price increases regardless of payment choice. Empirical sorting reduces this baseline redistribution by only 4–9 pp., leaving 91–96% intact. This supports the main-text treatment of payment markets as integrated economies.

OI.2 Structure of Analysis

The analysis has three steps. First, I measure payment share distributions across stores in Homescan and MRI, computing both unweighted and revenue-weighted covariance matrices. Second, I derive a sufficient statistic linking sorting to redistribution magnitude, valid to first order under local fee changes. Third, I apply this statistic and show sorting attenuates baseline redistribution by at most 10%.

OI.3 Measuring Payment Shares

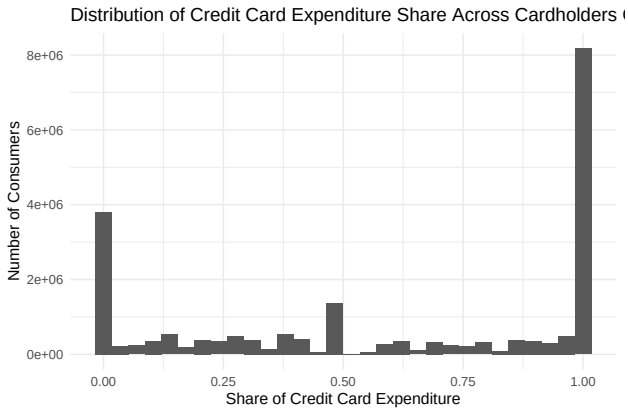
Homescan: Homescan provides transaction-level data with value-weighted shares of credit, debit, and cash spending across stores, but covers only grocery.

MRI: MRI-Simmons provides consumer-level data on payment choices and shopping across 214 large merchants in grocery, department stores, apparel, restaurants, electronics, and other retail sectors. These merchants cover a large share of U.S. consumer retail spending. The data include credit and debit spending amounts but not cash expenditures.

I classify each consumer by primary payment preference. A consumer is cash-preferring if they agree with "I prefer to pay cash for things I buy, whenever I can." Among non-cash consumers, I classify by whether they spend more on credit or debit cards. This classification captures real variation. Most credit-preferring consumers put over 80% of card spending on their preferred method (Figure OI.1).

To build payment shares at each merchant, I assume consumers use their preferred payment method at every store, equating a store's payment composition with the preference mix among its shoppers. This assumption fits the large national merchants in MRI, which accept all major payment methods. Consumers may vary methods across purchases (e.g., using credit for large transactions). Imputation assigns each consumer a single method, which has ambiguous effects on measured sorting. Within a store, it overstates sorting by sharpening merchant-level shares. Across diverse sectors, it can understate sorting by suppressing cross-sector variation in transaction-size composition. Homescan provides an empirical bound on this bias. It records actual payment choices (not imputed), and its covariance estimates are similar to MRI, suggesting imputation bias is small in practice.

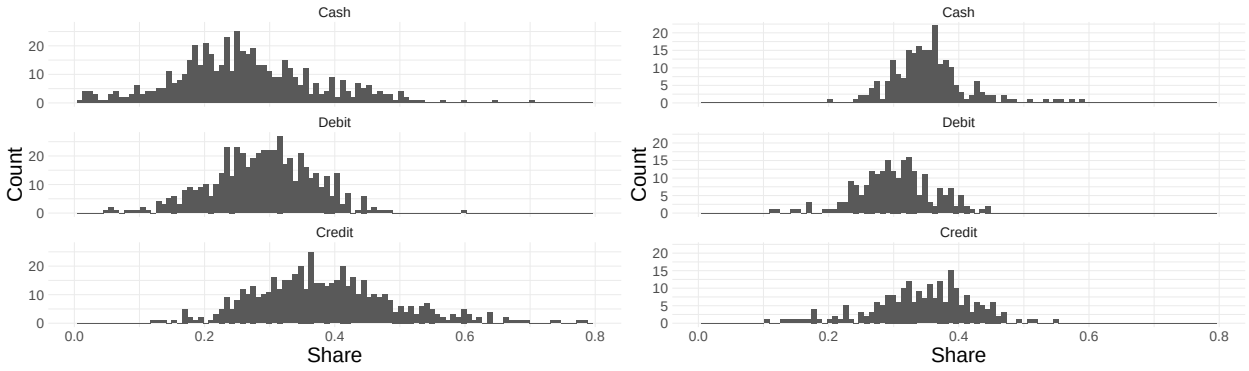
Figure OI.1: Distribution of Credit Card Expenditure Share Across Consumers with Cards



Summary of Results: Both datasets show wide dispersion in payment shares across stores, but no store has only one payment method (Figures OI.2a and OI.2b). In Homescan, credit sales average 40% of total sales but range from 10% to 80%.

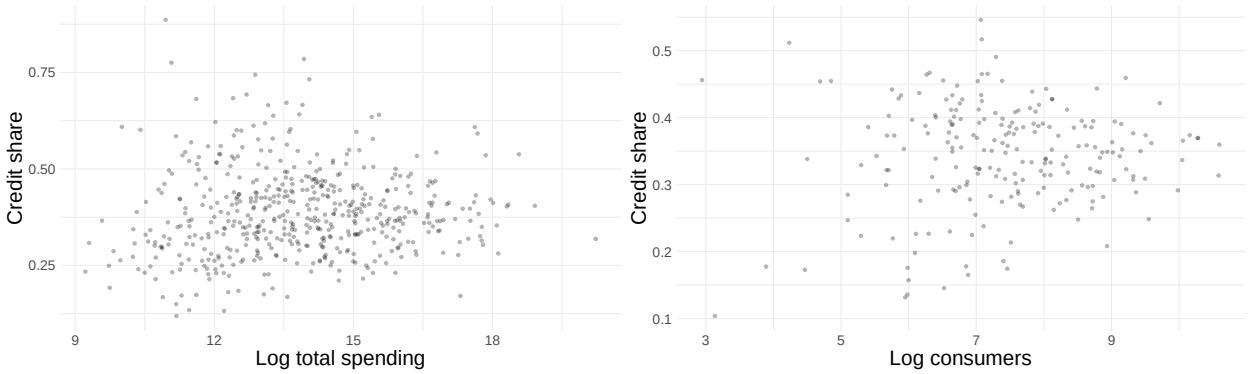
Larger stores have less dispersed payment mixes (Figures OI.3a and OI.3b). This firm size relationship matters because stores with the most sorting make up a small share of the economy. Since many consumers shop at the largest stores, substantial redistribution occurs across consumer types.

Figure OI.2: Share of Spending on Different Payment Methods Across Merchants



(a) Homescan **(b)** MRI

Figure OI.3: Credit card share and firm size



(a) Homescan **(b)** MRI

Table OI.1 shows weighted and unweighted covariances between payment shares (revenue weights in Homescan, customer weights in MRI). Cash-credit and credit-debit covariances are negative. The cash-debit covariance is slightly negative when unweighted but positive when revenue-weighted, reflecting that cash and debit users shop at more similar large stores than cash and credit users. Weighted variances are smaller than unweighted ones, consistent with larger stores having less dispersed payment mixes.

These negative covariances reduce redistribution from merchant fees, but the effect is small.

OI.4 Sufficient Statistics for Redistribution

I derive a sufficient statistic relating the revenue-weighted covariance matrix of payment shares to redistribution magnitude. The intuition is simple. Under uniform pricing, merchant fee increases hit all consumers at a given store regardless of payment method.

Table OI.1: Covariances

(a) Homescan - Unweighted

	Cash	Debit	Credit
Cash	0.0122	-0.0008	-0.0087
Debit		0.0062	-0.0031
Credit			0.0123

(b) Homescan - Weighted

	Cash	Debit	Credit
Cash	0.0056	0.0001	-0.0037
Debit		0.0045	-0.0020
Credit			0.0070

(c) MRI - Unweighted

	Cash	Debit	Credit
Cash	0.0033	-0.0003	-0.003
Debit		0.0034	-0.003
Credit			0.006

(d) MRI - Weighted

	Cash	Debit	Credit
Cash	0.0012	0.0001	-0.0013
Debit		0.0014	-0.0015
Credit			0.0028

Redistribution depends on how much different consumer types shop at the same stores. If credit and debit consumers visit the same merchants, credit fee increases burden both groups. The covariance between payment shares across merchants summarizes this overlap.

Suppose prices are log-linear in fees:

$$\log p_j = \log \overline{p} + \sum_k \mu_{jk} \tau_k$$

where $\mu_{jk} = \frac{q_{jk}}{\sum_l q_{jl}}$ is the share of spending on card k at merchant j, and τ_k is the merchant fee for card k (expressed as a decimal, e.g. $0.02 = 2\%$). This log-linear form approximates the main-text CES pricing formula. With elasticity σ and ad valorem merchant fees, the exact price is $p_j = \frac{\sigma}{\sigma-1}\frac{1}{1-\hat{\tau}_j}$ where $\hat{\tau}_j = \sum_k \mu_{jk}\tau_k$. This exact price yields the log-linear form $\log p_j \approx \log \overline{p} + \hat{\tau}_j$ for small fees.

Define $Q_j = \sum_l q_{jl}$ as total sales at merchant j. I measure welfare using compensating variation. For consumers spending on payment method l, the welfare effect of a marginal change in fee m is

$$\begin{aligned}\int_j q_{jl}\frac{\partial p_j}{\partial \tau_m} &= \int_j q_{jl}p_j\left(\mu_{jm} + \sum_k \frac{\partial \mu_{jk}}{\partial \tau_m}\tau_k\right) \\ &= \int_j p_j Q_j \mu_{jl}\mu_{jm} + \int_j p_j Q_j \mu_{jl} \times \left(\sum_k \frac{\partial \mu_{jk}}{\partial \tau_m}\tau_k\right) \\ &\propto \mathbb{E}_R\left[\mu_{jl}\mu_{jm}\right] + \mathbb{E}_R\left[\mu_{jl} \times \sum_k \frac{\partial \mu_{jk}}{\partial \tau_m}\tau_k\right]\end{aligned}$$

where $\mathbb{E}_R[\cdot]$ denotes the revenue-weighted expectation across merchants.

The welfare effect has two parts. The first is the revenue-weighted cross-moment $\mathbb{E}_R[\mu_{jl}\mu_{jm}]$ of spending shares on l and m. The second captures how payment shares respond to fees. The second term involves $\sum_k(\partial\mu_{jk}/\partial\tau_m)\tau_k$, which is $O(\tau)$ because share derivatives $\partial\mu_{jk}/\partial\tau_m$ are $O(1)$ while baseline fees τ_k are small (1–3 pp.). For a fee change $\Delta\tau_m$ that is itself $O(\tau)$, this term contributes $O(\tau^2)$, while the first term contributes $O(\tau)$. The second term is second-order for the fee changes relevant to policy analysis, so I focus on $\mathbb{E}_R\left[\mu_{jl}\mu_{jm}\right]$.

Normalize by the total spending of method-l users, which is $\int_j q_{jl}p_j = \int_j p_j Q_j \mu_{jl} \propto \mathbb{E}_R\left[\mu_{jl}\right]$. The proportionality constant (aggregate revenue $\int_j p_j Q_j$) cancels in the ratio defining w_{lm}. The complete welfare matrix is

$$\begin{aligned}w_{lm} &= \%\text{ welfare lost by } l \text{ from fee } m \\ &= \frac{\mathbb{E}_R\left[\mu_{jl}\mu_{jm}\right]}{\mathbb{E}_R\left[\mu_{jl}\right]} \\ &= \frac{\mathrm{Cov}_R\left(\mu_{jl},\mu_{jm}\right)}{\mathbb{E}_R\left[\mu_{jl}\right]} + \mathbb{E}_R\left[\mu_{jm}\right]\end{aligned}$$

Here w_{lm} is the compensating variation for consumers using payment method l from a 1 pp. increase in fees for method m, expressed as a % of baseline consumption.

The formula has a clear interpretation. If all stores have identical payment mixes (zero covariance), a debit consumer's burden from a 1 pp. credit fee increase equals the economy-wide credit share $\mathbb{E}_R[\mu_{jm}]$. Payment choice offers no shelter. With perfect segmentation, credit and debit consumers shop at disjoint stores ($\mu_{jm} \times \mu_{jl} = 0$ for all j), yielding $w_{lm} = 0$. Debit consumers bear no burden from credit fee increases. The revenue-weighted covariance $\mathrm{Cov}_R(\mu_{jl},\mu_{jm})$ measures how far merchants segment consumers. Negative covariances mean high-credit stores serve few debit consumers,

reducing redistribution.

OI.5 Implementing the Sufficient Statistic

Table OI.2 shows the % of welfare lost for consumers of the row payment method from a 1 pp. change in fees of the column payment. Credit card consumers are more exposed to credit card fees than the average credit share would imply, because stores where credit consumers shop have high credit transaction shares and hence prices more affected by credit fees. Both datasets show similar patterns.

The derivation calls for revenue-weighted covariances because the welfare integrand $\int_j q_{jl}\, \partial p_j / \partial \tau_m$ weights each store by consumer spending. Revenue-weighting gives large stores with many shoppers appropriate weight. Unweighted covariances treat all merchants equally, giving outsized influence to small stores with unusual payment mixes.

Sorting effects are small. Table OI.3 shows the ratio of welfare loss under actual sorting to the homogeneous-merchant baseline. Most ratios are close to 1. Diagonal cells (row l = column m) exceed 1, meaning sorting amplifies own-fee exposure. For example, the Credit/Credit cell in the MRI weighted panel is 1.023. Credit consumers face 2.3% more welfare loss from a 1 pp. credit fee increase than under homogeneous merchants, because sorting concentrates them at high-credit-share stores. Most off-diagonal cells fall below 1, meaning sorting attenuates cross-consumer redistribution. The Debit/Credit cell in the same panel is 0.986. Debit consumers face 1.4% less burden from a credit fee increase, because sorting places them at stores with lower credit shares. These signs match the negative cross-covariances in Table OI.1. With weighted covariances, sorting reduces redistribution from cash to credit users by only 4.1%, my preferred estimate given the theoretical case for revenue-weighting. With unweighted covariances, the reduction reaches 8.6%, an upper bound that overweights small merchants. Thus 91–96% of baseline redistribution remains intact. No large merchant serves only one payment type, so consumers cannot avoid card fee exposure through store choice. These calculations use the full MRI and Homescan samples, so standard errors are negligible given the large sample sizes.

OI.6 Implications for the Integrated Economy Assumption

The evidence validates the main text's "integrated" market assumption. Consumers of all types shop at overlapping merchants, so uniform pricing passes through the average cost of every accepted method. In a "segmented economy," credit consumers shop only at high-credit stores and cash consumers only at low-credit stores. Fee increases would then affect only credit users, eliminating redistribution. The data reject this scenario. No large merchant serves only one payment type.

Table OI.2: Percentage of welfare lost from fee increases

(a) Homescan

	Debit	Credit
Cash	0.320	0.365
Debit	0.334	0.375
Credit	0.315	0.399
Mean exp share	0.320	0.381

(b) MRI

	Debit	Credit
Cash	0.307	0.341
Debit	0.311	0.340
Credit	0.303	0.353
Mean exp share	0.307	0.345

Table OI.3: Ratio of welfare lost with actual sorting to homogeneous-merchant baseline. Rows indicate the consumer type bearing the welfare loss, and columns indicate the fee increased by 1 pp. Diagonal cells (Debit/Debit, Credit/Credit) measure own-type amplification from sorting. Off-diagonal cells measure cross-consumer redistribution attenuation. Cash has no interchange fee and therefore no diagonal entry.

(a) Homescan - Unweighted

	Debit	Credit
Cash	0.988	0.914
Debit	1.075	0.973
Credit	0.973	1.082

(b) Homescan - Weighted

	Debit	Credit
Cash	1.001	0.959
Debit	1.044	0.984
Credit	0.984	1.048

(c) MRI - Unweighted

	Debit	Credit
Cash	0.997	0.975
Debit	1.037	0.971
Credit	0.971	1.051

(d) MRI - Weighted

	Debit	Credit
Cash	1.001	0.989
Debit	1.015	0.986
Credit	0.986	1.023

Sorting reduces redistribution by only 4–9 pp., leaving 91–96% intact. This supports the counterfactual policy analysis. The model assumes price changes from altered fees affect all consumers at a given merchant, creating cross-consumer transfers. The 91–96% figure validates this assumption. Sorting does not meaningfully segment the market, so policy-induced fee changes generate the cross-consumer redistribution that the integrated economy framework predicts. Consumers cannot avoid card acceptance costs through store choice, making uniform pricing the empirically relevant regime for welfare analysis.

References

Adams, Robert, and Vitaly Bord. 2020. *The Effects of the COVID-19 Shutdown on the Consumer Credit Card Market: Revolvers versus Transactors.* FEDS Notes. Federal Reserve Board of Governors, October 21, 2020.

Berg, Tobias, Jan Keil, Felix Martini, and Manju Puri. 2024. "CBDCs, Payment Firms, and Geopolitics." *NBER Working Paper,* no. 32857 (July).

Berry, Steven, James Levinsohn, and Ariel Pakes. 2004. "Differentiated Products Demand Systems from a Combination of Micro and Macro Data: The New Car Market." *Journal of Political Economy* 112, no. 1 (February): 68–105.

Bilal, Adrien, and Hugo Lhuillier. 2025. "Outsourcing, Inequality and Aggregate Output." Pre-published, October. Working Paper. Accessed February 17, 2026.

Blakeley, Scott, and Ruth Fagan. 2015. "A History of Credit Card Transaction Costs and the Suppliers Newly Minted Right to Surcharge to Make Credit Cards a More Competitive Payment Channel." *The Credit and Financial Management Review* (December).

Boehm, Jennifer White. 2018. *Credit Cards US.* Mintel, July.

Bourguignon, Hélène, Renato Gomes, and Jean Tirole. 2019. "Shrouded Transaction Costs: Must-take Cards, Discounts and Surcharges." *International Journal of Industrial Organization* 63 (March): 99–144.

Briglevics, Tamás, and Oz Shy. 2014. "Why Don't Most Merchants Use Price Discounts to Steer Consumer Payment Choice?" *Review of Industrial Organization* 44, no. 4 (June): 367–392.

Caddy, James, Luc Delaney, and Chay Fisher. 2020. "Consumer Payment Behaviour in Australia: Evidence from the 2019 Consumer Payments Survey." *RBA DIscussion Paper* (June).

CardX. 2023. *State Laws on Surcharging,* January.

CFPB. 2021. *The Consumer Credit Card Market.* September.

Chakravorti, Sujit, and Alpa Shah. 2001. "A Study of the Interrelated Bilateral Transactions in Credit Card Networks." *Emerging Payments Occasional Paper Series* (July).

Chan, Iris, Sophia Chong, and Stephen Mitchell. 2012. "The Personal Credit Card Market in Australia: Pricing over the Past Decade." *RBA Bulletin* (March): 55–64.

Conrath, Craig W. 2014. *Plaintiff's Proposed Findings of Fact.* United States District Court Eastern District of New York, September.

Constantine, Lloyd. 2012. *Priceless: The Case That Brought Down the Visa/Mastercard Bank Cartel.* Skyhorse Publishing.

CU Today. 2016. "An Updated Look At Where Interchange Fits In CU Non-Interest Income." *CU Today* (September 1, 2016). Accessed September 30, 2024.

Ellickson, Paul B., Paul L.E. Grieco, and Oleksii Khvastunov. 2020. "Measuring Competition in Spatial Retail." *The RAND Journal of Economics* 51, no. 1 (March): 189–232. Accessed October 9, 2024.

Engert, Walter, Oleksandr Shcherbakov, and André Stenzel. 2024. *CBDC in the Market for Payments at the Point of Sale: Equilibrium Impact and Incumbent Responses.* Staff Working Paper 2024-52. Bank of Canada, December.

European Commission, DG Comp. 2015. *Survey on Merchants' Costs of Processing Cash and Card Payments: Final Results, March 2015.* LU: Publications Office, March.

Federal Reserve, Board. 2022. "Money and Payments: The U.S. Dollar in the Age of Digital Transformation." *Federal Reserve Discussion Paper* (January).

Felt, Marie-Hélène, Fumiko Hayashi, Joanna Stavins, and Angelika Welte. 2023. "Regressive Effects of Payment Card Pricing and Merchant Cost Pass-through in the United States and Canada." *Journal of Banking & Finance* 154 (September): 106968.

Huynh, Kim, Gradon Nicholls, and Oleksandr Shcherbakov. 2022. "Equilibrium in Two-Sided Markets for Payments: Consumer Awareness and the Welfare Cost of the Interchange Fee." *Bank of Canada Working Paper* (March).

International, Retail Banker. 2018. "Australia Brings New Law to Ban Unsolicited Credit Card Limit Increases." Retail Banker International, February 16, 2018. Accessed February 2, 2026.

Issa, Erin El. 2017. *Americans Favor Debit Over Credit for Their Go-To Card.* Nerdwallet, September.

Jones, Barbara. 2001. *U.S. v. VISA U.S.A., et Al.*, October.

Koulayev, Sergei, Marc Rysman, Scott Schuh, and Joanna Stavins. 2016. "Explaining Adoption and Use of Payment Instruments by US Consumers." *RAND Journal of Economics* 47 (2): 293–325.

Levitin, Adam J. 2005. "The Antitrust Super Bowl: America's Payment System, No-Surcharge Rules, and the Hidden Costs of Credit." *Berkeley Business Law Journal* 3, no. 1 (December): 265–336.

Lowe, Philip. 2005. "Payments System Reform: The Australian Experience." In *Payments System Research Conferences.* Santa Fe, New Mexico: Kansas City Federal Reserve, May.

Merchant, Samuel J. 2016. "Merchant Restraints: Credit-Card-Transaction Surcharging and Interchange-Fee Regulation in the Wake of Landmark Industry Changes." *OKLAHOMA LAW REVIEW* 68.

Mukharlyamov, Vladimir, and Natasha Sarin. 2025. "Price Regulation in Two-Sided Markets: Empirical Evidence from Debit Cards." *Journal of Financial Economics* 172:104094.

NACHA. 2017. *Understanding the Cost of Processing Card Payments.* Optimized Payments Consulting.

Nilson, Report. 2020. "U.S. Consumer Payment Systems." *Nilson Report* 1188 (December).

Nocciola, Luca, and Alejandro Zamora-Pérez. 2024. *Transactional Demand for Central Bank Digital Currency.* Working Paper Series 2926. European Central Bank, April.

Prager, Robin A, Mark D Manuszak, Elizabeth K Kiser, and Ron Borzekowski. 2009. "Interchange Fees and Payment Card Networks: Economics, Industry Developments, and Policy Issues." *Finance and Economics Discussion Series.*

Prelec, Drazen, and George Loewenstein. 1998. "The Red and the Black: Mental Accounting of Savings and Debt." *Marketing Science* 17, no. 1 (February): 4–28.

Rochet, Jean-Charles, and Jean Tirole. 2003. "Platform Competition in Two-Sided Markets." *Journal of the European Economic Association* 1, no. 4 (June): 990–1029.

———. 2006. "Two-Sided Markets: A Progress Report." *The RAND Journal of Economics* 37, no. 3 (September): 645–667.

Schuh, Scott, Oz Shy, Joanna Stavins, and Robert Triest. 2011. "An Economic Analysis of the 2010 Proposed Settlement between the Department of Justice and Credit Card Networks." *Public Policy Discussion Papers* (July).

Shin, Hyun Song. 2021. "CBDCs: An Opportunity for the Monetary System." *BIS Annual Economic Report* (June).

Sullivan, Michael. 2025. "Price Controls in a Multi-Sided Market." *Working Paper* (July 3, 2025).

Teh, Tat-How, Chunchun Liu, Julian Wright, and Junjie Zhou. 2023. "Multihoming and Oligopolistic Platform Competition." *American Economic Journal: Microeconomics* 15 (4): 68–113.

Visa. 2013. *Visa Surcharging FAQ.*

———. 2020. *Annual Report 2020,* September.

Westchester. 2019. *Credit Card Surcharges.* Westchester County Consumer Protection, May.

Weyl, E. Glen. 2010. "A Price Theory of Multi-Sided Platforms." *American Economic Review* 100, no. 4 (September): 1642–1672.

Zenger, Hans. 2011. "Perfect Surcharging and the Tourist Test Interchange Fee." *Journal of Banking & Finance* 35, no. 10 (October): 2544–2546.

Zinman, Jonathan. 2009. "Debit or Credit?" *Journal of Banking & Finance* 33, no. 2 (February): 358–366.