Regulating Competing Payment Networks

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Abstract

Payment networks fund consumer rewards through merchant fees. Because merchants rarely surcharge, consumers fail to internalize costs and overuse credit cards relative to the social optimum. I develop a quantitative model of platform competition to compare policy solutions. Capping merchant fees reduces rewards and credit card use, increasing total welfare by $27 billion. Because consumers are sensitive to rewards but merchants are insensitive to fees, network competition inflates rewards and exacerbates the costs of over-adoption. Dual-routing mandates that increase consumer multi-homing redirect competition from rewards toward merchant fees, increasing welfare. The direction of competition matters, not just its intensity.

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I Introduction

In the U.S., Visa and Mastercard (MC) process 80% of card transactions and earn profit margins above 60% (Visa 2020). At the same time, merchants pay around $120 billion in fees every year to accept cards (Nilson 2020c). These facts have motivated two decades of litigation and legislation built on a view that high merchant fees reflect weak competition. Key policy interventions include the Durbin Amendment's cap on debit interchange fees, the proposed Credit Card Competition Act (Andriotis 2022), and the Department of Justice (DOJ) monopolization lawsuit against Visa (Au-Yeung 2024).

I find that merchant fees are indeed too high, but weak competition is the wrong diagnosis. Networks set rewards for consumers and fees for merchants. The division of costs matters because merchants typically charge the same price for all payment methods, a phenomenon known as "price coherence" (Frankel 1998; Stavins 2018).[1] Under price coherence, card users capture rewards while the cost of higher merchant fees is spread across all consumers through higher retail prices. I estimate that consumers are ten times more sensitive to rewards than merchants are to fees. This incentivizes networks to charge high merchant fees to fund generous consumer rewards. High-merchant-fee credit cards thus proliferate because of, not in spite of, intense network competition.

Three forces explain why networks tax merchants to subsidize consumers. First, consumer payment choices respond strongly to subsidies. Networks charge interchange fees to merchants and channel the fees to card issuers, which incentivizes them to promote the networks' cards. A regulatory reduction in debit interchange fees — the Durbin Amendment — reduced debit card spending at regulated issuers by around 25% relative to exempt issuers. Second, card acceptance raises merchant sales. Event-study evidence shows that merchants on the margin gain 12% in sales when accepting credit. Third, while almost all merchants accept every network's cards, around 40% of consumers carry credit cards from only one network (i.e., they "single-home"). Together, these facts produce a partial "competitive bottleneck" (Armstrong 2006). Merchants risk losing substantial sales from single-homing consumers by dropping a network, so networks compete through rewards rather than fees.

Existing theory cannot resolve whether network competition raises or lowers fees and welfare. The U.S. market sits between two theoretical extremes. When all consumers single-home, each network is a monopoly gateway to its cardholders, so competition raises per-transaction merchant fees (Armstrong 2006; Edelman and Wright 2015). When consumers multi-home (i.e. carry cards from multiple networks), merchants can

[1] This occurs even though cash discounts and card surcharges are largely legal. I explore surcharging both theoretically and empirically in Online Appendix OH.

drop expensive networks without losing sales, so competition lowers fees (Anderson et al. 2018; Bakos and Halaburda 2020; Teh et al. 2023).

I thus build a structural model in which payment networks compete as two-sided platforms. A mix of single- and multi-homing consumers choose payment methods based on rewards, merchant acceptance, and exogenous non-price characteristics. Merchants choose which cards to accept and set retail prices to maximize profits net of merchant fees. Multiproduct networks maximize profits by setting fees and rewards, balancing merchant acceptance against consumer adoption.

I estimate consumer and merchant preferences by matching the reduced-form facts, moments from payment surveys, and aggregate market-level data. The estimated parameters match untargeted moments, including the acceptance response to American Express (AmEx) fee cuts, merchant profit margins, and network costs from accounting data. A 1-bp increase in Visa credit rewards raises Visa's consumer market share by 3.7%, while a 1-bp increase in Visa credit merchant fees reduces merchant acceptance by only 0.4%. Networks thus face strong incentives to raise merchant fees to fund rewards.

Credit card adoption is socially excessive because of price coherence. Because merchants do not surcharge, each consumer who adopts a credit card raises retail prices for all other consumers. Consumers individually face incentives to distort their payment choices to capture cross-subsidies, but collectively prefer lower credit card use. A revealed preference argument illustrates the inefficiency. Since credit cards pay rewards whereas cash and debit do not, the marginal user of credit cards must prefer the non-price characteristics of cash and debit. High rewards reduce consumers' aggregate non-price utility from payment choices, but the rewards themselves are merely transfers funded by higher retail prices.

The structural model measures the welfare loss from this coordination failure. I simulate a counterfactual in which credit card merchant fees are capped at 120 basis points (bp), roughly half their current level. Capping merchant fees cuts per-transaction revenue, so networks compete less aggressively for consumers through rewards. Networks cut rewards, and some consumers switch away from credit cards. By revealed preference, these marginal switchers prefer cash or debit absent rewards, so the total welfare gain is the eliminated cross-subsidy. This reduction in credit card use ultimately raises total welfare by $27 billion annually. The gains from capping merchant fees exceed the $12 billion consumer welfare gain from the CARD Act (Agarwal et al. 2015), suggesting that regulating networks is at least as important as regulating issuers.

The gains from credit fee caps are also progressive. Reduced merchant fees pass through to lower retail prices for all consumers, whereas the reduction in rewards falls mostly on high-income consumers who are more likely to use credit cards. Consumer surplus rises by 48 bp of consumption for low-income consumers, compared to only 15 bp for high-income consumers. There is no trade-off between equity and efficiency in regulating payment fees.

Two additional counterfactuals illustrate that the largest welfare losses in payment markets stem from the overuse of credit cards, not market power. First, repealing the Durbin Amendment's debit fee cap would raise total welfare by $7 billion per year. Under the usual market power story (Cuesta and Sepulveda 2021), removing the debit fee cap should reduce welfare. But higher debit merchant fees fund higher debit rewards, drawing consumers away from high-reward credit cards onto a lower-fee network. This shrinks the cross-subsidy and increases total welfare. This substitution effect matches prior work on the Durbin Amendment (Mukharlyamov and Sarin 2025) and illustrates that the current U.S. regime of capping debit but not credit fees is worse than laissez-faire.

Second, a merger to monopoly raises total welfare by $15 billion per year. Without competitive pressure to attract consumers, a monopoly network cuts rewards. Because consumers are highly sensitive to rewards, credit card use collapses. Per-transaction merchant fees rise, but credit card volume collapses, so the total merchant fee burden falls. Consumers lose $11 billion as network markups increase sharply, but the reduction in credit card use raises total welfare. While a merger is not a realistic policy proposal, the counterfactual shows how network competition inflates the total merchant fee burden by funding rewards. These predictions align with rising U.S. interchange fees despite increasing network competition (GAO 2009) and the global expansion of high-fee Buy Now, Pay Later products (Berg et al. 2025). The problem is not market power stifling output but rewards competition generating excessive credit card adoption.

In the absence of credit fee caps, policy can also redirect competition by increasing consumer multi-homing. Dual-routing requirements, such as those proposed in the Credit Card Competition Act, mandate that issuers put multiple networks on each card. Cardholders covered by such mandates multi-home by technological fiat, without having to sign up for a second card. I model these requirements as a change in preferences that generates a 20 percentage point increase in the share of multi-homing consumers. When consumers multi-home, merchants can decline expensive networks without losing sales, shifting competition toward merchant fees rather than consumer rewards. Networks respond by cutting credit card fees by 13 bp and rewards by 15 bp. Total welfare rises. These routing requirements are effective even when the secondary network is a large player. Increasing multi-homing is also much more effective than introducing a public option, such as a Central Bank Digital Currency (CBDC), that competes as a debit card (Berg et al. 2024). High rates of consumer multi-homing, not low market shares, force networks to compete for merchants rather than consumers.

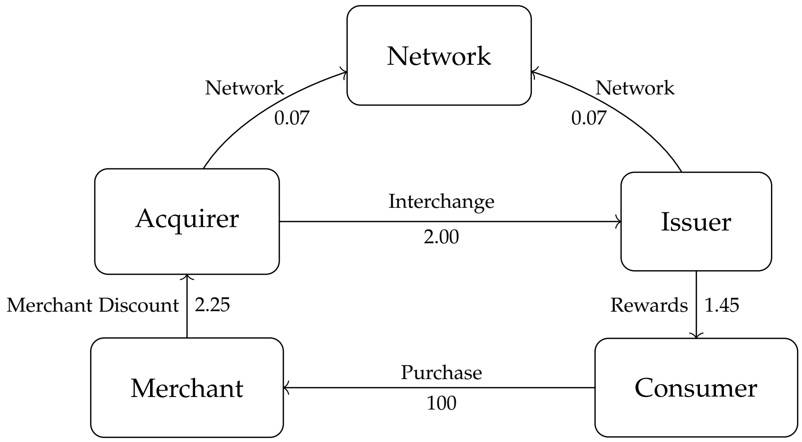
Related Literature The closest empirical work is Huynh et al. (2022), which estimates a structural two-sided model of consumer and merchant card adoption. I build on their work by modeling merchant and network competition. Merchant competition explains how credit card rewards inflate retail prices and redistribute consumption. Network competition endogenizes merchant fees and consumer rewards, enabling me to assess how price controls and competition affect total welfare.

The effects of network competition on fees and welfare are quantitative questions, but common modeling assumptions predetermine the answer. Homogeneous merchants guarantee that competition reduces fees (Guthrie and Wright 2007). Omitting merchant competition understates merchants' incentives to accept cards (Rochet and Tirole 2002; Wright 2012; Li et al. 2020) and misses how fees pass through to retail prices. My model relaxes both assumptions and lets the data determine whether competition raises or lowers fees and welfare.

My paper contributes to the empirical IO literature on two-sided markets (Rysman 2004; Lee 2013; Song 2021). My results on dual routing support the finding in Rosaia (2025) that consumer multi-homing intensifies platform competition. My paper also contributes to the literature on how platforms shape off-platform outcomes (Bergemann et al. 2025; Chen 2024; Bursztyn et al. 2025). Under price coherence, merchant fees strongly influence retail prices, explaining the welfare gains from credit fee caps. Sullivan (2025) finds that commission caps reduce welfare in food delivery, where price coherence is absent.

My paper also relates to a literature on price regulation in credit card markets. Whereas Nelson (2025) and Cuesta and Sepulveda (2021) show how interest rate caps increase welfare by expanding quantities, my paper shows that credit card merchant fee caps can increase welfare by reducing the use of credit cards. Knittel and Stango (2003) document that non-binding state interest rate caps served as focal points for tacit coordination in credit card markets during the 1980s. The credit fee caps I study are binding constraints that push fees below their competitive levels, so they function as direct price regulation rather than as coordination devices.

Figure 1: Payment flows in a payment network.



Notes: Representative credit card fees in 2019. The merchant discount fee comes from Nilson (2020b). The average network fee comes from example rate sheets from acquirers and from dividing the non-foreign exchange fees from Visa's 10k by the total payment volumes (Visa 2020; Helcim 2021). I split the network fees evenly between the two sides as in (Federal Reserve 2010). The interchange is derived from Visa's interchange schedule as the average of the rates for Visa Signature and Visa Infinite cards at a large retailer (Visa 2019). The rewards are from large banks' annual reports in 2019.

II Institutional Details and Data

Networks charge merchants fees and pay the revenue to issuers, who return most of it to consumers as rewards. The first subsection traces this fee flow, showing how merchant fees and rewards are linked. The second subsection describes the data sources used to identify how sensitive consumers and merchants are to rewards and fees.

II.A Network Pricing: Merchant Fees and Consumer Rewards

Payment networks are two-sided platforms that simultaneously set prices for merchants and consumers. While AmEx sets merchant fees and consumer rewards directly, "open-loop" networks like Visa and MC do so indirectly, through the *interchange fee* and *network fee*.

Visa and MC connect four parties: merchants, acquirers (merchants' banks), issuers (consumers' banks), and consumers (Benson et al. 2017). Figure 1 shows the payment flows with representative prices. When a consumer uses her credit card to buy \$100 of products at a large retailer, the merchant pays a \$2.25 merchant discount fee to her acquiring bank to process the transaction. The acquirer can be a bank like Wells Fargo or a fintech firm like Square. Of the merchant discount, around \$2 goes to the issuing bank (e.g., Chase) as interchange. The issuer and the acquirer collectively pay around \$0.14 in network fees to Visa. Financial reports show that cardholder rewards average around \$1.45 per \$100 of transaction value. [2]

[2]These figures are similar to the regulatory numbers reported in Drechsler et al. (2025), which finds that

Regulatory shocks confirm that interchange strongly affects merchant fees and rewards, but not borrowing costs. When the E.U. and Australia reduced interchange by regulation, merchant fees declined roughly one-for-one (Gans 2007; Valverde et al. 2016; European Commission 2020). Appendix Figure OB.1 shows that after Australia capped credit card interchange, rewards fell and consumer annual fees on rewards cards rose, while annual fees on non-reward cards and interest rates were unchanged. Interchange has little effect on interest rates because balance-carriers pay 70% of interest but generate only 10% of purchase volume (Adams et al. 2022).

II.B Data

I combine five data sources to measure consumer reward sensitivity, how card acceptance affects sales, and multi-homing rates. Appendix A provides data construction details.

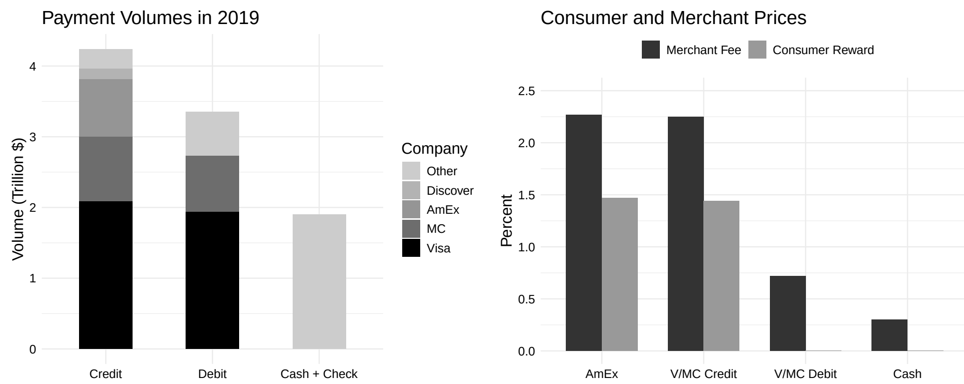
Aggregate Prices and Shares (2019): I use the Nilson Report's aggregate payment volumes and merchant fees in 2019. I collect average rewards data from the annual reports of the 6 largest banks, whose cards cover 80% of credit card purchase volumes. These data pin down baseline market shares and fee levels in the model. Figure 2 shows payment volumes, merchant fees, and rewards. Visa, MC, and AmEx process 90% of all card payments. All three major credit card networks charge merchant fees of around 2.25%, whereas debit networks charge around 0.7% due to the Durbin Amendment. Credit cards pay rewards around 1.4%, whereas aggregate debit rewards are effectively zero.

Issuer Payment Volumes (2007–2014). I construct an annual panel of 39 issuers from the Nilson Report covering 2007–2014 to study how the Durbin Amendment affected payment volumes. The issuers include both banks and large credit unions. I merge this data with NCUA call reports for credit unions and Y-9C reports for bank holding companies to get issuer-level financial data.

Homescan (2013–2023). The NielsenIQ Homescan panel tracks the payment decisions of around $100,000$ households at large consumer packaged goods stores from 2013–2023. I use this panel to measure how consumers split spending across the cards in their wallets and how card acceptance affects sales. Appendix Table OA.1 reports summary statistics. Appendix Table OA.2 compares Homescan payment shares to aggregate shares. The Homescan sample is broadly representative except for AmEx, which is underrepresented at 4% versus 10% aggregate share. This reflects Homescan's exclusion of sectors like travel where AmEx dominates. For this reason, AmEx-specific calibration moments (merchant fees, rewards) are sourced externally rather than from Homescan.

banks' interchange income averages 1.82% of purchase volume while rewards costs average 1.57%.

Figure 2: Aggregate payment volumes, merchant fees, and rewards in 2019



Notes: The left chart shows payment volumes measured in trillions from Nilson (2020c, 2020d). Visa and MC operate credit and debit card networks, whereas AmEx primarily offers credit and charge cards. Discover is much smaller than the other three networks. The right chart shows merchant fees from Nilson (2020b) and rewards from banks' annual financial reports. Aggregate debit rewards fell to effectively zero after the Durbin Amendment, though some small, exempt issuers continued to offer them (Hayashi 2012). The cost of cash is from Felt et al. (2023).

Consumer Payment Surveys. I combine the 2017–2019 waves of the Atlanta Federal Reserve's Diary of Consumer Payment Choice (DCPC) and its companion Survey (SCPC) to build a transaction-level dataset over three-day windows (Greene and Stavins 2021). The rich demographic detail in these surveys identifies income gradients in payment preferences. The diary and survey share a common panel of respondents. Whereas Homescan oversamples large retailers, the DCPC captures transactions at small stores, allowing me to better estimate overall card acceptance rates. Table 1 shows summary statistics on consumers' payment preferences. Cards are accepted for around 95% of transactions.[3] Debit cards are the most popular payment method. Credit card users have higher incomes than cash or debit card users, and around one-quarter of transactions are online. I also conduct a second-choice survey in 2024 to estimate substitution patterns across payment methods (Berry et al. 2004).

III Reduced-Form Facts

Three reduced-form facts characterize the two-sided structure of the payment market. Issuers' incentives drive consumer payment choices; card acceptance increases merchant sales; and a mix of single- and multi-homing consumers limits merchants' ability to steer between networks. These facts point toward a partial competitive bottleneck, but the degree of consumer multi-homing leaves the net effect of competition on fees and

[3]Online Appendix Table OC.3 shows that diary-based acceptance rates closely match those from Yelp business listings.

Table 1: Summary statistics by consumer type in the Diary of Consumer Payment Choice (DCPC)

	Cash	Debit	Credit
Share	0.20	0.43	0.36
Uses credit card	0.70	0.79	1.00
Uses rewards credit card	0.47	0.53	0.90
Uses debit card	0.73	1.00	0.82
Owns bank account	0.86	1.00	0.99
Credit utilization	0.18	0.27	0.06
Household income (000's)	68.29	81.39	116.23
Card acceptance	0.93	0.96	0.96
Credit score above 650	0.65	0.70	0.96
Online transaction	0.19	0.27	0.28
N	1552	3265	2824

Notes: Consumers are split into three groups by preferred non-bill payment instrument. Share reports the fraction of the sample in each column. Card acceptance is the expenditure share at merchants that accept cards. All other variables report consumer-level averages. Online transaction reports the share of transactions done online.

welfare an empirical question.

III.A Issuer Incentives Drive Consumer Payment Choices

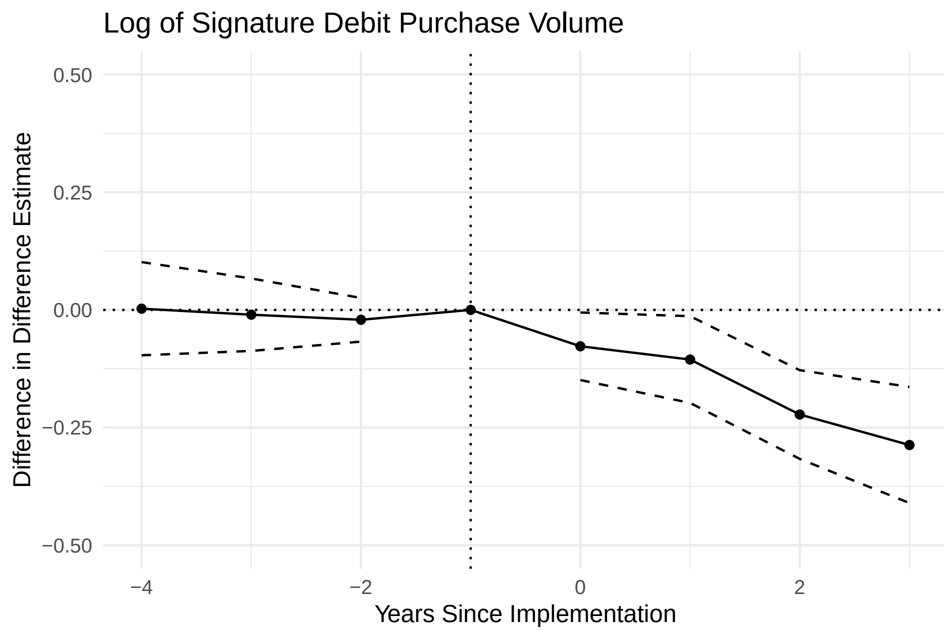
The Durbin Amendment provides quasi-experimental evidence that issuers' incentives strongly affect consumer payment choices. Enacted as part of the 2010 Dodd-Frank Act, it capped debit interchange fees for banks and credit unions with over \$10 billion in assets starting in October 2011, reducing large issuers' debit interchange revenue by roughly 75 bps, leaving credit interchange untouched. Large issuers raised checking account fees (Kay et al. 2018; Mukharlyamov and Sarin 2025), ended debit rewards programs (Hayashi 2012; Schneider and Borra 2015), cut debit card advertising (Hayashi 2012), and scaled back bank teller sales incentives (Johnson 2010). Many small issuers, by contrast, continued debit rewards programs and increased debit marketing (CU Online 2012; Orem 2016).

I estimate the effect on payment volumes by comparing debit card volumes at large and small issuers.[4]

$$y_{it} = \sum_{k \neq -1} \beta_k I\left\{t = k\right\} \times T_i + \delta_i + \delta_t + \epsilon_{it} \tag{1}$$

[4]Small issuers are an imperfect control group because they may have been indirectly affected by the Durbin Amendment through competitive spillovers. However, such spillovers are likely to attenuate, rather than amplify, the estimated treatment effect. If small issuers also reduced debit promotion in response to competitive pressure from large issuers shifting toward credit, the difference between treated and control groups would understate the true effect of losing debit interchange revenue.

Figure 3: The effect of the Durbin Amendment on debit card volumes



Notes: Data are from the Nilson Report. The points show the difference-in-differences estimates of the effects of the Durbin Amendment on debit card volumes. Dashed lines show 95% confidence intervals. The vertical line marks $t = -1$, which is 2010, the year before the policy took effect in Q3 2011. Standard errors are clustered at the issuer level.

where y_{it} is the log of signature debit purchase volume at issuer i in year t, T_i indicates whether issuer i had more than \$10 billion in assets in 2010, and δ_i and δ_t are issuer and year fixed effects. I define $t = 0$ as 2011 and focus on institutions with between 2 and 200 billion in assets, excluding issuers that made large acquisitions during the sample period. This comparison of large and small issuers differences out the effects of the Durbin routing requirements, the CARD Act, and potential changes in merchant acceptance, all of which affect debit and credit card use symmetrically across issuer size.

Weakening large issuers' incentives to promote debit led to around a 25% relative decline in signature debit volumes. Figure 3 plots the estimated effects of being above the cutoff on signature debit card volumes. To evaluate how much of the decline could be explained by lost debit rewards, Online Appendix OD.1.2 restricts the sample to the 15 issuers that paid debit rewards pre-Durbin and compares issuers that cut rewards against those that kept them. Debit volumes at the banks that cut rewards grow about 25% more slowly than at those that kept rewards, a gap that matches the baseline estimate and informs the calibration of the rewards elasticity in Section V.A.

Online Appendix OD.1 presents robustness checks on the estimate and the mechanism. I focus on signature debit because it has the highest coverage in the Nilson Report.

The relative decline drops to 17% for total debit volumes, although estimates are noisier because fewer banks report total debit early in the sample. Credit card volumes at large banks appear to rise relative to small banks after Durbin, though pre-trends are not cleanly zero. Treated and control banks had similar pre-Durbin payment mixes; the estimates are stable across asset cutoffs and merger exclusions; and the effect reflects within-bank payment switching rather than cross-bank switching or a post-Durbin increase in credit card rewards at large issuers.

III.B Card Acceptance Increases Merchant Sales

Merchants face strong incentives to accept cards because doing so increases sales. I identify the causal effect of credit card acceptance on sales using changes in merchant acceptance policies. Between 2015 and 2023, I identify multiple instances in the Homescan data where a grocery store begins or stops accepting credit cards. Homescan does not report acceptance directly. It records the payment method that consumers self-report for each trip. I infer acceptance changes from large shifts in credit card payment shares, validated with news sources, and classify a merchant as accepting credit cards only if more than 5% of its sales are paid by credit card.[5] I then compare the shopping behavior of consumers with high and low credit card usage at treated merchants relative to control grocers that did not change their acceptance policy.

The merchants in these event studies are highly selected. Around 98% of all Homescan trips occur at stores that already accept credit cards, so merchants that change acceptance are unusual. This pattern is expected if credit card acceptance increases sales for the bulk of merchants. When extrapolating these sales gains to the broader merchant population in the model, I account for this selection.

I compare spending by credit card users versus non-users, at merchants that changed acceptance versus those that did not, before versus after the change. I estimate

$$y_{hjte} \sim \text{Poisson}(\lambda_{hjte}) \tag{2}$$

$$\log \lambda_{hjte} = \delta_{ejtqz} + \phi_{ej} C_h + \sum_{k \neq -1} \beta_{ek} C_h \mathbf{1}\{t = k\} + \sum_{k \neq -1} \gamma_k C_h T_{je} \mathbf{1}\{t = k\} \tag{3}$$

where y_{hjte} is the dollars spent by household h at retailer j in period t relative to the acceptance change in event e, δ_{ejtqz} are event-retailer-period-income quintile-3-digit zip

[5] Consumers occasionally misreport signature debit transactions as credit card payments (Rysman et al. 2025), which can produce a small positive credit share even at non-accepting merchants. At grocery chains known not to accept Visa — identified from stores that switched acceptance during the sample — the residual measured credit share is around 1.5%. The 5% threshold lies well above this noise floor while remaining well below the share at any confirmed acceptor.

code fixed effects, $T_{je} = 1$ for treated grocers that begin to accept credit cards, $T_{je} = -1$ for those that stop, and C_h is household h's credit card share of payments measured in the year prior to the event. The coefficients of interest, γ_k, capture the dynamic effects of credit card acceptance on sales to credit card users.[6] I use a Poisson specification following Cohn et al. (2022), who show that Poisson regression is preferred for difference-in-differences designs with non-negative outcomes that include many zeros.[7] Standard errors are clustered at the household level.

This strategy allows the focal merchants to experience other unobserved shocks contemporaneous with the acceptance change. The event-retailer fixed effects ϕ_{ej} absorb baseline spending differences between credit card users and non-users at each store, while the event-period interactions β_{ek} allow the credit-user spending gap to evolve over time in a way that is common across treated and control retailers. The key identifying assumption is that merchants do not differentially target credit card users relative to other consumers of similar income levels, so the strategy accommodates situations in which merchants target higher-income consumers at the same time that they start accepting credit cards. A violation would occur if the acceptance change were accompanied by a co-branded credit card campaign that simultaneously shifts both merchant acceptance and consumer card holdings. I verified that no such campaigns accompanied the events I study.[8]

Figure 4 shows that over the first two years of acceptance, sales to credit card users rise by approximately 12%. Online Appendix Table OA.3 reports the regression coefficients for both trips and spending. Even though most credit users own debit cards (Table 1), accepting credit still increases sales. The Homescan data do not identify the mechanism directly, but merchant and network testimony from antitrust trials points to the credit line providing additional purchasing power (Online Appendix OF.1). Credit is strongly preferred for larger purchases, and merchants report that debit does not substitute for it.

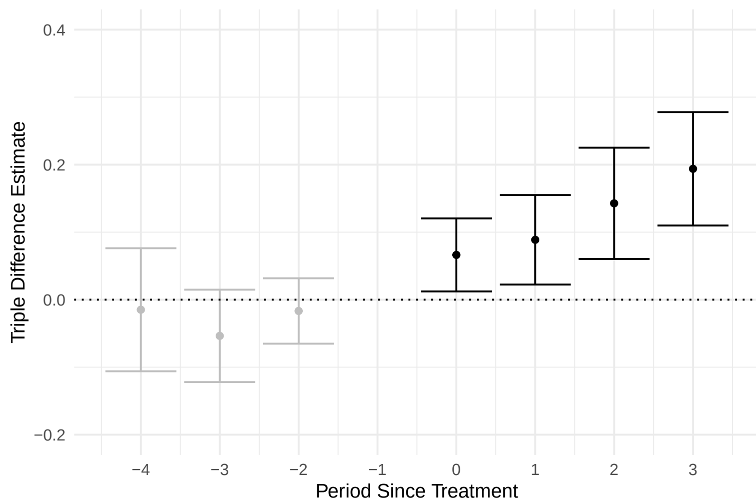
An alternative explanation is that credit card acceptance increases sales by lowering consumers' effective prices through rewards. Online Appendix OD.2 studies Dis-

[6]Because the treatment groups are very small relative to the large control group, and treated stores in one event are excluded from the control group of another, the staggered-treatment complications addressed by recent difference-in-differences estimators do not arise here.

[7]A log transform of dollar spending is not feasible here because many household-retailer-period observations have zero spending, so taking logs would require either dropping zeros, which eliminates the extensive margin response, or adding an arbitrary constant, either of which biases the estimate.

[8]I excluded events involving warehouse stores for this reason. Changes in which credit cards a warehouse store accepts are often accompanied by co-branded card campaigns designed to shift consumers' card holdings along with the acceptance change, a coordinated shift rather than a change in merchant acceptance holding fixed consumer payment behavior.

Figure 4: Triple-difference estimates of the effect of credit card acceptance on sales to credit card consumers



Notes: Data are from Homescan. The graph presents estimated coefficients from a triple-difference model of the effect of changes in credit card acceptance on dollar sales to credit card users compared to other consumers, aggregated across retailers. The coefficients reflect percentage changes in sales, and the error bars show 95% confidence intervals. Periods are six months.

cover's quarterly rewards programs and finds that rewards influence which credit card consumers use but not which merchants they visit.

III.C Merchants Multi-home More Than Consumers

Merchants overwhelmingly accept all cards, yet only around 60% of consumers use credit cards from two or more networks. Because declining a network's cards risks losing single-homers, merchants have little incentive to drop any network. This asymmetry limits merchants' bargaining power and reduces competitive pressure on merchant fees.

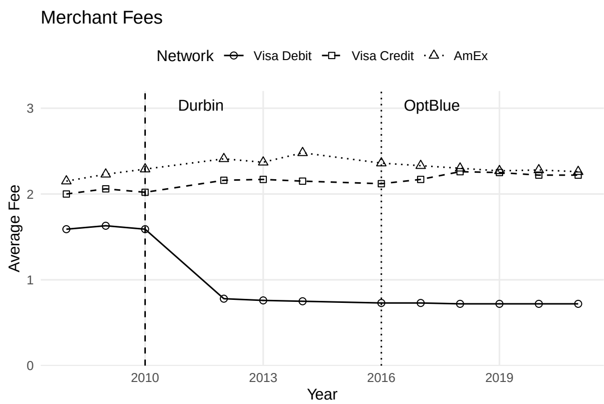
III.C.1 Almost All Merchants Multi-home

As of 2019, most merchants accept either all credit cards or none at all. The most natural margin for selective acceptance is AmEx, given its historically higher merchant fees. Figure 5a shows that the gap between AmEx's and Visa's credit card merchant fees fell by around 15 bps over the past decade, driven by AmEx's OptBlue program that cut fees for small businesses (Glasheen 2020). Figure 5b shows that as AmEx's fees converged with Visa's, so did merchant acceptance. By 2019, the number of merchants accepting AmEx approximately equaled the number accepting Visa.[9]

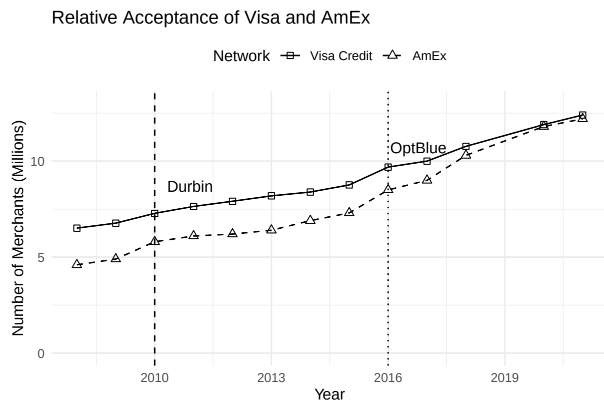
[9]Similar aggregate acceptance counts could be consistent with merchants specializing in disjoint sets of networks. Historical Yelp reviews, primarily from 2010–2018 before the convergence in Visa and AmEx acceptance, suggest otherwise. Merchants progressively add payment methods rather than specialize in

Figure 5: Merchant fees and credit card acceptance

(a) Merchant fees



(b) Credit card acceptance



Notes: Data are from the Nilson Report. The left panel plots average merchant fee levels for Visa Debit, Visa Credit, and AmEx. The right panel plots the number of merchants accepting Visa and AmEx. The dotted lines mark the imposition of the Durbin Amendment and the start of AmEx's OptBlue program.

III.C.2 Many Consumers Single-home

Whether merchants can steer consumers between networks depends on how many consumers carry cards from more than one. If most consumers single-home, a merchant that declines a network loses those consumers entirely. If most multi-home, the merchant can redirect them to a rival.

I study consumer multi-homing using the Homescan shopping data, defining a network as Visa credit, MC credit, AmEx, or any debit card. I define "carrying" a card based on observed usage, not self-reported ownership. A consumer is classified as carrying a card type if they use it during that year. I characterize household-years by their primary (most-used) and secondary (second-most-used) networks. Consumers put around 95% of their card spending on these top two networks (Online Appendix Table OA.4). These usage shares reflect consumer preferences rather than merchant acceptance policies, since most Homescan merchants are large and accept all major payment methods.[10]

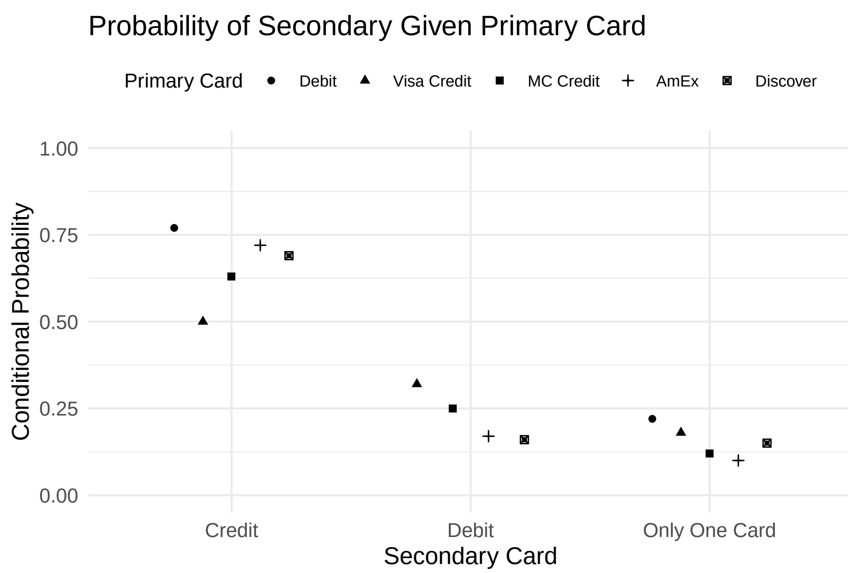
Around 60% of primary credit card consumers carry credit cards from multiple networks.[11] Each group in Figure 6 represents a different secondary card, and each point

particular networks (Online Appendix OD.3).

[10] Appendix A details the sample restrictions, including the exclusion of merchants with a low share of transactions from any network and the aggregation of Visa and MC debit into a single network for the consumer multi-homing moments.

[11] This usage-based measure aligns closely with ownership-based data. In the Diary of Consumer Payment Choice, 58% of credit card users report holding cards from two or more networks (Appendix Table OA.5).

Figure 6: Consumer multi-homing behavior



Notes: Data are from Homescan. The figure shows the probability that consumers use a secondary credit card, secondary debit card, or no secondary card, conditional on different primary cards.

represents a different primary card. The first set of dots for Visa credit, MC credit, AmEx, and Discover show the probability that a primary user of each network has a secondary card that is also a credit card. Visa credit users multi-home on credit cards the least at 50%, while AmEx users multi-home most at around 73%. Those dots also show that around three-quarters of all primary debit users use a secondary credit card, suggesting that credit access is not the reason they opt for debit. When a merchant declines a network's cards, it risks losing the remaining consumers who single-home. This mix of single- and multi-homing consumers limits but does not eliminate merchants' ability to steer consumers between credit card networks.

III.D The Competitive Bottleneck

These patterns resemble a "competitive bottleneck" in which networks compete primarily for consumers, not merchants. Standard theoretical models assume either pure single-homing, under which competition unambiguously raises merchant fees, or pure multi-homing, which reverses the result (Anderson et al. 2018; Bakos and Halaburda 2020). Given that some consumers single-home and others multi-home, neither benchmark applies cleanly, and the net effect of competition on fees and welfare must be estimated.

Figure 7: Illustration of how multi-homing consumers choose payment methods at the point of sale.

	w.p. π	w.p. $1-\pi$
(a) Primary V / Secondary MC	V $\rightarrow$ MC $\rightarrow$ Cash	MC $\rightarrow$ V $\rightarrow$ Cash
(b) Primary V / Secondary D	V $\rightarrow$ Cash	D $\rightarrow$ Cash

Notes: With probability π, a consumer tries their primary card first. With probability $1-\pi$, they try their secondary card first. Consumers who multi-home on two credit cards substitute between them when one is declined. Consumers who multi-home on credit and debit do not substitute between them.

IV Model

To quantify how network competition shapes fees, rewards, and welfare, I build a model with two-sided multi-homing, merchant competition, and price coherence.

IV.A Structure of the Game

I model competition between card networks as a static game with three stages between networks, consumers, and merchants. In the first stage, profit-maximizing networks set per-transaction fees for merchants and promised adoption utility for consumers. In the second stage, consumers and merchants make adoption and pricing decisions. In the third stage, consumers make consumption decisions over merchants. The second and third stages micro-found demand for payments. Section IV.F discusses key assumptions.

IV.B Stage 3: Consumer Shopping and Payments

Consumers' payment decisions depend on merchants' acceptance decisions, and their shopping decisions depend on their ability to use preferred payment methods. These choices give merchants incentives to accept cards in the second stage.

IV.B.1 Payment Behavior at the Point of Sale

At the point of sale, consumers' primary and secondary cards and merchant acceptance determine payment behavior. Consumers may use zero, one, or two cards. Those without cards pay cash. Those with one card pay with it if the merchant accepts it and otherwise pay cash.

Consumers with two cards can substitute between them (Figure 7). One card is the primary. With probability π, the consumer tries the primary card first, then the secondary if it is the same card type as the first, and then cash. With probability $1-\pi$, the roles reverse.[12] Credit and debit cards are segmented. A consumer who wishes to use credit does not substitute to debit if her credit card is declined (and vice versa).

Formally, define the set of all inside payment methods (i.e., cards) as $\mathcal{J}_1 = \{1, \dots, J\}$, and the set of all payment methods as $\mathcal{J} = \{0\} \cup \mathcal{J}_1$, where 0 refers to cash. A wallet $w = (w_1, w_2)$ has primary and secondary payment methods, w_1 and w_2. Let $\mathcal{W}$ denote the set of all possible wallets. It is

$$\mathcal{W} = \underbrace{(0,0)}_{\text{Cash}} \cup \underbrace{\{(w_1, 0) : w_1 \in \mathcal{J}_1\}}_{\text{One Card}} \cup \underbrace{\{(w_1, w_2) : w_1, w_2 \in \mathcal{J}_1, w_1 \neq w_2\}}_{\text{Two Cards}}$$

For $j \in \mathcal{J}_1$, let $\pi^w_{M,j}$ be the probability that a consumer with wallet w pays with card j when the merchant accepts $M \subset \mathcal{J}_1$, with $\pi^w_{M,0} = 0$. The cash share is the residual $1 - \sum_{j=1}^{J} \pi^w_{M,j}$.[13]

IV.B.2 Consumption Decisions Over Merchants

Consumers have constant elasticity of substitution (CES) preferences over a continuum of merchants, each selling a differentiated variety. Consumers observe merchants' acceptance decisions and prices before choosing where to shop. Merchants are vertically differentiated by a type $\gamma \sim G$ that governs the importance of card acceptance.

A consumer with wallet w that consumes $q^w(\omega)$ of each variety ω has utility

$$\left(\int \left(1 + \gamma(\omega)\, v^w_{M^*(\omega)}\right)^{\frac{1}{\sigma}} q^w(\omega)^{\frac{\sigma-1}{\sigma}} \, \mathrm{d}\omega \right)^{\frac{\sigma}{\sigma-1}} \tag{4}$$

where σ is the elasticity of substitution between merchants, $v^w_M = \sum_{j=1}^{2} \pi^w_{M,w_j}$ is the payment surplus from wallet w at a merchant accepting cards M, and $\left(1 + \gamma v^w_M\right)$ is the quality of merchant ω for consumer w. Consumers maximize utility by spending their income $y(1 + f^w)$, where f^w is the percentage reward from adopting wallet w. Card acceptance raises quality, reallocating spending toward card-accepting merchants rather than increasing total spending. Rewards increase income but do not affect relative consumption across merchants.[14]

Let all other merchants charge prices $p^*(\gamma)$ and accept payment methods $M^*(\gamma) \subset \mathcal{J}_1$. Standard CES results yield that a type γ merchant who sets price p and accepts

[12] Consumers may switch between the two cards due to transaction-level shocks that I do not model. For example, a credit card consumer may use the card with the best reward for the merchant.

[13] Online Appendix OE.1 explicitly works out these probabilities in a simplified model with two credit cards and one debit card.

[14] This is consistent with the Discover evidence in Online Appendix OD.2

$M \subset \mathcal{J}_1$ sells q^w to a consumer with wallet w:

$$q^w\left(\gamma, p, M, P^w, y, f^w\right) = \left(1 + \gamma v^w_M\right) \times \frac{p^{-\sigma}}{\left(P^w\right)^{1-\sigma}} \times y\left(1 + f^w\right) \tag{5}$$

$$\left(P^w\right)^{1-\sigma} = \int \left(1 + \gamma v^w_{M^*(\gamma)}\right) p^*\left(\gamma\right)^{1-\sigma} \, \mathrm{d}G\left(\gamma\right) \tag{6}$$

where P^w is a CES price index that depends on other merchants' actions and on the consumer's wallet.

Consumers spend more at merchants that accept their most-used cards. This distinction between ownership and active use helps explain why credit card acceptance can increase sales even when all credit cardholders also own debit cards.

In equilibrium, a consumer with income y optimally consumes $y \times q^{w*}\left(\gamma\right)$ from each merchant type γ, given equilibrium pricing p^* and acceptance M^*:

$$q^w\left(\gamma, p^*\left(\gamma\right), M^*\left(\gamma\right), y\right) = y \times q^{w*}\left(\gamma\right) \tag{7}$$

IV.C Stage 2: Pricing, Acceptance, and Adoption

Merchants maximize profits by choosing prices and payment acceptance. Under price coherence, merchants set uniform prices for all consumers and thus create the externality that makes credit card use socially excessive.

Profits equal per-dollar quantities q^w times margins, weighted by spending power across consumer payment types. Appendix B.1 shows that profits equal

$$\Pi\left(\gamma, p, M\right) = \sum_{w \in \mathcal{W}} \tilde{\mu}^w \times q^w\left(\gamma, p, M, 1\right) \times \left[p\left(1 - \frac{\left(1+\gamma\right)\tau^w_M}{1 + \gamma v^w_M}\right) - 1\right] \tag{8}$$

$$\tilde{\mu}^w = \int \tilde{\mu}^w_y y \, \mathrm{d}F\left(y\right)$$

where $\tilde{\mu}^w_y$ is the market share of wallet w among consumers with income y, F is the income distribution, τ_j is the per-dollar fee on card j, and $\tau^w_M = \sum_{j=1}^{J} \pi^w_{M,j}\tau_j$ is the average fee incurred by wallet w when the merchant accepts M. Because I normalize $\tau_0 = 0$ for cash, fees τ_j represent the cost of card j relative to cash. The income-weighted market share $\tilde{\mu}^w$ weights payment choices by income.

IV.C.1 Merchant Pricing

Conditional on acceptance M, merchants pass fees into prices. Appendix B.1 shows the optimal uniform price is

$$\hat{p}\left(\gamma, M, \tau\right) = \frac{\sigma}{\sigma - 1} \times \frac{1}{1 - \hat{\tau}}, \hat{\tau} = \frac{\sum_w \mu^w \tau_M^w \left(1 + \gamma\right)}{\sum_w \mu^w \left(1 + \gamma v_M^w\right)} \tag{9}$$

where the average fee uses *demand shares* μ^w, normalized weighted sums of $\tilde{\mu}^w$:

$$\mu^w = \frac{1 + f^w}{\left(P^w\right)^{1-\sigma}} \times \frac{\tilde{\mu}^w}{C}, C = \sum_w \frac{1 + f^w}{\left(P^w\right)^{1-\sigma}} \times \tilde{\mu}^w \tag{10}$$

Demand shares reflect how other merchants' acceptance decisions affect consumer composition at each merchant through P^w.

In equilibrium, merchants set optimal prices $p^*\left(\gamma\right)$ given other merchants' pricing and adoption strategies:

$$\hat{p}\left(\gamma, M^*\left(\gamma\right), \tau\right) = p^*\left(\gamma\right) \tag{11}$$

IV.C.2 Merchant Acceptance

Acceptance decisions trade off higher sales against higher fees. Let $\widehat{\Pi}\left(\gamma, M\right)$ be profits from accepting $M \subset \mathcal{J}_1$ at the optimal price. Appendix B.2 derives a fast approximate algorithm for optimizing $\widehat{\Pi}$ over M, yielding optimal acceptance $\widehat{M}$:

$$\widehat{M}\left(\gamma, \tau\right) = \underset{M \subset \mathcal{J}_1}{\operatorname{argmax}} -a_M + b_M \gamma \tag{12}$$

$$a_M = \sum_{w \in \mathcal{W}} \mu^w \tau_M^w,\ b_M = \frac{1}{\sigma} \sum_{w \in \mathcal{W}} \mu^w \left(v_M^w - \sigma \tau_M^w\right) \tag{13}$$

Adding a more expensive card incurs fees from all consumers who use it but raises sales only among single-homers. The incremental fee cost a_M covers all consumers who use the card, whereas the incremental volume gain (the v_M^w component of b_M) comes from single-homers who cannot substitute. If all consumers who use credit cards multi-home across credit networks, this incremental sales gain vanishes and merchants accept only the lowest-fee network. Online Appendix OE.2 verifies these intuitions in a two-card economy. Merchants' fee sensitivity therefore depends on the type distribution G and consumer behavior.

In equilibrium, merchants adopt optimal bundles given other merchants' behavior:

$$\widehat{M}\left(\gamma, \tau\right) = M^*\left(\gamma\right) \tag{14}$$

IV.C.3 Consumer Adoption

Consumers choose up to two cards to maximize utility. The utility from a wallet w for a consumer i is

$$\log V_i^w = \log U^w + \frac{1}{\alpha_i}\left(\Gamma_i^w + \epsilon_i^w\right) \tag{15}$$

where U^w is pecuniary utility, α_i is rewards-sensitivity, Γ_i^w is mean non-pecuniary utility, and ϵ_i^w are wallet-level T1EV shocks.

Pecuniary Utility: Consumers prefer cards with high rewards and wide acceptance. The pecuniary utility for single-homing consumers is:

$$\log U^w = f^j - \log P^w, w = (j, 0), j \in \mathcal{J}_1 \tag{16}$$

where f^j is the reward rate per dollar of income and P^w is the CES price index from Equation 6. At adoption, consumers are fully informed about merchant acceptance, and greater acceptance lowers P^w. This expression can be derived from the log indirect utility of the CES problem (4) by dropping baseline income and using the approximation $\log(1+f) \approx f$.

Because pecuniary utility is derived from the CES problem, a 1 pp. increase in rewards exactly offsets a 1% increase in retail prices, so higher rewards and fees do not mechanically reduce welfare. By not normalizing the pecuniary utility of the outside option to zero, the model allows for externalities in which one consumer's payment choice affects the prices paid and thus welfare of other consumers.

For multi-homing agents, pecuniary utility is the weighted average of single-homing utilities:

$$\log U^w = \pi \log U^{(w_1,0)} + (1-\pi)\log U^{(w_2,0)}, w = (w_1, w_2) \in \mathcal{J}_1 \times \mathcal{J}_1, w_1 \neq w_2 \tag{17}$$

This specification implies consumers do not multi-home to increase acceptance coverage. I adopt this because even as AmEx acceptance has converged with Visa Credit, multi-homing rates between them have not changed (Online Appendix OD.4). The expression closely approximates one that directly uses the CES price index of wallet w whenever merchant acceptance depends only on card type (credit or debit) rather than network identity (Online Appendix OE.3).

Non-pecuniary Utility: Non-pecuniary utility captures within-wallet complementarities and adoption costs. Let card j have characteristics $X^j = \left(X_k^j\right)_{k=1}^K \in \mathbb{R}^K$. Mean non-pecuniary utility for consumer i is

$$\Gamma_i^w = \omega\left(\Xi^{w_1} + \beta_i X^{w_1}\right) + (1-\omega)\left(\Xi^{w_2} + \beta_i X^{w_2}\right) + \sum_{l=1}^{K}\sum_{m=1}^{K} \chi_i^{lm} X_l^{w_1} X_m^{w_2} \tag{18}$$

where Ξ^j is mean unobserved utility for card j, β_i is consumer i's value from characteristics, ω is the weight on primary-card characteristics, and χ_i^{lm} are consumer-specific interaction terms capturing within-wallet complementarity or substitution motives.[15]

Consumer Heterogeneity: Preferences vary with income and exhibit unobserved heterogeneity. Let $\log\tilde{y} \equiv \log y - \mathbb{E}[\log y]$ denote demeaned log income. The consumer-specific parameters are:

$$\log\alpha_i = \log\alpha_0 + \alpha_y \log\tilde{y} \tag{19}$$

$$\beta_i = \beta_y \log\tilde{y} + \tilde{\beta}_i, \quad \tilde{\beta}_i \sim N(0, \Sigma) \tag{20}$$

$$\chi_i^{lm} = \chi^{lm} + \chi_y^{lm} \log\tilde{y} \tag{21}$$

Demeaning ensures that α_0, Ξ, and χ^{lm} represent preferences at median income. Here α_y is the income elasticity of reward-sensitivity, β_y captures how card preferences vary with income, Σ is the covariance of unobserved preference heterogeneity, and χ_y^{lm} governs how within-wallet complementarities vary with income. Income dependence in χ_i^{lm} allows higher-income consumers to derive greater value from holding both a rewards credit card and a debit card for distinct transaction types.

Choice Probabilities The logit choice probability gives that

$$\tilde{\mu}_i^w = \frac{\exp\left(\alpha_i \log U^w + \Gamma_i^w\right)}{\sum_{m\in\mathcal{W}} \exp\left(\alpha_i \log U^m + \Gamma_i^m\right)} \tag{22}$$

$$\tilde{\mu}_y^w = \int \tilde{\mu}_i^w \,\mathrm{d}H(\beta_i), \quad \beta_i \sim N\left(\beta_y \log\tilde{y}, \Sigma\right) \tag{23}$$

IV.D Stage 1: Network Competition

Multiproduct payment networks maximize profits, anticipating consumer and merchant actions.

[15] l and m index the two characteristics of the primary and secondary card: whether it is an inside good and whether it is credit. Thus χ^{12} measures the interaction between any primary card and a credit secondary. χ^{21} measures the interaction between a credit primary and any secondary. χ^{22} measures an additional interaction specific to credit in both positions. Online Appendix OE.8 microfounds these parameters in a two-stage adoption-and-usage model.

IV.D.1 Profits

Network profits equal transaction fees minus costs and rewards. Fee profits T_j equal the transaction margin times total dollar volume.

$$T_j = \left(\tau_j - c_j\right) d_j \tag{24}$$

$$d_j = \sum_{w \in \mathcal{W}} \tilde{\mu}^w \times \int \frac{(1+\gamma)\,\pi^w_{M^*(\gamma),j}}{1+\gamma v^w_{M^*(\gamma)}} q^{w*}(\gamma)\, p^*(\gamma)\ \mathrm{d}G(\gamma) \tag{25}$$

where c_j is the cost of processing \$1 on method j.

Total reward costs equal

$$S_j = f^j \left(\tilde{\mu}^{(j,0)} + \sum_{k>0, k\neq j} \pi \tilde{\mu}^{(j,k)} + (1-\pi)\,\tilde{\mu}^{(k,j)} \right) \tag{26}$$

where f^j is the reward paid to a consumer single-homing on j. The three terms count single-homers on j, multi-homers who primarily use j, and multi-homers who use j as a secondary card.

For a network n that owns cards $\mathcal{O}_n \subset \mathcal{J}_1$, it earns profits:

$$\Psi_n = \sum_{j \in \mathcal{O}_n} \left(T_j - S_j\right) \tag{27}$$

IV.D.2 Conduct and Equilibrium Determinacy

Networks set transaction fees τ_j and pecuniary adoption benefits A_j, taking other networks' actions as given. Equivalently, networks set consumers' expectations about network acceptance, fees, and rewards, given expectations for rivals. The adoption benefit A_j compares rewards and payment convenience relative to cash.

$$A_j = \log U^{(j,0)} - \log U^{(0,0)} = f^j - \left(\log P^{(j,0)} - \log P^0\right) \tag{28}$$

Networks set A^*_j and τ^*_j for their cards $\mathcal{O}_n$ to maximize expected profits under small trembles in all actions:

$$\left(A^*_j, \tau^*_j\right)_{j\in\mathcal{O}_n} = \underset{\left(\overline{A}_j, \overline{\tau}_j\right)_{j\in\mathcal{O}_n}}{\operatorname{argmax}}\ \mathbb{E}\left[\Psi_n\left(\left(A_j,\tau_j\right)_{j\in\mathcal{O}_n}, \left(A_k,\tau_k\right)_{k\notin\mathcal{O}_n}\right)\right] \tag{29}$$

$$X_k \sim N\left(\overline{X}_k, \nu_x^2\right) \quad \text{for } X \in \{A, \tau\},\ k \in \mathcal{J}_1,$$

where $\overline{X}_k$ is the network's choice for $k \in \mathcal{O}_n$ and the equilibrium value X_k^* for $k \notin \mathcal{O}_n$. Small trembles select a unique equilibrium when profits are not differentiable in fees (Teh et al. 2023). I set $\nu_x = 10^{-4}$. The trembles can be interpreted as small fee heterogeneity across merchants. Online Appendix OE.4 discusses the conduct assumption.

IV.E Equilibrium

An equilibrium is a tuple $\left(\tau^*, A^*, \tilde{\mu}_y^w, p^*(\gamma), M^*(\gamma), q^{w*}(\gamma)\right)$ satisfying: consumption is optimal (7); merchant pricing and acceptance maximize profits (11, 14); consumers choose optimal wallets (22); and networks maximize profits (29). Online Appendix OE.5 details the solution algorithm.

IV.F Discussion of Key Assumptions

The welfare results depend on several modeling assumptions, of which credit-debit segmentation at the point of sale is the most consequential. This section defends that assumption and addresses a set of smaller ones that matter for interpretation.

Segmentation Between Debit and Credit The baseline treats credit and debit as segmented at the point of sale. Intuitively, some transactions are best served by credit cards, e.g., large transactions, and others by debit cards, e.g., routine purchases. Appendix OE.8 shows that this segmentation at the transaction level can still be consistent with the Durbin evidence that rewards matter if consumers choose which payment methods to adopt in a first stage and how to use them in a second stage.

Although the segmentation assumption has mixed support on the consumer side, it is more consistent with certain aspects of merchant behavior. Antitrust testimony and consumer surveys support segmentation, but Discover's rewards experiment shows some substitution at the margin (Appendix OD.2). However, under substitution, merchant credit card acceptance would depend on credit-debit multi-homing rates, and debit fee caps would discipline credit fees. Antitrust testimony in *Ohio v. AmEx* contradicts the first, and Durbin halved debit interchange without moving credit interchange.

Allowing for credit-debit substitution does not significantly change welfare results for most counterfactuals. Online Appendix OF estimates two alternatives that incorporate credit-debit substitution. Welfare results are close to the baseline for every counterfactual other than uncapping debit fees. For the Durbin counterfactual, the baseline model is the most credible since the alternatives make counterfactual predictions for how credit card fees and acceptance should have responded to the Durbin Amendment.

Two-Card Restriction Consumers choose up to two cards and treat cards of the same type (e.g., both credit cards) as interchangeable at the point of sale. In the data, consumers put around 95% of their card spending on just two networks (Online Appendix Table OA.4). This setup understates consumer flexibility by excluding a potential third fallback option, but potentially overstates the willingness to substitute among the top-two cards. A consumer who puts 99% of their spending on one card and 1% on another may be less willing to substitute than the model implies. Sullivan (2025) takes an alternative approach and infers substitution patterns from within-consumer persistence in platform choice.

Fixed Costs I omit fixed costs of card acceptance because they cannot be separately identified from heterogeneity in sales benefits γ without exogenous shocks to consumer adoption as in Higgins (2024). The absence of fixed costs rules out a feedback loop in which lower consumer adoption reduces merchant acceptance. I therefore focus on an intermediate credit fee cap resembling Canadian levels, well within the range that has not triggered acceptance cascades elsewhere.

Merchant Types Merchants differ only in the sales benefit γ. This one-dimensional type rationalizes hierarchical acceptance but predicts identical relative shares among accepted card networks at all card-accepting stores. If consumers with heterogeneous payment preferences sort across stores, the redistributive effects of fees would be dampened (Gans 2018). Online Appendix OI shows such sorting is quantitatively small in retail.

Non-Rewards Credit Card Characteristics The data lack non-rewards credit card characteristics such as interest rates, credit limits, or annual fees. I assume these do not change when rewards change. Counterfactuals are best interpreted as short-run predictions holding these characteristics fixed. Australia's interchange caps did not raise non-rewards annual fees, and the spread between credit card rates and term loans was unchanged (Online Appendix Figure OB.1), consistent with high-volume transactors accounting for little credit card borrowing (Adams et al. 2022).

Price Coherence Merchants charge the same price regardless of payment method (price coherence). This friction causes merchant fees and rewards to distort consumer payment choices. Online Appendix OH discusses the history and theory. Only about 5% of U.S. transactions feature payment-specific pricing despite legal permission (Stavins 2018).

Merchants with the strongest gains from card acceptance are those whose consumers value card payments highly and respond little to surcharges, so even small menu costs deter surcharging.

Issuers and Acquirers The model combines issuers, acquirers, and networks into a single entity that maximizes joint profits. This is a valid assumption so long as the contracting space between these parties is rich enough. The DOJ's 2024 antitrust suit against Visa alleges payments to issuers and potential competitors to maintain dominance, evidence consistent with this view of the contracting environment. Double marginalization and other vertical frictions within the payment chain are left to future work.

V Estimation

Estimation links the reduced-form facts to quantitative predictions about regulation and competition. The key primitives are consumers' preferences over payment options, merchants' gains from accepting cards, and networks' marginal costs.

V.A Estimation Procedure

I estimate all parameters jointly, but the identification argument has three components. Consumer demand is identified by quasi-experimental price variation, second-choice surveys (Berry et al. 2004), and demographic moments (Petrin 2002). Network costs come from first-order conditions on rewards. Merchant types are identified from event-study evidence on card acceptance effects and acceptance rates. The model approximates the market structure as of 2019. I estimate standard errors by bootstrapping the joint distribution of data moments. Appendix C contains the estimation details.

V.A.1 Consumer Demand

The key consumer demand parameters are price sensitivity (α_0), substitution patterns (Σ), income gradients ($\alpha_y, \beta_y, \chi_y^{lm}$), and multi-homing complementarities (χ^{lm}).

The effect of the Durbin Amendment on debit card volumes identifies the price-sensitivity coefficient α_0. I simulate a 25 bps decline in debit rewards, holding fixed merchant acceptance. I match the resulting percentage change in debit volumes to the difference-in-difference estimate. Hayashi (2012) estimates that pre-Durbin debit rewards were around 25 bps, which I confirm with archived bank websites. The simulated moment holds merchant acceptance fixed because cardholders at regulated and exempt issuers face the same merchants. Any change in merchant behavior after Durbin is differenced out by the control group.

Durbin-exposed banks cut rewards along with non-price steering. The baseline calibration nonetheless targets the full 25% relative decline. Among the subsample of banks that paid debit rewards pre-Durbin, those that ended rewards saw debit volumes grow more slowly than those that kept rewards by a margin similar to the baseline specification. Online Appendix OD.1.2 argues that if banks differ in their productivities across steering levers, rewards-paying banks did less non-price steering, so the within-subsample comparison reflects mainly the rewards change. Section VI.F discusses how the counterfactuals change under a more conservative target that attributes only half of the debit decline to the rewards channel.

My second-choice survey reveals the covariance matrix Σ of the random coefficients (Berry et al. 2004). The characteristic vector X_j is an indicator for an inside good and an indicator for being a credit card. The inside-good indicator equals 1 for all cards, whether credit or debit. Online Appendix OD.5 shows that consumers view credit and debit cards as two separate categories and that cash substitutes more effectively for debit cards than credit cards. The volatility of the random coefficients is correspondingly large.

Wallet complementarity parameters are identified by multi-homing patterns in the Homescan data. Three parameters measure wallet interactions. χ^{12} is credit's value in the secondary position, χ^{21} is a secondary card's value for credit-primary consumers, and χ^{22} is the utility for managing two credit accounts.[16]

Demographic data identify how preferences vary with income. Higher-income respondents in the second-choice survey are more willing to switch cards for better rewards, identifying α_y. The empirical income distribution pins down ν_y, and the DCPC data on how preferred payment methods vary with income identify the conditional preference gradient β_y. Homescan multi-homing patterns by income (Figure 6) identify both χ^{lm} and its income gradient χ^{lm}_y. The multi-homing rate is 4.3 pp. higher above median income than below (Online Appendix Table OA.6), and the model matches this gradient exactly.

V.A.2 Network Costs

I recover network costs by inverting first-order conditions with respect to rewards. High rewards are profitable only when networks earn positive margins from merchants, so marginal costs must be low relative to observed fees.

[16]The fourth interaction χ^{11} (any-primary, any-secondary) is normalized to zero: the only wallet where it would be separately identified is (debit,debit), which is negligible in the data.

V.A.3 Merchant Types

I recover the distribution of merchant types G by combining event-study evidence on grocery chains' card adoption from the Homescan panel, acceptance rates from the DCPC, and networks' optimal pricing conditions. U.S. payment markets are mature. In 2013, 98% of Homescan trips occurred at stores already accepting credit cards, so recovering the merchant-type distribution is closer to a calibration than a conventional estimation.

I model grocery chains that changed their acceptance policies as the lowest type willing to accept cards. This ultimately reveals σ. Denote γ^* as the sales increase from accepting cards for the marginal merchant type. Under the baseline substitution assumption, these firms trade-off γ^*% more sales from credit users against additional card fees of τ% of sales. As σ increases, merchant margins decrease, and thus a greater sales gain γ^* is needed to justify accepting cards. I choose a value of σ so that γ^* matches the event study estimates.[17]

I parameterize G as a two-parameter Gamma distribution. The expenditure-weighted acceptance rate from DCPC respondents and networks' first-order conditions on fees near the marginal merchant type identify its shape.[18] Merchant price-sensitivity at the observed equilibrium follows from a standard insight in two-sided markets. Networks charge high fees to merchants and use the revenue to fund rewards for price-sensitive consumers, so merchants must be relatively insensitive to fees compared to consumers. Given estimates of consumer sensitivity, merchant sensitivity comes from networks' first-order conditions.

V.A.4 Calibrated Parameters

I calibrate two sets of parameters. Aggregate spending shares from the 2019 Nilson Report (Figure 2) pin down the unobserved characteristics Ξ. I normalize $\tau_0 = 0$ for cash using the 30 bps cost-of-cash estimate from Felt et al. (2023) for the U.S., then bootstrap from a distribution centered at that value with a standard deviation of 10 bps to incorporate uncertainty in the cost of cash into other parameter estimates.

Table 2: Estimated parameters

Panel A: Consumer Preference Parameters

Parameter	Est	SE
Log Price Sensitivity ($\log \alpha_0$)	6.75	0.34
Card-Credit Complement (χ^{12})	4.65	0.59
Credit-Card Complement (χ^{21})	3.97	0.48
Credit-Credit Complement (χ^{22})	-4.82	0.86
Visa Debit Utility (Ξ)	-4.00	0.59
Visa Credit Utility (Ξ)	-5.95	0.50
MC Debit Utility (Ξ)	-4.18	0.64
MC Credit Utility (Ξ)	-6.19	0.56
Amex Utility (Ξ)	-6.26	0.56
Primary Weight (ω)	0.62	0.02
P(Use Primary) (π)	0.83	0.00

Panel B: Consumer Heterogeneity Parameters

Parameter	Est	SE
Card Volatility	0.93	0.37
Credit Volatility	2.40	0.96
Correlation of β	-0.78	0.06
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)	0.63	0.46
Card-Credit Income (χ_y^{12})	0.56	0.21
Credit-Card Income (χ_y^{21})	0.51	0.18
Credit-Credit Income (χ_y^{22})	-0.44	0.17

Panel C: Merchant Parameters

Parameter	Est	SE
Merchant CES	5.61	1.25
Average γ	0.26	0.07
S.D. of γ	0.11	0.03

Panel D: Network Cost Parameters (bps)

Parameter	Est	SE
Cash	30	10
Visa Debit	38	16
MC Debit	55	8
Visa Credit	38	16
MC Credit	52	9
Amex	50	9

Notes: S.D. refers to the standard deviation, and R.C. refers to the random coefficients for having a credit card and not being cash. The Ξ are the unobserved characteristics. The characteristic vector has two components: an inside-good indicator ($X^1 = 1$ for all inside goods, credit and debit alike) and a credit indicator ($X^2 = 1$ for credit cards only). The standard deviation of R.C. and T1EV shocks, χ, Ξ are all measured in pp. of pecuniary utility for the median consumer. In Panel B, volatility parameters are the standard deviations of the random coefficients, ρ is the correlation between the card and credit random coefficients, ν_y is the standard deviation of the log-income distribution, and α_y, β_y, χ_y are the income gradients of reward sensitivity, preferences, and complementarities, respectively. Merchant types γ are distributed according to a Gamma distribution.

Table 3: Estimated consumer own-reward and cross-reward semi-elasticities.

Instrument	Visa Debit	Visa Credit	MC Debit	MC Credit	AmEx
Cash	-0.9	-0.3	-0.4	-0.1	-0.1
Visa Debit	3.1	-0.3	-1.7	-0.1	-0.1
Visa Credit	-0.6	3.7	-0.2	-1.4	-1.3
MC Debit	-4.3	-0.3	5.7	-0.1	-0.1
MC Credit	-0.5	-3.5	-0.2	5.8	-1.5
AmEx	-0.5	-3.5	-0.2	-1.6	6.1

Notes: Each entry shows the effect of a 1-bp change in the rewards of the column payment method on the market share of the row payment method. The change is measured as a percentage of the row payment method's market share.

V.B Merchant and Consumer Sensitivities and Credit Aversion

The estimated parameters support the competitive bottleneck: consumers are far more sensitive to rewards than merchants are to fees, so networks compete for consumers rather than merchants. The estimates also reveal substantial credit aversion. Consumers who take credit cards for the rewards still incur a non-pecuniary cost, so cutting back on credit card use generates real welfare gains. Table 2 reports parameter estimates.

The consumer substitution matrix in Table 3 shows that consumers view credit cards, debit cards, and cash as distinct segments. A 1-bp increase in Visa credit rewards raises Visa's share by 3.7%, drawn mostly from MC credit (down 3.5%), while MC debit falls only 0.3% and cash 0.3%. Consumers freely substitute between networks' credit cards but not between credit and debit, or between cards and cash.

This asymmetry is large. Consumers are roughly ten times as sensitive to rewards as merchants are to fees. A 1-bp increase in Visa's merchant fees, holding fixed consumer adoption, reduces merchant acceptance by 0.4% (S.E. 0.2%). This asymmetry underpins the competitive bottleneck. Merchants cannot credibly threaten to drop cards that consumers expect to use, so networks compete for consumers rather than for merchant acceptance.

The parameters reveal substantial "credit aversion" — a non-pecuniary cost that consumers incur when using credit. The median consumer would pay with debit if credit cards did not pay rewards. A consumer with median income is indifferent between a Visa debit card and a Visa credit card paying 1.2% in rewards.[19] This cost is large, consistent with survey evidence that consumers who avoid credit cards cite budget control, distaste for carrying debt, and the hassle of managing revolving accounts (Online Appendix OD.6). This distortion is central to welfare analysis. Rewards competition induces consumers to use credit cards despite the cost. Reductions in credit card use raise welfare by eliminating this distortion.

Reward sensitivity is increasing in income ($\alpha_y > 0$). While higher-income consumers tend to be less price-sensitive in retail markets (Sangani 2024), greater financial sophistication and attention to product terms make higher-income consumers more responsive

[17]The standard errors in my estimate of σ account for uncertainty in the event-study estimates but not for model error from extrapolating beyond the grocery sector. Restaurants, e-commerce, and service providers face different customer mixes and transaction sizes, and the data contain no comparable natural experiments outside grocery.

[18]The acceptance rate is the share of merchants above the marginal type, weighted by transaction volume. Online Appendix Table OC.3 compares DCPC acceptance rates to Yelp business attributes by sector; the two sources agree closely in aggregate.

[19]This is the difference in non-pecuniary utility between single-homing on Visa debit versus Visa credit, scaled by the primary-card weight ω.

to differences in fees and rewards (Hastings et al. 2017). Because high-income consumers are both more likely to use credit cards and more reward-sensitive, rewards competition among networks is particularly intense.

V.C Goodness of Fit

I assess fit by examining three sets of untargeted moments regarding consumers, merchants, and networks.

V.C.1 Consumer Demand

The baseline equilibrium matches untargeted adoption shares from the DCPC. Around 41% of consumers have a primary debit card, around 33% have a primary credit card, and the rest use cash for all transactions (Online Appendix Table OA.12). This match is not automatic because I target spending shares, not adoption shares. Recovering correct adoption shares confirms the estimated correlation between payment preferences and income. Online Appendix Figure OB.3 also shows that the model matches the joint distribution of primary and secondary cards in consumers' wallets.

V.C.2 Merchant Demand

I validate merchant parameter estimates against three types of evidence. AmEx's 2016–2019 OptBlue program cut merchant fees by 15 bps relative to Visa (Figure 5a), and the share of Visa merchants not accepting AmEx shrank from around 9–17 pp. to almost zero (Figure 5b). [20] Simulating this shock in the model, the gap shrinks by 14.1 pp. This out-of-sample prediction is the most direct test of the model's ability to predict merchant responses to fee changes, which is central to the counterfactual analysis.[21] The estimated average sales effect of 26% is consistent with experimental evidence: Higgins (2024) finds that debit card adoption at corner stores increases sales by 20–60%, and Berg et al. (2025) finds that accepting Buy Now, Pay Later raises sales by around 20%. The estimated retail margin of 17.8% is similar to the aggregate margins of 13–17% implied by macro studies of misallocation (Edmond et al. 2023; Sraer and Thesmar 2023).

V.C.3 Network Parameters

Network cost parameters match accounting data. The estimated debit marginal cost for the combination of issuers, acquirers, and the network averages around 46 bps. Ac-

[20] AmEx's 2019 annual report confirms its U.S. network went from covering 90% to 99% of card spending during this period. The count of merchants Nilson (2020a) shows a larger reduction in the acceptance gap.

[21] The semi-elasticity linearizes the acceptance cutoff at near-universal acceptance. The OptBlue fee reduction is large enough that the cutoff responds nonlinearly, so the per-basis-point acceptance change differs from the linearized estimate.

counting estimates put issuer costs at 20–40 bps, acquirer costs at 5–10 bps, and network costs at around 5 bps (Lowe 2005; Mukharlyamov and Sarin 2025; NACHA 2017; Visa 2020).

VI Counterfactuals

I use the estimated model to show that equilibrium fees and rewards are too high, but that increasing network competition without breaking the competitive bottleneck makes the problem worse. I simulate five counterfactual policies: capping credit card fees, repealing the Durbin Amendment, merging all three networks, increasing consumer multi-homing through dual-routing mandates, and introducing a central bank digital currency. All counterfactuals fix consumers' preferences β_i, baseline income y, and merchants' sales benefits to card consumers γ. Consumer adoption, merchant acceptance, retail prices, and network prices adjust endogenously.[22] The baseline is the observed 2019 equilibrium, where networks maximize profits subject to the Durbin Amendment's debit fee cap while credit fees remain unregulated. Welfare comparisons are relative to this status quo.

VI.A Capping Credit Card Merchant Fees

Capping credit card merchant fees at 120 bp, roughly half their current level, while leaving debit fee caps unchanged corrects the price-coherence adoption externality and raises total welfare by $27 billion per year. Lower merchant fees reduce credit card rewards, correcting excessive adoption driven by price coherence. The gains are progressive. Low-income consumers benefit from lower retail prices, while high-income consumers lose from reduced rewards.

VI.A.1 Effects on Prices and Shares

Capping credit card merchant fees reduces rewards and card use, illustrating the see-saw principle in Rochet and Tirole (2003). Table 4 shows that networks respond to the credit fee cap by cutting credit card rewards by around 1.1 pp., largely eliminating rewards. Spending on credit falls by nearly half as consumers substitute toward debit and cash (Table 4). Price and quantity changes together reduce total merchant fees and rewards by roughly equal amounts. I normalize total model income to the $10 trillion in 2019 consumer spending (Nilson 2020c), so each bp corresponds to $1 billion. Hence fees and rewards fall by around $58 billion each.

[22] Although merchants' types γ are fixed, their incentives to accept cards can change because the effect of card acceptance on total sales depends on γ and the share of consumers using each card.

Table 4: Counterfactual Effects on Prices and Shares

	Price Controls		Change Competition		
	Cap Fees	Uncap Debit	Monopoly	Dual Routing	CBDC
Δ Prices (bps)					
Credit Fees	-105 (0)	-3.3 (0.7)	36 (3)	-13 (3)	0.8 (0.1)
Credit Rewards	-110 (0)	-6 (1)	-90 (30)	-15 (3)	0.7 (0.2)
Debit Fees	0.0 (0.0)	25 (0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)
Debit Rewards	1.3 (0.2)	25 (0)	-37 (7)	0.4 (0.0)	3.9 (1.0)
Δ Shares of Total Spending (pp.)					
Cash	6 (2)	-7 (1)	29 (1)	0.0 (0.1)	-1.8 (0.1)
Debit	13 (2)	13 (2)	-6 (1)	0.8 (0.5)	-4.4 (0.1)
Credit	-19 (3)	-6 (1)	-23 (1)	-0.8 (0.6)	-0.6 (0.1)
Δ Fees, Rewards ($Bn)					
Total Fees	-58 (2)	4.4 (1.4)	-40 (3)	-7 (2)	-1.0 (0.4)
Total Rewards	-57 (1)	0.5 (1.6)	-66 (9)	-8 (2)	0.7 (0.3)

Notes: Bootstrap standard errors are in parentheses. The "cap fees" scenario caps credit card merchant fees at 120 bp. The "uncap debit" scenario raises the cap on debit card merchant fees by 25 bps. Monopoly refers to merging all three networks. Dual routing increases the multi-homing parameter by the equivalent of 20 bps in rewards for the median consumer. CBDC introduces a zero-fee public payment option. Its own market share is the residual of the changes in the shares of the other payment methods. Dollar values are computed by normalizing to $10 trillion of total consumer purchases (Nilson 2020c).

VI.A.2 Welfare

The gains from the credit fee cap stem from correcting excessive adoption, not from reducing market power. I measure consumer welfare by compensating variation:

$$\mathrm{CS} = \int \mathbb{E}\left[\max_{w} \log V_i^w(y)\right] \times y \,\mathrm{d}F(y) \tag{30}$$

The inner expectation computes surplus for households at a given income as a share of baseline income. The outer integral weights by baseline income to yield aggregate welfare. Most gains accrue to consumers ($28 billion), not merchants ($0.4 billion). Networks lose only $1.5 billion—around 6% of baseline profits. The total gain is roughly double the $12 billion consumer welfare gain from the CARD Act (Agarwal et al. 2015), highlighting the importance of regulating networks in addition to issuers.

Table 6 isolates the welfare sources by holding different margins fixed. The first row holds merchant prices and acceptance at their baseline while networks re-optimize fees and rewards and consumers adopt new payment methods. The second row additionally allows merchant retail prices to adjust, holding acceptance fixed. The third row allows acceptance to adjust as well.

Table 5: Welfare Effects of Counterfactual Policies

	Price Controls		Change Competition		
	Cap Fees	Uncap Debit	Monopoly	Dual Routing	CBDC
Δ Welfare ($Bn)					
Consumers	28 (3)	4.3 (1.6)	-11 (11)	3.3 (1.4)	3.7 (1.0)
Merchants	0.4 (0.2)	-0.7 (0.2)	-4.6 (1.8)	-0.1 (0.0)	0.3 (0.1)
Networks	-1.5 (0.3)	3.0 (0.2)	31 (6)	0.6 (0.0)	-2.4 (0.6)
Total	27 (4)	7 (2)	15 (7)	3.8 (1.4)	1.6 (0.5)
Δ Consumer Surplus by Income (bps consumption)					
Low	48 (3)	7 (2)	13 (7)	6 (2)	4.6 (1.3)
Median	37 (3)	5 (2)	0.9 (9.5)	4.0 (1.6)	4.0 (1.1)
High	15 (4)	2.4 (1.6)	-29 (14)	1.3 (1.1)	3.4 (0.9)

Notes: Bootstrap standard errors in parentheses. Cap Fees caps credit card merchant fees at 120 bp. Uncap Debit raises the debit fee cap by 25 bps. Monopoly merges all three networks. Dual Routing increases the multi-homing parameter by the equivalent of 20 bps in rewards for the median consumer. CBDC introduces a zero-fee public payment option. 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 2020c).

Even though the credit fee cap targets merchants, merchants benefit little in equilibrium. The first row shows that merchants benefit from lower fees, but the second row shows that they dissipate these profits by lowering retail prices to compete for consumers.

The harm to networks is also modest. The first row shows that lower rewards reduce profits as networks lose consumers. The third row shows that networks recover a substantial share when merchants increase card acceptance in response to lower fees. Profits decline by only $1.5 billion, or around 6% of baseline profits.

Consumers gain $28 billion even though Table 4 shows fees and rewards falling by roughly equal amounts. The reason is that the credit fee cap moderates excessive adoption of credit cards. By revealed preference, the marginal credit card user is indifferent between credit and debit or cash. Rewards compensate for non-pecuniary costs of credit card use, including budget control, debt aversion, and account-management hassle. I refer to these costs as "credit aversion" (Online Appendix OD.6). Lower rewards cause this marginal consumer to switch away from credit. But while lost rewards are merely transfers, the credit aversion that switchers avoid is a real social benefit. The full total welfare gain of reduced credit aversion materializes only across the first two rows of Table 6.[23]

[23] The first row of Table 6 conflates two offsetting forces: a large gain from reduced credit aversion and a loss from reduced consumption when rewards fall but retail prices remain fixed. Positive retail

Table 6: Welfare Decomposition by Channel: 120 Bps Cap

	Consumer		Merchant		Network		Total	
Network Effect	-30	(2)	50	(2)	-6	(1)	14	(4)
Price Passthrough	59	(2)	-49	(3)	0.6	(0.2)	11	(2)
Merchant Adoption	-1.3	(0.9)	-0.7	(0.2)	3.9	(0.7)	1.9	(1.1)
Total	28	(3)	0.4	(0.2)	-1.5	(0.3)	27	(4)

Notes: Bootstrap standard errors in parentheses. Network Effect freezes merchant retail prices and acceptance at baseline while networks re-optimize fees and rewards. Price Passthrough then allows merchants to re-optimize retail prices, holding acceptance fixed. Merchant Adoption allows merchants to adjust acceptance decisions. All values in $Bn, normalized to $10 trillion of total consumer purchases (Nilson 2020c).

Credit card adoption is socially excessive because of price coherence. Because merchants do not surcharge, each new cardholder raises retail prices for everyone else. Consumers collectively prefer lower retail prices and lower credit card use, but individually face incentives to defect to earn cross-subsidies. The credit fee cap corrects this prisoner's dilemma by reducing the rewards that drive excessive adoption.

VI.A.3 Distributional Effects

Fee and reward cuts redistribute consumption toward lower-income consumers. Consumer surplus rises by 48 bp of consumption for low-income consumers (log income at -2 SD), 37 bp for median-income consumers, and 15 bp for high-income consumers (log income at $+2$ SD). Lower retail prices benefit everyone, while reward reductions fall disproportionately on higher-income consumers who are more likely to use credit. All groups gain on net because reduced credit aversion is spread across the income distribution. To the extent that one believes revealed preference does not apply in payment markets, the average gain in consumer surplus can be subtracted from each group. Such a correction would still leave gains for low- and median-income consumers, but losses for high-income consumers.

VI.B Repealing the Durbin Amendment

The credit fee cap raises welfare by correcting adoption distortions, not by reducing market power. If they did, capping fees on any payment instrument should help. The Durbin Amendment provides a direct test, since it caps debit but not credit card fees. I study repealing the Durbin Amendment by raising the cap on debit card fees by 25 bps, matching the share of the 75 bp interchange decline that flowed through to rewards

markups mean that reducing total consumption increases deadweight loss. However, this welfare channel is reversed in the second row as merchant price cuts then expand consumption.

(Hayashi 2012).[24]

Repealing the Durbin Amendment moderates the rewards race. If the debit fee cap were lifted by 25 bps, merchant fees would rise and networks would increase debit rewards. Consumers would switch to debit, especially reward-sensitive ones. As the marginal credit consumer becomes less reward-sensitive, networks pull back on rewards competition, triggering the see-saw principle and lowering credit merchant fees. Credit rewards fall 6 bps and credit fees fall 3.3 bps as credit networks pull back. Net of the debit increase, total merchant fees rise by $4.4 billion but rewards rise by only $0.5 billion, reflecting substitution toward lower-reward debit.

Repealing the Durbin Amendment generates large welfare gains. Consumers gain $4.3 billion as higher debit rewards draw consumers away from credit cards. Total welfare rises by $7 billion. These gains are progressive: low-income consumers gain 7 bps of consumption, versus 2.4 bps for high-income consumers. The current regime, capping debit but not credit, is worse than both laissez-faire and capping both. Uniform regulation benefits consumers (Rochet and Tirole 2011). Asymmetric regulation does not.

VI.C Welfare Effects of Reducing Network Competition

One might expect that increasing competition among networks would substitute for fee regulation. In payment markets, the opposite holds. Competition fuels the rewards arms race that amplifies distortions from price coherence. I test this by modeling a merger to monopoly, with fees and rewards set to maximize industry profits.

Without competitive pressure to fund rewards, a monopolist cuts credit card rewards by 90 bps. Because rewards are the primary reason consumers carry credit cards, spending on credit collapses. The credit share falls 23 pp. The merger reduces aggregate merchant fees by $40 billion despite a 36 bps rise in per-transaction fees, because far fewer transactions clear on high-fee credit cards. Unlike in Armstrong (2006), where competition raises per-transaction merchant fees, here it raises the total fee burden by shifting payment composition toward high-fee credit cards.

The merger increases total welfare by $15 billion because eliminating rewards competition more than offsets the consumer losses. Consumers lose $11 billion (though imprecisely estimated) while networks gain $31 billion. Lower credit card use reduces retail prices for all consumers, but lower rewards mainly harm high-income cardhold-

[24] Durbin reduced debit interchange by roughly 75 bps, but not all of this flowed through to debit rewards. Banks also absorbed the loss through higher checking account fees (Kay et al. 2018; Mukharlyamov and Sarin 2025). I ignore the increase in checking account fees since they do not influence the relative costs and benefits of different payment methods.

ers. Low-income consumers gain 13 bps in consumption while high-income consumers lose 29 bps. These results do not support mergers, since the consumer losses are large and imprecisely estimated. They do show that rewards competition is so harmful that increases in market power can raise total welfare.

VI.D Consumer Multi-Homing and Dual Routing

Rather than regulating fees directly, policy can redirect the locus of network competition. Routing requirements, like those in the Credit Card Competition Act, would force banks to issue cards that are compatible on multiple networks (Andriotis 2022). This increases effective multi-homing rates and allows merchants to route payments to cheaper networks, shifting the locus of competition from the consumer side toward merchant fees (Teh et al. 2023). I model this by raising the χ^{22} parameter, which captures the complementarity of holding two credit cards, thereby increasing consumer multi-homing. For the median consumer, this is equivalent to a 20 bps reward increase for those bundles. Credit card multihoming then rises by 20 pp. from a baseline level of around 60%. Credit card fees fall 13 bps and rewards fall 15 bps. Consumer welfare, excluding the mechanical impact of increasing χ^{22}, still rises $3.3 billion, and total welfare rises $3.8 billion.[25]

The intuition for these effects follows from the merchant acceptance condition in Section IV.C.2. A merchant's fee cost from accepting card j depends on all consumers who use it, but the incremental sales gain comes only from single-homers who would otherwise pay cash. When consumers single-home on one credit network, merchants must accept that network to capture those sales—what trial testimony in Ohio v. American Express called "cardholder insistence" (Conrath 2014). When a consumer carries credit cards from multiple networks, the merchant can decline the expensive network's card without losing the sale—the consumer simply pays with the cheaper alternative. The incremental sales gain from accepting the expensive network shrinks. Networks must then compete on merchant fees rather than relying on consumer lock-in to extract rents from the merchant side.

Current proposed dual-routing legislation often requires that the secondary network not be a large established network. This exclusion is unnecessary. The power of the dual-routing mechanism stems from increasing multi-homing, not from reducing the

[25]Because dual routing directly modifies χ^{22}, it mechanically raises consumer surplus even at unchanged prices and portfolios. I net this mechanical component—around $4.5 billion—out of the reported consumer surplus so that the $3.3 billion figure reflects only the equilibrium response. Online Appendix OE.7 derives the adjustment. To the extent that changing preferences complicates the interpretation of welfare, the effects on fees and rewards are more robust as they are a consequence of how merchant acceptance depends on consumer multi-homing across networks.

size of the largest networks. The exclusion may even be counterproductive if merchants are unwilling to invest in accepting smaller networks.

VI.E 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 resulting 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 \$3.8 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 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.

VI.F Discussion

Online Appendix OG re-estimates the model under alternative assumptions about consumer constraints, pass-through, and reward sensitivity.

Constraints vs Preferences Consumer payment choices in the model reflect preferences, not constraints. Some consumers' choice to primarily use debit over credit is evidence of "credit aversion." Survey evidence documents concrete motives, including budget control, debt aversion, and account-management hassle (Online Appendix OD.6).

An alternative interpretation is that some consumers cannot obtain credit cards. The presence of exogenous constraints does not affect the estimated welfare effects. Online Appendix OG.2 uses credit score data from the DCPC to estimate a model in which some consumers are credit-constrained, with the extent of the constraint varying with income. The alternative specification predicts smaller credit aversion for the median consumer (lower Ξ for credit and a weaker income gradient β_y^L). Because constrained consumers do not respond on the credit margin, the unconstrained subset must be more reward-sensitive to rationalize the same Durbin moment. The estimated consumer and total welfare results are similar to the baseline model.

Pass-through The CES functional form implies full pass-through from merchant fees to retail prices. One reason full pass-through is a reasonable baseline for interchange is because interchange is an aggregate shock to all merchants (Amiti et al. 2019). I also lack the required merchant-level interchange data matched to retail prices to test pass-through. Online Appendix OG.1 compares the full pass-through baseline against zero pass-through, in which retail prices are unresponsive to merchant fees in either direction. The alternative shifts the consumer-merchant welfare split but yields similar equilibrium fees and rewards.

Reward Sensitivity A more conservative specification targets only half the observed Durbin decline, attributing the remainder to non-price steering. Online Appendix OG.3 re-estimates the model against this lower-bound target. The halved target produces negative marginal costs for Visa, which conflict with accounting data on issuer, acquirer, and network costs. The credit fee cap remains welfare-improving in this specification. The monopoly counterfactual is the most sensitive to this calibration: its welfare gain reverses sign under the halved target. If non-rewards steering imposes real costs without direct consumer benefits, these estimates understate the true losses from high merchant fees.

Choice of Credit Fee Cap The 120 bp cap keeps the counterfactual close to observed fee levels, avoiding the large out-of-sample extrapolation required by more aggressive caps. Online Appendix OG.4 compares this cap to a 30 bps cap modeled after the tourist test of Rochet and Tirole (2011) and to the Ramsey planner's solution. The 120 bps cap achieves roughly 93% and 77% of the respective welfare gains with less out-of-sample extrapolation.

VII Conclusion

Rising credit card use and rising merchant costs both follow from intense network competition channeled toward the wrong side of the market. Because consumers are far more sensitive to rewards than merchants are to fees, networks compete for cardholders with generous rewards funded by merchant fees. Price coherence ensures that these fees pass through to higher retail prices borne by all consumers, including those who pay with cash and debit. The rewards draw more consumers to credit cards, increasing merchants' costs.

The counterfactual results speak to contemporary legal and policy debates in payments and platform markets. The Supreme Court's 2018 decision in *Ohio v. American*

Express held that plaintiffs must show net harm to the two-sided market as a whole, requiring evidence on both sides of the platform. This paper provides a structural framework for carrying out that analysis, linking consumer rewards, merchant fees, and retail prices within a single equilibrium model of a two-sided card market. Applied to credit card merchant fees, the framework shows that a modest cap reduces both fees and rewards yet raises total welfare by $27 billion per year through more efficient payment choice.

The Durbin Amendment counterfactual shows that capping the wrong fees makes things worse. Congress capped debit interchange in 2010 because it appeared supracompetitive, but those fees fund rewards that draw consumers away from high-fee credit cards. Repealing the cap would raise welfare by $7 billion per year, making the current U.S. regime of capping debit but not credit fees worse than laissez-faire.

The merger counterfactual challenges the view that high merchant fees reflect too little competition. In fact, it's precisely network competition that encourages the adoption of high-merchant-fee payment methods. A monopoly network raises per-transaction fees, which is the harm that antitrust cases have targeted. Yet aggregate merchant costs fall because the monopolist has no rival to outbid for cardholders, so it cuts rewards and credit use declines. The merger increases total welfare by $15 billion because eliminating rewards competition reduces the overuse of credit cards. Buy Now, Pay Later is the latest technology to woo consumers with generous terms funded by high merchant fees (Berg et al. 2025). Whether these services raise welfare depends on whether they shift competition toward merchants or simply open another front in the war for cardholders.

A broader lesson from the counterfactuals is that which side of the market networks compete for matters as much as how intensely they compete. The dual routing counterfactual illustrates this. When consumer multi-homing forces networks to compete for merchants rather than cardholders, both credit card fees and rewards fall, and total welfare rises on net.

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A Data Details

A.1 Issuer Payment Volumes

I build an annual panel of issuer payment volumes from the Nilson Report, supplemented with FFIEC call reports (banks) and NCUA call reports (credit unions), to estimate consumers' reward sensitivities. For credit unions, I proxy interchange income with non-interest income. CU Today (2016) find that interchange accounts for roughly half of non-interest income even after the Durbin Amendment. The panel spans 2007–2014.

I exclude issuers with assets below $2 billion or above $200 billion to remove systemically important banks subject to other regulations. I also exclude issuers whose acquisitions exceeded 50% of equity during 2006–2018, since their volume changes mainly reflect portfolio expansion rather than organic consumer choices. Table OA.8 reports summary statistics of institutions in the panel. Signature debit has the highest coverage (the top 200 issuers were reported in 2007), so I use it as the main volume measure. The analysis sample requires at least one observation of both signature debit and credit card volumes on each side of the Durbin Amendment, restricting to issuers that offered both products throughout.

A.2 Aggregate Shares and Prices

The Nilson Report publishes annual consumer purchases by payment method, including network-specific volumes for Visa, MC, AmEx, and Discover (Figure 2) and an estimate of cash spending. Its concept of consumer purchases covers most Personal Consumption Expenditures (PCE) but excludes items like imputed rent that do not trigger a payment between two parties. I restrict the model to Visa, MC, and AmEx but scale their volumes to match aggregate credit and debit card totals, using 2019 shares.

The Nilson Report provides annual merchant fees from acquirer surveys, split by V/MC Credit, AmEx, and V/MC Debit. I take 2019 Visa Credit, Visa Debit, and MC Debit fees from network financial data and recover MC Credit and AmEx fees in the estimation, treating their Nilson values as measured with error (Online Appendix C.3).

I collect total rewards expense from the annual reports of AmEx, Chase, Citi, Bank of America, Capital One, and US Bank, which together cover about 80% of US credit card volume in 2019. Dividing by credit card spending gives volume-weighted average rewards of 1.74% (non-AmEx) and 1.85% (AmEx) for 2019.

Total rewards expense overstates consumer benefits because it ignores annual fees. AmEx reports annual fees of about 38 bps of volume in 2019. For other banks, Adams and Bord (2020) find average annual fees of 20 bps over 2014–2019. Annual fees roughly doubled from 2015 to 2019 (CFPB 2021). Under a linear trend, the 20 bps mid-period average implies about 15 bps in 2015 and 30 bps in 2019. I subtract 30 bps from non-AmEx rewards to get the net consumer benefit for 2019.

A.3 Homescan

The NielsenIQ Homescan panel tracks payment decisions of over 100,000 households at consumer packaged goods stores. I use the full 2013–2023 panel for payment event studies but draw multi-homing moments from 2017–2019 households.

A.3.1 Defining Payment Preferences

I first drop households with more than 1% missing payment information, removing 28.9% of the sample (concentrated in 2013–2014). I classify a household as cash-only if its cash share exceeds a cutoff calibrated to match the DCPC share who prefer cash for non-bill payments (19.7%). Among non-cash consumers with more than 20 card trips, I define the primary card as the one with the most trips and the secondary card (if any) as the one with the second-most trips. This restriction removes 8% of non-cash consumers. Table OA.9 shows that trip-based and spending-based rankings are highly correlated: the top-trip card is also the top-spending card for about 96% of consumers (volume-weighted across card types).

When counting trips, I focus on stores accepting all four main card brands to separate consumer preferences from merchant acceptance. I drop store-years with fewer than 500 trips (0.7% of the remaining sample), then remove stores where any network's transaction share falls below 1.5% (15.7% of the remaining sample). Store-years below this threshold are classified as non-acceptors and dropped to avoid confounding acceptance with non-acceptance in the multi-homing moments. Figure OB.4 shows the resulting distribution of payment mix across merchant-years.

Although Visa and MC operate separate debit networks, almost no consumers multi-home across them (Figure OB.2), so I aggregate Visa Debit and MC Debit into a single "debit" category when constructing the multi-homing moments. This aggregation does not affect estimates of credit card multi-homing. The structural model in Section IV retains distinct Visa Debit and MC Debit products on the fee side while using this aggregation for consumer adoption moments.

A.3.2 Payment acceptance event studies

I build event-study samples around acceptance changes at grocery stores, selecting households in zip codes where a grocer operates in year $Y-1$ whose preferred payment method I can define in that year. I use data from 24 months before and after each change, setting months with no observed transactions to zero within each household's observed span.

A.4 Diary of Consumer Payment Choice

The Diary of Consumer Payment Choice (DCPC) provides consumer demographics, stated payment preferences, and transaction-level records of method choice and merchant acceptance. I use the 2017–2019 waves, conducted by the Federal Reserve Bank of Atlanta and fielded through USC's Understanding America Study. For card transactions, acceptance is observed directly. For cash transactions, the diary asks whether the merchant would have accepted a card. The DCPC also asks respondents to report their credit score, which I use to parameterize credit access in the credit-constrained robustness check (Online Appendix OG.2).

A.5 Second-Choice Survey

I ran an online second-choice survey of English-speaking US adults under 50 via Prolific in two waves (June and August 2024), approved under IRB STU00221445. The survey elicited: primary payment method for in-person transactions, household income, primary bank and consideration set, second choice if the primary method became unavailable, and rewards sensitivity. For credit users, rewards sensitivity was whether they would switch if rewards halved; for debit users, whether they would switch if credit rewards doubled. The final sample contains 357 primary credit and 383 primary debit users; Table OA.10 reports summary statistics. Online Appendix OC.3 provides additional design details.

B Model Details

B.1 Merchant Profits and Optimal Pricing

Merchant profits equal the integral of per-unit margins times quantities across consumer types:

$$\Pi\left(\gamma, p, M\right) = \int \sum_{w \in \mathcal{W}} \tilde{\mu}_y^w \times q^w\left(\gamma, p, M, y\right) \times L_M^w\left(\gamma, p\right) \, \mathrm{d}F\left(y\right) \tag{31}$$

where $\tilde{\mu}_y^w$ is the mass of consumers at income level y with wallet w.

Per-unit margins. The average margin L_M^w weights each instrument by its share of sales:

$$L_M^w\left(p\right) = \underbrace{\frac{1 - \pi_{M,w_1}^w - \pi_{M,w_2}^w}{1 + \gamma v_M^w}}_{\text{share on cash}} \times \left(p - 1\right) + \sum_{j=1}^{2} \underbrace{\frac{\pi_{M,w_j}^w\left(1 + \gamma\right)}{1 + \gamma v_M^w}}_{\text{share on card } w_j} \times \left(p\left(1 - \tau_{w_j}\right) - 1\right) \tag{32}$$

Collecting terms yields

$$L_M^w\left(p\right) = p\left(1 - \frac{(1+\gamma)\tau_M^w}{1 + \gamma v_M^w}\right) - 1 \tag{33}$$

where $\tau_M^w = \sum_{j=1}^{J} \pi_{M,j}^w \tau_j$ is the wallet-average fee.

Profits. CES preferences are homothetic, so $q^w(\gamma, p, M, y) = q^w(\gamma, p, M, 1) \cdot y$; the income distribution then integrates out of Π. Using $\tilde{\mu}^w q^w(\gamma, p, M, 1) = C \mu^w p^{-\sigma}\left(1 + \gamma v_M^w\right)$ (with C the aggregate demand constant and μ^w the demand shares from Equation 10), merchant profits become:

$$\Pi\left(\gamma, p, M\right) = C \times \sum_{w \in \mathcal{W}} \mu^w\left(1 + \gamma v_M^w\right) p^{-\sigma} \times \left[p\left(1 - \frac{(1+\gamma)\tau_M^w}{1 + \gamma v_M^w}\right) - 1\right] \tag{34}$$

This matches Equation 8 in the main text.

Optimal price. Setting $\partial \Pi / \partial p = 0$:

$$\sum_{w \in \mathcal{W}} \mu^w\left(1 + \gamma v_M^w\right)\left[\left(1 - \sigma\right) p\left(1 - \frac{(1+\gamma)\tau_M^w}{1 + \gamma v_M^w}\right) + \sigma\right] = 0 \tag{35}$$

Solving for p gives the optimal price in Equation 9.

B.2 Linearizing Merchant Profits

Define quasi-profits $\overline{\Pi}$ by:

$$\overline{\Pi}\left(\gamma, M, \tau\right) \equiv C \times \left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma}\left\{-a_M + b_M\gamma + \frac{1}{\sigma}\right\} \tag{36}$$

where C is the aggregate demand constant from Equation 10, and

$$a_M = \sum_{w \in \mathcal{W}} \mu^w \tau_M^w, \qquad\qquad b_M = \frac{1}{\sigma}\sum_{w \in \mathcal{W}} \mu^w \left(v_M^w - \sigma\tau_M^w\right) \tag{37}$$

recovering the coefficients in Equation 12. The v_M^w component captures incremental volume; the $-\sigma\tau_M^w$ captures lost margin due to fees.

Theorem 1. *For any γ, M, and τ with $\tau^{\max} \equiv \max_j \tau_j$,*

$$\widehat{\Pi}\left(\gamma, M, \tau\right) - \overline{\Pi}\left(\gamma, M, \tau\right) = \left(1+\gamma\right) O\left(\left(\tau^{\max}\right)^2\right)$$

Proof. The optimal payment-specific prices are $p_j = \frac{\sigma}{\sigma-1}\frac{1}{1-\tau_j}$ for each payment method j. By the envelope theorem, any price within $O(\tau_j)$ of p_j delivers the same profit up to second-order terms in τ_j. Setting $\overline{p} = \frac{\sigma}{\sigma-1}$ and collecting terms recovers the linear approximation. Collecting terms in γ:

$$\Pi\left(\gamma, \overline{p}, M\right) = C \times \left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma}\left(-a_M + b_M\gamma + \frac{1}{\sigma}\right) = \overline{\Pi}\left(\gamma, M, \tau\right)$$

□

Online Appendix OE.6 confirms that $\overline{\Pi}$ is numerically accurate.

C Estimation Details

I estimate the model by matching data and simulated moments. Inference is by bootstrap. Table OA.7 maps each data source to the parameters it identifies.

C.1 Bootstrap Inference

Standard errors come from 100 bootstrap samples. Each sample redraws data moments independently across datasets, preserving within-block correlation at fixed sample sizes. For each draw, I re-estimate the full model and re-simulate all counterfactuals. Reported standard errors are the standard deviations of these bootstrap distributions.

C.2 Consumer Parameters

Random coefficients Σ. Two sets of survey moments pin down Σ. In the 2024 second-choice survey, I compute the share of credit card users who would switch to cash if credit cards did not exist and the analogous share for debit users. I simulate these by dropping the relevant wallets from the choice set and computing joint first- and second-choice probabilities using the logit formula of Berry et al. (2004), integrating over income and random coefficients. The second set of moments is the shares diverting to the same card type on a different network when their bank drops their primary card, also from the 2024 survey. I adjust for within-network bank moves (Online Appendix OD.5.3). To match these, I perturb Ξ^{w_1} for each primary card and measure the market-share-weighted diversion share.

Mean reward sensitivity α_0. I target the last post-period coefficient from the Durbin event study using issuer-level Nilson data (2007–2014; Figure 3). I simulate the equilibrium effect of a 25 bps cut to debit rewards to match it.

Income gradients β_y and α_y. For β_y: I compute mean log income by primary payment type in the DCPC (2017–2019; Table OA.11). Since $\Pr(\text{wallet} = w \mid y)$ is given by $\tilde{\mu}_y^w$, Bayes' rule pins down expected income by payment type, and β_y is set to match (Table OA.11).

For α_y: I target the elasticity of switching probability with respect to income among credit card holders asked whether they would switch issuers if rewards halved (Table OD.5). In a conditional logit with small issuer shares ($s_{ij} \ll 1$), switching probability is proportional to α_i, so this elasticity directly reveals α_y.

Multi-homing parameters χ^{lm}, χ_y^{lm}, ω, π. From Homescan (2017–2019), I compute the conditional probability $\hat{P}(l \mid k)$ that a household's secondary card is type l given primary type k, for $(k,l) \in \{$(credit, debit), (debit, credit), (credit, credit)$\}$. I compute these separately for above- and below-median income households. The model counterparts are the analogous conditional probabilities, re-derived from the simulated adoption shares $\tilde{\mu}_y^w$ separately for each income group. The level of each conditional probability (averaged across income groups) identifies χ^{lm}; the income gradient identifies χ_y^{lm}. The weight ω is matched to the gap between Visa's share among primary and secondary credit cards. The spending share π is matched to the average primary card spending share among multi-homing households (Table OA.4). These eight moments exactly identify the eight multi-homing parameters: six conditional probabilities (three card-type pairs $\times$ two income groups), the Visa primary/secondary gap, and the spending share.

Mean unobserved characteristics $\bar{\Xi}_j$. I match dollar spending shares by network from the Nilson Report (2019). In the model, $d_j / \sum_{j'} d_{j'}$ gives the simulated counterpart, where d_j is defined in Equation 25.

C.3 Network Parameters

Visa Debit, Visa Credit, and MC Debit fees come directly from network financial data (2019). MC Credit and AmEx fees are less precisely measured, so I estimate them.

Adoption utilities A_j and network marginal costs c_j. I seek A_j and c_j satisfying two conditions: each network's first-order condition for A_j holds at c_j, and inverting Equation 28 yields implied rewards matching observed per-dollar rates $r_j = f^j / s_j$, where s_j is the spending share of a single-homer on network j. Cash and debit rewards are set to zero.

Mean merchant benefit $\bar{\gamma}$ and unobserved merchant fees. Visa Credit's first-order condition with respect to its merchant fee pins down $\bar{\gamma}$. The analogous first-order conditions for MC Credit and AmEx identify their merchant fees.

C.4 Merchant Parameters

Benefit dispersion ν_γ. I target the share of spending at card-accepting merchants (Table 1). In the model, this share is spending at merchants above γ^*, the acceptance cutoff for the grand bundle of credit cards (Equation 44), divided by total spending $\sum_{j'} d_{j'}$ (with $d_{j'}$ defined in Equation 25). Given $\bar{\gamma}$, the acceptance rate pins down ν_γ.

CES elasticity σ. I target the average of the four post-period coefficients from the grocery event study (Section III.B). The simulated counterpart is the same cutoff γ^* (Equation 44), which depends on σ through merchants' quasi-profits (Equation 12).