Regulating Competing Payment Networks

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Abstract

Merchants rarely price discriminate by payment method. This enables card networks like Visa to fund consumer rewards with merchant fees. I develop and estimate a model of platform competition to compare how regulation, increased network competition, and public entry affect U.S. consumer payments. I find that the current U.S. payment system is regressive and inefficient, and that network competition exacerbates these problems. I model consumer adoption and merchant acceptance of multiple cards, merchant pricing, and network competition. I estimate the model by matching data on the effects of debit rewards reductions and a large grocer's decision to accept credit cards. The estimated model matches external evidence on networks' costs, merchants' margins, and the effects of AmEx's OptBlue program on merchant acceptance. Uniform caps on merchant fees are progressive and increase annual welfare by $31 billion by reducing rewards and credit card use. Because higher income households are more likely to use credit cards, fee caps save the median household around $50 every year but cost high-income households $1000. Because consumers are reward-sensitive, but merchants are fee-insensitive, competition has the opposite effects. Few consumers adopt public options without rewards, limiting their benefits.

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I Introduction

Payment markets are highly concentrated and costly in many countries. In the United States, Visa, Mastercard (MC), and American Express (AmEx) processed 90% of card payments in 2019, and merchants paid over $120 billion in fees to accept cards (Nilson 2020a). Globally, regulators have adopted three strategies to curb high fees: price ceilings, competition policy, and government entry. Notable examples include interchange fee regulation in the E.U., the 2024 monopolization lawsuit against Visa in the U.S., and fast retail payment systems like UPI (India), PIX (Brazil), and FedNow (U.S.).

Predicting the effects of these policies is challenging because payment markets are two-sided. Networks compete for merchants and consumers by adjusting merchant fees and consumer rewards. In theory, capping merchant fees can harm consumers by reducing rewards (Rochet and Tirole 2003) while increased competition may push networks to increase fees and pay more rewards (Edelman and Wright 2015). Despite the diversity of regulatory approaches, there is little empirical evidence on their relative merits.

This paper fills that gap by developing and estimating a quantitative model of payment network competition. Data on bank payment volumes, consumer card holdings, and merchant card acceptance suggest that consumer adoption is reward-sensitive, whereas merchant acceptance is fee-insensitive. I use the data to estimate a model of consumer adoption, merchant acceptance, and network competition. With the estimated model, I simulate how regulation and competition affect prices and welfare.

I find that poorly designed price regulations have severely distorted the U.S. payment system and that network competition exacerbates these distortions. I estimate large gains from moving towards uniform merchant fees on credit and debit cards. Capping both credit and debit card fees or removing debit fee caps reduces regressive transfers and increases annual welfare by $31 billion and $8 billion, respectively. A merger to monopoly decreases total rewards and fees by reducing credit card usage, yielding an annual welfare gain of $20 billion. This counterintuitive outcome reflects the two-sidedness of the market, in which networks primarily compete for consumers with more generous rewards rather than for merchants with lower fees. Government platforms create benefits, but adoption is modest because they do not pay rewards. Ultimately, the gains from revising price regulations dwarf the gains from a public option.

Payment markets are inefficient because of price coherence. Even though cash discounts and card surcharges are legal, merchants in the U.S. typically charge consumers uniform prices for different payment methods (Stavins 2018).[1] This pricing rigidity gen-

[1] I explore surcharging both theoretically and empirically in Appendix D.

erates regressive and wasteful pecuniary externalities. When merchants pass on merchant fees into retail prices, lower-income cash and debit card users ultimately pay for high-income credit card users' rewards (Felt et al. 2020).[2] The externalities are wasteful because consumers bear costs, which I term "credit aversion," to use credit cards and earn rewards. These include any incremental adoption costs of credit cards or behavioral desires to stay out of debt.[3] But while credit aversion is a social cost, the rewards are merely transfers. In equilibrium, too many consumers use credit cards because they fail to internalize their effects on merchants and other consumers. Policies that reduce credit card use are thus progressive and welfare-increasing.

I document three reduced-form facts to motivate the importance of two-sided competition in payments. First, I use a bank-level panel of payment volumes to show that the 25 basis point reduction in debit rewards after the 2010 Durbin Amendment caused debit card spending to decline by 29%. Second, I present event-study evidence that when a large grocer started to accept credit cards, the grocer increased sales to credit card consumers by around 15%. The large effect of card acceptance on sales suggests that acceptance should be insensitive to merchant fees. Third, I show that while most merchants accept all networks, many consumers only carry credit cards from one network. Merchants thus put sales at risk when they decline consumers' preferred payment methods. Networks respond by competing primarily for consumers with higher rewards, not for merchants with lower fees.

The importance of two-sided competition informs a structural model in which payment networks compete in merchant fees and consumer rewards. I model three kinds of players: consumers, merchants, and payment networks. Consumers choose up to two cards to put in their wallets and where to shop. Consumers prefer cards that pay high rewards and that are widely accepted. They buy more from merchants that set low prices and accept the consumers' cards. Merchants choose the subset of payment methods to accept and pass on merchant fees into higher retail prices for all consumers. In deciding whether to accept a card, merchants trade off the benefits from higher sales against the cost of merchant fees. Multiproduct networks maximize profits by adjusting fees and rewards.

My model combines three necessary ingredients for a quantitative model: consumer multi-homing, merchant heterogeneity, and merchant competition. Edelman and Wright (2015) show that platform competition hurts consumers but assume that consumers carry

[2]While the cross-subsidies that I identify resemble those transfers from naifs to sophisticates in Gabaix and Laibson (2006) or Agarwal et al. (2022), the policy implications are different. Whereas disclosure helps in models of shrouding, no information intervention would help cash and debit users in my model.

[3]Appendix B.6 presents evidence for this behavioral interpretation.

only one card at a time (single-home). Merchants are then unable to decline high-fee cards without losing substantial sales. In such models, competition necessarily raises merchant fees and lowers welfare. Rochet and Tirole (2011) compare profit-maximizing and socially optimal interchange fees but assume homogenous merchants. When merchants are homogenous, competition necessarily lowers merchant fees (Guthrie and Wright 2007; Anderson et al. 2018). Rochet and Tirole (2003) and Teh et al. (2022) capture consumer multi-homing and merchant heterogeneity but ignore competition between retailers. By ignoring competition, these papers understate merchants' incentives to accept cards and thus shut down an important channel for the excess adoption of cards (Wright 2012). My empirical model combines consumer multi-homing, merchant heterogeneity, and merchant competition to examine how competition affects prices and welfare in payment markets.

I combine the reduced-form facts and aggregate data to recover consumer and merchant preferences. I estimate that consumers are seven times more sensitive to rewards than merchants are sensitive to fees. A one-basis-point (1-bp) increase in Visa credit rewards increases Visa's market share among consumers by 3.6%. In contrast, a 1-bp increase in merchant fees for Visa credit cards causes only a 0.5% decline in the share of merchants that accept Visa. The strong negative effect of the Durbin Amendment on debit card spending pins down consumers' high reward sensitivity, whereas the strong positive sales effects from card acceptance provide evidence of merchants' fee insensitivity.

In my main counterfactual, I find substantial benefits from capping credit and debit card merchant fees at the cost of cash. Fee caps are common globally and approximate the effects of other important regulatory changes such as mandating dual routing or repealing anti-steering provisions (Zenger 2011; Durbin 2023). Such a policy would reduce credit card use, be progressive, and increase welfare. Lower merchant fees pass through to a 233 bp decline in credit card rewards. The combination of lower merchant fees and credit card rewards creates a progressive transfer. Lower retail prices benefit low-income consumers, whereas the decline in rewards hurts high-income consumers. Lower credit card use ultimately increases annual consumer and total welfare by $36 billion and $31 billion, respectively. For context, the CARD Act was a major piece of credit card legislation estimated to have increased consumer welfare by around $12 billion (Agarwal et al. 2015). Thus, the gains from regulating networks are at least as large as those from regulating issuers.

My model shows that uniform caps on merchant fees are essential for increasing welfare. The Durbin Amendment's caps on debit card interchange fees (a major portion of the merchant fee) were regressive and reduced total welfare by $8 billion. By cutting debit interchange, the policy eliminated debit card rewards, amplified credit card reward competition, and increased credit card use. Thus, my model shows that inconsistent regulation can be worse than no regulation.

In contrast to the large gains from improved price regulation, private competition is regressive and welfare-reducing. I study an extreme reduction in competition by merging all three networks. Because consumers are reward-sensitive, whereas merchants are fee-insensitive, the merger decreases total rewards and fees by $72 and $54 billion, respectively. The reduction in rewards redistributes consumption from higher-income consumers to lower-income consumers. Overall consumer welfare falls by $4.2 billion (S.E. 12.0) but total welfare rises by $20 billion (S.E. 7). These estimates show that competition exacerbates the excessive adoption of high-fee, high-reward payment methods. The model's predictions align with trends in the U.S., where competition between Visa, MC, and AmEx has driven up interchange fees (GAO 2009), and globally, where high-fee Buy Now, Pay Later products are expanding (Berg et al. 2022). Thus, revised regulation, not just more competition, is necessary to correct the market failure arising from price coherence in payment markets.

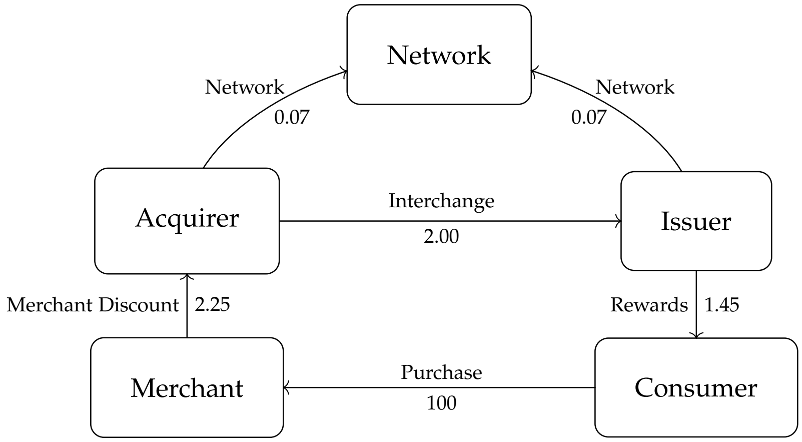
My model also speaks to proposals to increase competition through government entry. I model a public option as a debit payment network that charges no markups on merchants and pays no rewards. Before accounting for fixed development costs, public entry creates a modest $6 billion of benefits. The lack of rewards limits consumer adoption. Ultimately, the gains from a public option are smaller than those from repealing the Durbin Amendment.

I.A Related Literature

My paper primarily contributes to the industrial organization literature on two-sided markets by estimating a quantitative model of platform competition with variation from natural experiments (Rysman 2004; Lee 2013; Rosaia 2020; Song 2021). New theoretical work emphasizes that the effects of platform competition depend crucially on whether consumers single or multi-home (Anderson et al. 2018; Bakos and Halaburda 2020). By modeling a mix of single and multi-homing consumers, I provide a more realistic model of platforms' pricing incentives than past empirical work.

My paper contributes to the literature on the effects of platform pricing on off-platform outcomes (Bergemann et al. 2024; Chen 2024). With price coherence, merchant fees strongly influence off-platform retail prices, which helps explain the welfare gains I find from fee caps. In contrast, Sullivan (2023) finds that merchant commission caps

Figure 1: Illustration of payment flows in a payment network.



Notes: Prices are meant to capture typical fees paid. The merchant discount fee comes from Nilson (2020a). 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 (B. o. G. 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.

reduce welfare in food delivery markets, where price coherence is absent.

The closest related empirical work is Huynh et al. (2022), who also estimate 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, redistribute consumption, and ultimately hurt consumers. Network competition endogenizes merchant fees and consumer rewards, enabling me to assess how price controls and competition affect prices and total welfare.

I also contribute to the growing literature on the industrial organization of financial markets. Important examples include models of imperfect competition in deposit banking (Egan et al. 2017; Honka et al. 2017), mortgages (Allen et al. 2014; Buchak et al. 2020; Benetton 2021; Robles-Garcia 2022), credit cards (Nelson 2020; Cuesta and Sepulveda 2021), and insurance (Cohen and Einav 2007; Koijen and Yogo 2015). My contribution is to take a structural approach to a two-sided market of payments.

II Institutional Details and Data

II.A Network Pricing: Merchant Fees and Consumer Rewards

This section explains how payment networks influence merchant fees and consumer rewards. With every card swipe, the merchant pays a fee, and the consumer may receive a reward. While AmEx sets merchant fees and consumer rewards directly, "open-loop" networks like Visa and MC influence merchant and consumer prices by adjusting the *interchange fee* and *network fee*.

Visa and MC connect four types of players: merchants, merchants' banks (acquirers), consumers' banks (issuers), and consumers (Benson et al. 2017). Figure 1 illustrates the typical flow of money between these players with representative prices. When a consumer uses her credit card to buy \$100 of product 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 player like Square. The acquirer uses some of that fee to cover its costs but also sends around \$2 to the issuing bank (e.g., Chase) as interchange. The issuer and the acquirer collectively pay around \$0.14 in network fees to Visa. While some of the interchange covers the issuer's costs, a large part is returned to the consumer as a reward. On average, for a credit card, the rebate is \$1.45.

Regulatory shocks are the best evidence for how interchange strongly affects merchant fees and rewards while having limited effects on borrowing. When the E.U. and Australia mandated interchange fee reductions, merchant fees declined roughly one-for-one (Joshua S Gans 2007; Valverde et al. 2016; European Commission 2020). Appendix Figure A.12 shows that after the Reserve Bank of Australia capped credit card interchange, rewards fell, annual fees on rewards credit cards rose, whereas annual fees on non-reward credit cards and interest rates were left unchanged. One reason interchange has such a small effect on interest rates is that consumers who regularly carry balances generate 70% of the interest expense but only 10% of the purchase volume (Adams et al. 2022).

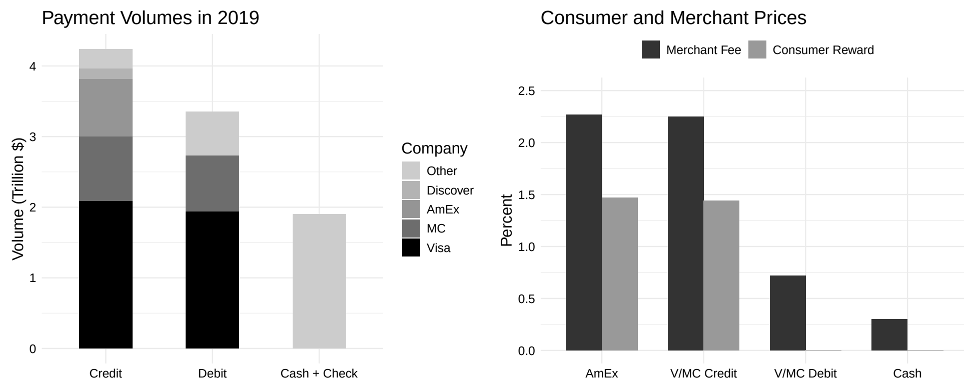
II.B Data

I use a variety of consumer-level, bank-level, and aggregate data to estimate consumer and merchant demand for payments. Appendix A contains more data construction details.

Aggregate Prices and Shares: I use the Nilson Report's aggregate payment volumes and merchant fees. I scrape average rewards data from the annual reports of the 7 largest banks, whose cards cover 80% of credit card purchase volumes. The Nilson Report also provides data on the number of merchants that accept cards. Figure 2 documents payment volumes, merchant fees, and rewards. Visa, Mastercard (MC), and American Express (AmEx) process 90% of all card payments. All three major credit card networks charge similar merchant fees of around 2.25%, whereas the debit networks charge around 0.7% due to the Durbin Amendment. I use these aggregate prices and shares to estimate consumer preferences, the network cost parameters, and merchants' fee sensitivity.

Issuer Payment Volumes: I construct an annual panel of issuer payment volumes from the Nilson Report. I use this panel to study the effects of the Durbin Amendment on

Figure 2: Aggregate payment volumes, merchant fees, and consumer rewards



Notes: The left chart shows payment volumes measured in trillions from Nilson (2020b, 2020c). Visa and MC own credit and debit cards, 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 (2020a) and rewards from banks' annual financial reports. Debit cards no longer offer rewards checking in the wake of Durbin (Hayashi 2012). The cost of cash is from Felt et al. (2020)

payment volumes. My main difference-in-difference analysis focuses on a subset of 39 issuers, 18 of them above $10 billion in assets and 21 below. My sample excludes issuers that made large acquisitions exceeding 50% of equity. Appendix Table A.14 reports summary statistics at the issuer level.

Homescan: The NielsenIQ Homescan panel tracks the payment decisions of around $100,000$ households at large consumer packaged goods stores. I use this to measure consumer multi-homing behavior and to evaluate the effects of card acceptance on sales. The key advantage of the Homescan data is that I see many transactions, making it more appropriate than other data for measuring how consumers allocate spending across the cards in their wallets. Appendix Table A.15 reports the main summary statistics at the household level. Appendix Table A.16 shows that Homescan slightly overrepresents cash and debit transactions while underrepresenting American Express.

Consumer Payment Surveys: I use three different survey datasets to understand consumer and merchant behavior. First, I combine the Atlanta Federal Reserve's Diary of Consumer Payment Choice (DCPC) and Survey of Consumer Payment Choice (SCPC) to build a transaction-level dataset on consumers' payment choices over three-day windows (Greene and Stavins 2021). Whereas Homescan oversamples large stores that accept cards, the DCPC allows me to measure transactions at small stores, enabling a better estimate of the share of transactions conducted at merchants that accept cards. Table 1 shows summary statistics on consumers' payment preferences. Cards are widely accepted for

Table 1: Summary statistics for different consumer types in the payment diary sample.

	Cash	Debit	Credit
Share	0.21	0.44	0.35
Pays with credit card	0.70	0.81	1.00
Owns rewards credit card	0.46	0.53	0.89
Pays with debit card	0.73	1.00	0.81
Owns bank account	0.88	1.00	0.99
Credit utilization	0.22	0.29	0.08
Household income (000's)	68.13	80.90	118.49
Card acceptance	0.94	0.96	0.97
Credit score above 650	0.67	0.70	0.97
Online transaction	0.19	0.27	0.28

Notes: Consumers are split into three groups: those who prefer to use cash as their main non-bill payment instrument, those who prefer debit, and those who prefer credit cards. The share variable reports the share of the sample in each column. Card acceptance is the expenditure share in each group of merchants that accept cards. All other variables report averages across consumers for each group. Online transaction reports the share of transactions that are done online.

around 95% of transactions.[4] 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. Second, I conduct a second-choice survey to estimate how consumers substitute between payment methods (Berry et al. 2004). Third, I use data from the MRI-Simmons Ultimate Study of Americans (USA) survey on consumers' use of financial services, demographic characteristics, and shopping behavior to study the sorting of consumers with different payment preferences across merchants.

III Reduced-Form Facts

This section presents reduced-form evidence to support models in which payment network competition increases merchant fees and consumer rewards. Theoretical models predict that platform competition tends to benefit the single-homing side and the side more responsive to fees or rewards (Rochet and Tirole 2003; Armstrong 2006). I use shocks to debit card rewards and credit card acceptance to show that consumers are reward-sensitive and merchants are fee-insensitive. I then show that whereas almost all merchants accept cards from every network, many consumers concentrate their spending on one network. Thus, theory predicts that competition benefits consumers at the cost of merchants. My empirical model builds on these observations to estimate consumer and merchant demand for payments.

[4]Appendix Table A.13 shows that most transactions in the survey are for grocery, shopping, and restaurants. Card acceptance is high in those sectors but low for general services.

III.A Consumers' Sensitivity to Rewards

I use a regulatory shock, the Durbin Amendment, to show that rewards strongly affect consumers' payment choices. Enacted as part of the 2010 Dodd-Frank Act, the Durbin Amendment capped debit interchange fees for banks and credit unions with over $10 billion in assets starting in October 2011 (Mukharlyamov and Sarin 2024). This law reduced large issuers' revenue from debit card transactions, prompting them to end debit rewards (Hayashi 2012; Schneider and Borra 2015). In contrast, many small issuers continued their debit rewards programs (Orem 2016).

I compare debit card volumes at large and small issuers to estimate the effect of rewards on payment volumes. I estimate:

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

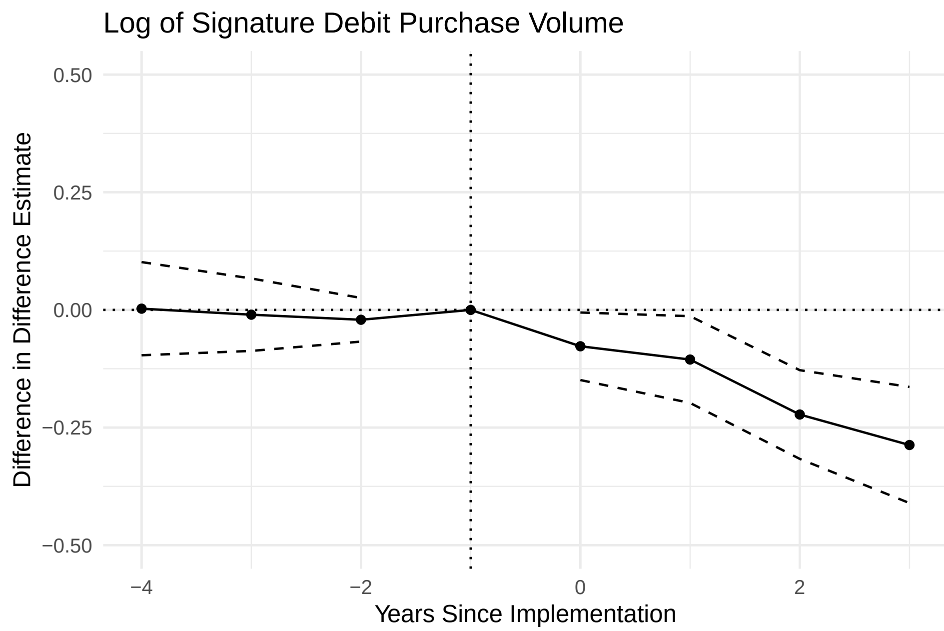
where y_{it} is the log of signature debit[5] purchase volume at issuer i, T_i refers to whether issuer i had more than $10 billion in assets in 2010, and δ_i and δ_t represent issuer and year fixed effects, respectively. I define $t = 0$ as 2011. I focus on institutions with between 2 and 200 billion in assets. By comparing large and small issuers, I difference out the effects of the Durbin routing requirements, the CARD Act, and potential changes in merchant acceptance on debit and credit card use.

The regression shows that consumers are sensitive to rewards. Using the Wayback machine, I confirm Hayashi (2009)'s estimates that the average pre-Durbin debit rewards program advertised rewards of around 25 bps of transaction value. Figure 3 plots the estimates and shows that reduced rewards led to a 29% decline in signature debit volumes.[6]

[5] I use signature debit to proxy for total debit transactions because the data coverage is better in the early part of the sample (Appendix Figure A.1). Figure A.15 shows the regression with overall debit volumes and shows that the share of debit transactions on signature cards did not change after Durbin.

[6] In the Appendix, I include additional results and robustness checks. Figure A.13 also shows that deposit growth did not change and that consumers at small banks were no more likely to report having switched banks in the past year when compared to consumers at large banks. These facts suggest that Durbin had an effect primarily by inducing consumers to switch between debit and credit within banks and not by inducing consumers to switch banks to earn debit card rewards. Table A.21 shows the regression estimates and validates that my estimated interchange decline is consistent with Durbin's effect, given that credit interchange was not affected and made up around one-third of total interchange revenue. Figure A.16 shows that the pre-policy debit versus credit mix at the treatment and control issuers were similar. Figure A.18 shows the distribution of institution-level estimates in both the treatment and control groups to verify that outliers do not drive the results in either group. Figure A.14 verifies that the decline in debit card volumes at large banks is not driven by a relative increase in credit card rewards for the consumers who have deposit accounts at large banks. Figure A.17 shows that the estimates are robust to varying the minimum and maximum asset cutoffs.

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-difference estimates of the effects of the Durbin Amendment on debit card volumes. Dashed lines show 95% confidence intervals. The vertical line marks the year before the policy implementation in Q3 2011, which is $t = 0$. Standard errors are clustered at the issuer level.

III.B Merchant Benefits from Card Acceptance

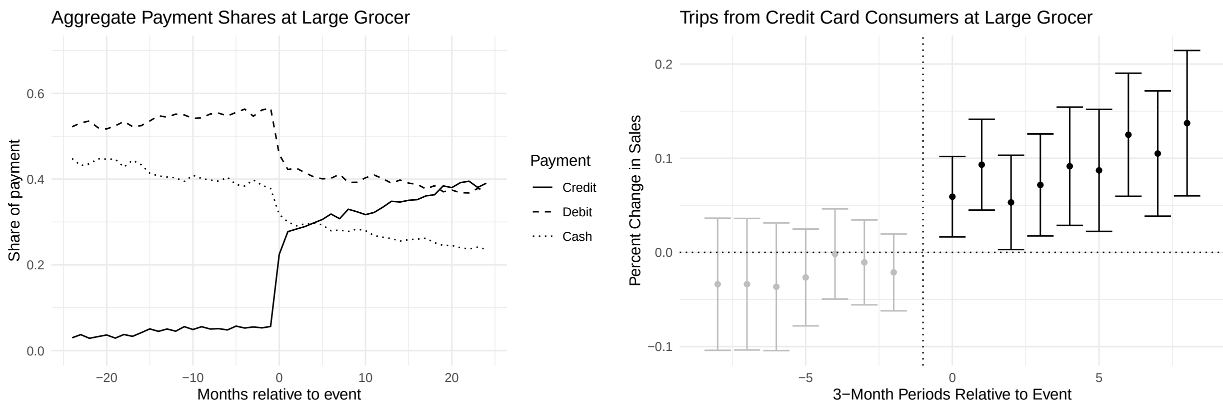
After a large U.S. grocer began accepting credit cards in addition to debit cards, credit card consumers shopped more at the retailer. Sales increased because consumers value the flexibility of paying with their preferred payment method and not because consumers could earn more rewards. The evidence from this case suggests that the revenue gains from card acceptance outweigh the incremental costs for most merchants, even at high merchant fees.

III.B.1 The Effects of Accepting Credit Cards

I use a triple-difference approach to estimate how much credit card acceptance increases sales to credit card consumers. Conceptually, I combine two empirical strategies. First, I compare spending patterns between credit card and non-credit card consumers at the treated grocer before and after credit card acceptance. Second, I refine the estimate by comparing these same consumer groups across all other grocers. My final estimate subtracts the difference between these two comparisons.

Figure 4: The effects of credit card acceptance at a large U.S. grocer.

(a) Payment mix **(b)** Effects on the number of trips



Notes: Data is from Homescan. The left panel tracks the monthly evolution of payment methods at the grocer that started accepting credit cards. The right panel presents quarterly estimated coefficients from a triple-difference model of the effect of credit card acceptance on the number of shopping trips by credit card users. The coefficients reflect percentage changes in the number of trips, and the error bars show 95% confidence intervals. The reported credit card purchases prior to the event reflect measurement error from consumers' reporting of the payment method, see footnote 8.

The estimating equation for the dynamic specification is:

$$\begin{aligned} y_{ijt} &\sim \text{Poisson}\left(\lambda_{ijt}\right) \\ \lambda_{ijt} &= \alpha_{z(i)jt} + \delta C_i + \phi T_j C_i + \sum_{k \neq -1} \beta_k C_i I\{t = k\} + \sum_{k \neq -1} \gamma_k C_i T_j I\{t = k\} \end{aligned} \tag{2}$$

where y_{ijt} is the number of trips by consumer i at retailer j in quarter t, $\alpha_{jtz(i)}$ are retailer-quarter-zip code fixed effects, T_j is an indicator for the treated grocer, and C_i is the credit card share of payments for consumer i, measured in the year prior to the event. I use the number of trips as my main proxy for sales because dollars per trip can exhibit fat tails. I index $t = -1$ as the quarter before adoption. The coefficients of interest are γ_k, which capture the dynamic effects of credit card acceptance on sales to credit card consumers. I estimate the model using Poisson regression, so the coefficients γ_k should be interpreted as percentage increases in sales. This strategy is robust to changes in the general popularity of grocers over time and regions (α), baseline differences in shopping patterns between credit card and non-credit card consumers (δ, ϕ), and the possibility that credit card users experience higher income growth than other consumers (β).[7]

Consumers changed their payment and shopping behavior after the grocer began accepting credit cards. Figure 4a shows how the share of trips by different payment methods evolved, with credit card transactions making up 40% of total payments two years

[7] Appendix Figure A.19 shows the double-difference estimates and that credit card consumers have a different trend in the number of trips.

after the change.[8] Figure 4b shows the estimated dynamic effects, indicating that trips by credit card users increased by approximately 15% following the grocer's decision.[9]

III.B.2 Mechanism for Sales Increase

Credit card users shop more at the grocer because consumers value the flexibility of paying with credit -— not because of rewards. I distinguish between the two hypotheses by analyzing Discover's quarterly 5% cashback program, which periodically offers rewards at grocery stores but not at discount or warehouse stores.[10] Past work has shown that consumers treat these two types of retailers as close substitutes (Ellickson et al. 2020).

Consumers do not appear to change their shopping decisions in response to rewards. Figure 5a plots time series of the share of trips to grocery stores versus discount/warehouse stores for Discover and non-Discover consumers. The grey areas in the chart highlight when Discover's rewards for grocery stores were active. One would expect more grocery trips during reward periods by Discover consumers compared to non-Discover consumers if rewards influenced shopping behavior. Instead, Discover and non-Discover users shop similarly during rewards periods.

The data suggest that consumers have strong non-price motivations -— such as liquidity constraints, budgeting preferences, or transaction size -— to use debit or credit for a given transaction.[11] Figure 5b plots how Discover users pay at grocery stores over time. If debit and credit were interchangeable at the transaction level, we would expect some debit volume to shift towards Discover during the reward periods. Instead, the plot shows that the rewards incentivize consumers to reduce their use of other credit cards while leaving their use of debit cards unchanged.[12] The strong effect of rewards

[8] The reported credit card purchases prior to the event reflect measurement error from consumers' reporting of the payment method. Although past work by Cohen and Rysman (2013) has raised concerns that consumers are confused about the distinction between signature debit cards and credit cards, Appendix Table A.16 shows that the self-reported data lines up well on average with aggregate payment statistics.

[9] Appendix Table A.22 shows the estimated coefficients when y is the number of trips and the total dollars spent.

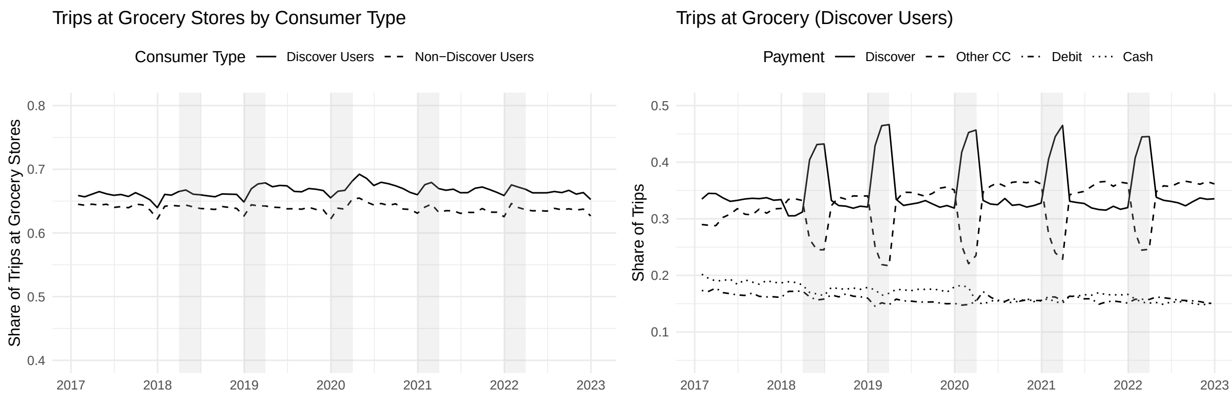
[10] Appendix B.1 shares more institutional details and discusses extensive robustness checks in interpreting the cashback program.

[11] Merchant testimony in Appendix B.5 highlights that credit cards are strongly preferred for larger ticket sizes because of the credit line. Appendix B.3.2 presents indirect evidence from merchants' card acceptance decisions supporting this segmentation.

[12] Although credit and debit cards are not substitutes at the transaction level, they can still be substitutes at the adoption stage. Appendix C.7 formalizes the distinction between adoption and usage in a two-stage model as in Koulayev et al. (2016). Transaction-specific rewards do not change usage decisions if a consumer has rigid transaction-specific preferences over credit or debit. However, offering rewards on all her debit transactions can still tip her decision about which card to adopt. The distinction be-

Figure 5: Effects of Discover's quarterly reward program at grocery stores

(a) Share of transactions at grocery stores **(b)** Payment mix at grocery stores



Notes: Grey shaded areas indicate quarters where Discover offers 5% cash back at grocery stores but not at discount retailers, warehouse stores, or other retailers. The left panel shows how shopping decisions for Discover and non-Discover consumers across retailer types change in response to the rewards. The right panel shows how the payment mix responds to the rewards. Shares are measured as a percentage of trips. Both samples condition on consumers that have transactions on Discover.

on the use of Discover also addresses concerns that the lack of a sales response is purely due to consumer inattention. This result suggests that consumers view credit and debit cards as offering distinct transaction services. When this is the case, accepting credit in addition to debit can increase sales.

III.B.3 The Profitability of Credit Card Acceptance

The estimated sales effect suggests that credit card acceptance is highly profitable for most grocers. Given that credit card fees are around 1.5 pp. higher than debit card fees, credit card acceptance is profitable as long as margins exceed 20%.[13] Census statistics indicate gross margins in the grocery industry were around 27% during this period, suggesting that credit card acceptance is profitable for most merchants. Increases in credit card fees should, therefore, have only a small effect on merchant acceptance.

III.C Consumer and Merchant Multi-homing

The effects of platform competition depend crucially on whether consumers and merchants transact across multiple platforms—that is, their multi-homing behavior. While most merchants accept all cards, only around 60% of consumers use cards from two credit card networks. As a result, merchants are compelled to meet consumers where

tween usage and adoption explains why broad, permanent shifts in rewards—such as those following the Durbin Amendment—can induce substantial substitution between credit and debit, whereas short-term, transaction-specific incentives—such as Discover's cashback—do not.

[13]At such a profit margin, profits to credit card consumers increase by $0.20 \times 0.15 = 0.03$ per dollar of debit sales whereas fees paid for these consumers increase by $2 \times 0.015 \approx 0.03$ per dollar of debit sales.

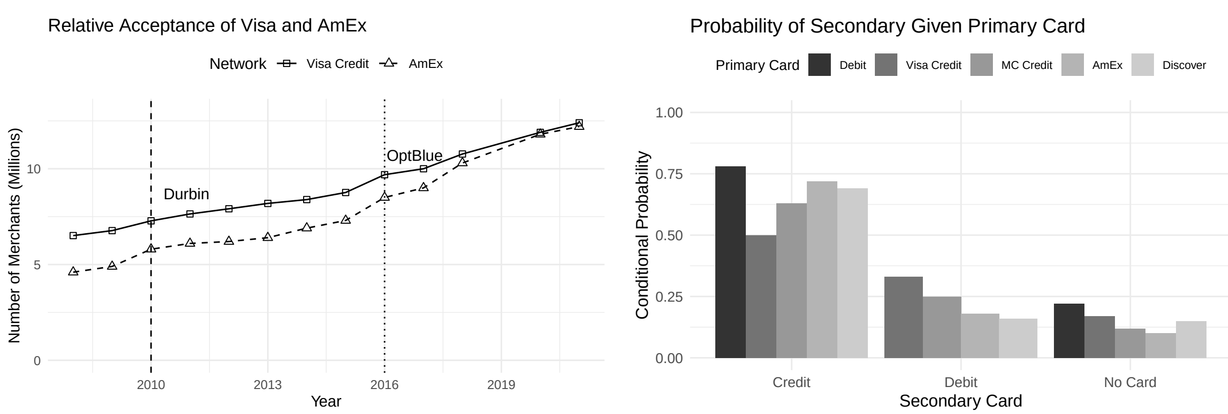
they are by accepting the payment methods consumers prefer. This dynamic limits merchants' ability to refuse high-fee credit cards, reducing competitive pressure on merchant fees.

III.C.1 Almost All Merchants Multi-home

Most merchants accept either all credit cards or none at all. I draw this conclusion from two key observations. First, Yelp reviews from before 2017 suggests that merchant strategies follow a hierarchical pattern, ranging from cash-only to progressively including debit cards, Visa with MC, and then AmEx (Appendix B.2). Second, by 2019 the number of merchants that accept AmEx approximately equals the number of merchants that accept Visa. Figure 6a plots data from the Nilson Report on the number of merchants that accept Visa and AmEx. Since every Visa/MC merchant also accepts AmEx, almost all merchants accepting credit cards accept cards from all three networks.

Figure 6: Consumer and merchant multi-homing behavior and network fees

(a) Merchant acceptance of Visa and AmEx **(b)** Probability of multi-homing consumers



Notes: The left panel uses data from the Nilson Report to illustrate the closing gap in the number of merchants accepting Visa and AmEx. The dotted lines mark the imposition of the Durbin Amendment which reduced debit card merchant fees and the start of AmEx's OptBlue program that cut AmEx's merchant fees. The right panel uses data from Homescan and shows the probability that consumers use a secondary credit card, secondary debit card, and no secondary card, conditional on different primary cards.

III.C.2 Many Consumers Single-home

Only around 60% of consumers carry credit cards from multiple networks. Since accepting credit cards increases sales, merchants risk substantial sales if they reject cards from one network even while accepting others. I study consumer multi-homing behavior using the Homescan shopping data. For this analysis, I define a network as Visa credit, MasterCard (MC) credit, AmEx, or any debit card.[14] In Appendix Table A.20, I find that

[14]Even though Homescan groups Visa debit and MC debit together, this does not affect the interpretation of primary and secondary cards because data from the DCPC shows that almost no consumers use

consumers put around 95% of their card spending on two networks. Given this fact, I characterize household-years by their primary and secondary cards, in which their primary card is the most-used network, and the secondary card is the second-most used network.[15]

Figure 6b shows data on consumer multi-homing behavior. The first set of bars shows the share of consumers that carry a secondary credit card as a function of their primary card. Around 60% of primary credit card consumers carry credit cards from multiple networks. Among primary credit card users, Visa users have the lowest multi-homing rate of 50%, whereas AmEx users have the highest rate around 72%.The remaining credit card consumers are roughly split between secondary debit cards and just using one credit card. Thus, merchants have a limited ability to steer consumers between credit card networks.

III.D Summarizing the Reduced-Form Facts

The sharp drop in debit volumes after the Durbin Amendment shows that consumers respond strongly to rewards. On the other side of the market, the large effect of card acceptance on sales and limited consumer multi-homing suggest that merchants who reject cards from high-fee credit card networks risk large declines in sales (Facts 2 and 3). Consumers are reward-sensitive, and merchants should be fee-insensitive; competition creates only weak incentives for networks to cut merchant fees.

However, these reduced-form results are not sufficient. Existing models produce clear predictions only when all or none of the consumers multi-home (Teh et al. 2022). Since some consumers multi-home whereas others single-home, I estimate a quantitative model to assess the effects of regulation and competition in payment markets.

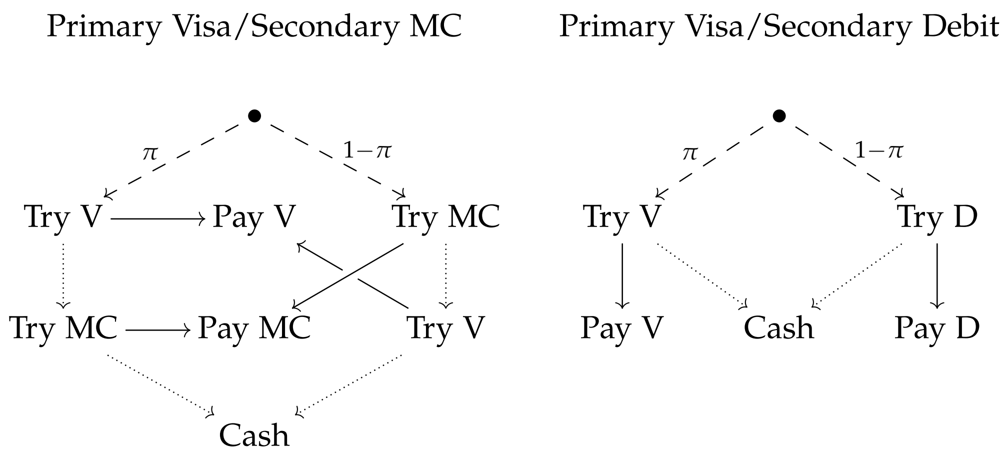
IV Model

I develop a model of competing payment networks. The model captures three key features crucial for determining the effects of platform competition: consumer multi-homing, merchant heterogeneity, and merchant competition. After estimating the model, I solve it under different conditions to assess how changes in competition and regulation affect equilibrium prices, quantities, and welfare.

multiple debit cards for day-to-day purchases. I show this fact in Figure A.25

[15]These usage shares reflect consumer preferences rather than merchant acceptance policies. Most of the merchants in Homescan are large and accept all major payment methods. To be conservative, I exclude merchants with a particularly low share of transactions from any network. I discuss this in detail in the Data Appendix A.

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



Notes: Solid lines denote actions taken when the payment method is accepted, and dotted lines indicate what happens when a payment method is declined. Dashed lines indicate moves by nature. The left chart shows that with probability π, a primary Visa and secondary MC consumer will try to pay with Visa, then MC, and then cash. With probability $1-\pi$, the order of Visa and MC are reversed. The right diagram shows that consumers who multihome on credit and debit cards do not substitute between them when one is not accepted

IV.A Structure of the Game

I model competition between card networks as a static game with three stages and three kinds of players: 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 consumers' and merchants' demand for payments. In the first stage, networks compete while facing these demand curves. Consumers vary in their income and preferences over payment methods, whereas merchants vary in how much card acceptance increases their sales to card consumers. The model makes several simplifying assumptions I discuss in Section IV.F.

IV.B Stage 3: Consumer Shopping and Payments

In the third stage, consumers make payment and consumption decisions.

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

At the point of sale, consumer payment behavior is determined by their primary and secondary cards and the cards the merchant accepts. Due to decisions earlier in the game, consumers carry zero, one, or two cards. Consumers who do not carry cards pay with cash. Consumers who carry one card pay with it if the merchant accepts it and otherwise pay with cash.

Consumers who carry two cards can potentially substitute between them if they are the same type (i.e., credit or debit). Figure 7a shows this case. One card is designated as the primary card. With probability π, the consumer first tries to pay with the primary card. If the primary card is not accepted, the consumer tries to pay with the secondary card. If the secondary card is not accepted, the consumer pays with cash. With probability $1-\pi$, the roles of the primary and secondary cards are reversed.[16] If the two cards are not the same type, then consumers do not substitute between them.[17] Figure 7(b) illustrates this alternative. At merchants that accept all of the cards, this simple model matches the evidence on how multi-homing consumers split their spending across cards.

Formally, define the set of all inside payment methods (i.e., cards) as $\mathcal{J}_1 = \{1, \ldots, J\}$, 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

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

Based on the payment process described above, let $\pi^w_{M,j}$ be the probability that a consumer with wallet w pays with an inside payment option $j > 0$ when the merchant accepts the cards $M \subset \mathcal{J}_1$.[18] When $j = 0$, define $\pi^w_{M,0} = 0$ for all w.

IV.B.2 Consumption Decisions Over Merchants

Card consumers spend γ percent more when they use their card, where the value of $\gamma \sim G$ varies across merchants. Thus, merchants in the model accept cards to increase sales, and the total sales increase depends on the merchant's type γ and the share of consumers who want to use cards.[19] I use constant-elasticity of substitution (CES) preferences to model how consumers allocate their spending across merchants subject to a budget constraint. The budget constraint means that card acceptance reallocates

[16] 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.

[17] Section III.B.2 presents evidence that credit and debit cards provide distinct transactional services.

[18] Appendix Table A.23 explicitly works out these probabilities in a simplified model with Visa and MC as two credit cards and then one debit card.

[19] A low γ firm may be a small business with loyal customers for whom the payment method is unimportant. A high γ firm may be an e-commerce firm that benefits from significantly higher sales if the checkout process is convenient. The outside option of cash for an e-commerce firm can be interpreted as a gift card or some other payment mechanism whose pricing is not determined by the payment networks. Because merchants accept cards to increase sales, card acceptance can be excessive because of a partial form of merchant internalization (Rochet and Tirole 2002; Wright 2012). One dimension of heterogeneity matches hierarchical payment acceptance (Appendix B.2).

spending rather than increasing overall spending.

Suppose that all other merchants charge prices $p^*(\gamma)$ and accept payment methods $M^*(\gamma) \subset \mathcal{J}_1$. Suppose a given merchant of type γ sets a price p and accepts payment methods $M \subset \mathcal{J}_1$. In Appendix C.1, I show that a consumer with wallet $w = (w_1, w_2)$, exogenous baseline income[20] y, and percentage lump sum rewards f^w buys q^w, where:

$$q^w(\gamma, p, M, y) = (1 + \gamma\pi_M^w) \times \frac{p^{-\sigma}}{(P^w)^{1-\sigma}} \times y \times (1 + f^w) \tag{3}$$

$$(P^w)^{1-\sigma} = \int \left(1 + \gamma\pi^w_{M^*(\gamma)}\right) p^*(\gamma)^{1-\sigma} \, \mathrm{d}G(\gamma) \tag{4}$$

$$\pi_M^w = \pi_{M,w_1}^w + \pi_{M,w_2}^w$$

In this demand function, π_M^w captures the probability that the consumer pays with a card.[21] The price index P^w summarizes the influence of other merchants' actions. Under the CES interpretation, payment acceptance increases product quality through convenience, and rewards increase income by a fixed percentage.[22]

This demand specification has several features. First, sales only depend on the probability that a card is used and not on which card is used. Consumers who carry multiple credit cards buy the same amount if either credit card is accepted. Second, consistent with the evidence in Section III.B.1, rewards do not affect relative consumption choices across merchants.

In equilibrium, there is a function q^{w*} such that a consumer with baseline income y optimally consumes $y \times q^{w*}(\gamma)$ from each merchant type γ, given all merchants' equilibrium pricing p^* and adoption M^* decisions:

$$q^w(\gamma, p, M, y) = y \times q^{w*}(\gamma) \tag{5}$$

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

Merchants maximize profits by choosing prices and payment acceptance. Profits equal per-dollar quantities q^w multiplied by margins, weighted by the spending power of consumers with different payment preferences. I assume that the only cost of accepting

[20]The exogeneity of income means that there are no deadweight losses from consumers under-consuming due to higher merchant fees. In an extended model with elastic labor supply, high merchant fees create an additional distortion by reducing labor supply.

[21]By defining $\pi_{M,j}^w = 0$, $\pi_M^w = \pi_{M,w_1}^w + \pi_{M,w_2}^w$ captures both the probability a single-homing consumer uses the primary card and the probability that a multi-homing consumer uses either the primary or secondary card.

[22]In reality, rewards may incorporate other perks. If reward programs create gains from trade, I assume those gains are independent of the level of fees.

payments is the merchant fee. Thus I ignore any fixed costs of adoption. Appendix C.2 shows that merchant profits can be expressed as

$$\Pi(\gamma, p, M) = \sum_{w \in \mathcal{W}} \tilde{\mu}^w \times q^w(\gamma, p, M, 1) \times \left[p \left(1 - \frac{(1+\gamma)\tau_M^w}{1+\gamma\pi_M^w} \right) - 1 \right] \tag{6}$$

$$\tilde{\mu}^w = \int \tilde{\mu}_y^w y \, \mathrm{d}F(y) \tag{7}$$

where $\tilde{\mu}_y^w$ is the market share of wallet w among consumers with baseline income y, F is the distribution of income, τ_j is the per-dollar fee for transactions on card j, and $\tau_M^w = \sum_{j=1}^J \pi_{M,j}^w \tau_j$ is the average fee associated with a wallet w consumer at a merchant with type $\gamma = 0$. The income-weighted market share $\tilde{\mu}^w$ weights consumers' payment choices by their incomes. The above expressions for profits yield simple expressions for optimal pricing and acceptance strategies.

IV.C.1 Merchant Pricing

Conditional on the payment acceptance decision M, merchants optimally pass the average transaction fee uniformly to all consumers. Appendix C.3 shows that the optimal price is

$$\hat{p}(\gamma, M, \tau) = \frac{\sigma}{\sigma - 1} \times \frac{1}{1-\hat{\tau}}, \hat{\tau} = \frac{\sum_w \mu^w \tau_M^w (1+\gamma)}{\sum_w \mu^w \left(1 + \pi_M^w \gamma\right)} \tag{8}$$

where the average fee uses *demand shares* μ^w, which are normalized weighted sums of the income-weighted market shares $\tilde{\mu}^w$. These demand shares are defined as:

$$\mu^w = \frac{1+f^w}{(P^w)^{1-\sigma}} \times \frac{\tilde{\mu}^w}{C}, C = \sum_w \frac{1+f^w}{(P^w)^{1-\sigma}} \times \tilde{\mu}^w \tag{9}$$

Demand shares are necessary because the composition of a given merchant's consumer base depends on the acceptance decisions of other merchants. As more merchants accept cards, card consumers divert their spending away from the remaining cash-only merchants and toward the card-accepting merchants. The demand shares capture this influence through the price index P^w.

The merchant type γ also affects the optimal price by changing the composition of consumers. When high γ merchants accept cards, they attract more card consumers when compared to a low γ merchant that accepts cards. Retail prices differ as a result.

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

$$\hat{p}(\gamma, M^*(\gamma), \tau) = p^*(\gamma) \tag{10}$$

IV.C.2 Merchant Acceptance

Merchants' acceptance decisions trade off the benefits of additional sales against the costs of paying higher merchant fees. Let $\widehat{\Pi}(\gamma, M)$ be the profit function from accepting a particular subset of payments $M \subset \mathcal{J}_1$, accounting for the optimal price. In Appendix C.4, I derive and validate a fast approximate algorithm for optimizing $\widehat{\Pi}$ over M. This yields an optimal acceptance strategy $\widehat{M}$:

$$\widehat{M}(\gamma, \tau) = \underset{M \subset \mathcal{J}_1}{\operatorname{argmax}} -a_M + b_M \gamma \tag{11}$$

$$a_M = \sum_{w \in \mathcal{W}} \mu^w \tau_M^w, \; b_M = \frac{1}{\sigma} \sum_{w \in \mathcal{W}} \mu^w \left(\pi_M^w - \sigma \tau_M^w\right) \tag{12}$$

Intuitively, the intercept a_M captures the loss from paying fees, whereas b_M captures the profits from higher sales. Both terms depend on the number of consumers who adopt a given card.

Adding a more expensive card incurs fees from both multi-homing and single-homing consumers who use the card but increases sales only from the single-homers. Thus, merchants accept only the lowest-fee network if all consumers multi-home across credit card networks. Appendix C.4.1 verifies these intuitions in a simple two-card economy. The relationship between consumers' card holdings and merchant acceptance means that merchants' sensitivity to fees depends on the distribution of merchant types G and consumer behavior.

In equilibrium, merchants adopt optimal bundles given the optimal adoption and pricing behavior of other merchants:

$$\widehat{M}(\gamma, \tau) = M^*(\gamma) \tag{13}$$

IV.C.3 Consumer Adoption

Consumers choose up to two cards to put in their wallet, and are more likely to choose cards that pay high rewards and are widely accepted. The utility from a wallet w for a consumer i is

$$\log V_i^w = \log U^w + \frac{1}{\alpha_i}\left(\Gamma_i^w + \epsilon_i^w\right) \tag{14}$$

where U^w is the consumer's pecuniary utility, α_i is the consumers' rewards-sensitivity, Γ_i^w represents mean non-pecuniary utility, and ϵ_i^w are wallet-level T1EV shocks. I discuss the definitions of each of these terms below.

Pecuniary Utility: Card adoption brings consumers pecuniary benefits through rewards and payment convenience. For single-homing consumers, I define the pecuniary utility term as

$$\log U^w = f^w - \log P^w, w \in \{(j,0), j \in \mathcal{J}_1\} \tag{15}$$

where f^w represents percentage, lump sum, rewards and P^w is the CES price index from Equation 4. The pecuniary utility for single-homing agents is micro-founded in the consumer's optimal consumption problem across merchants. The optimized value of log utility for a consumer with CES preferences that generate the demand curve in Equation 28 is approximately $\log U^w$.[23] A one percentage point increase in rewards and a one percent increase in retail prices cancel out each other's effects on pecuniary utility. Thus, there are no mechanical reasons for increases in rewards and merchant fees to reduce welfare. When payment methods are more widely accepted, this increases utility by reducing the price index in Equation 4.

Pecuniary utility for multi-homing agents is defined to be the weighted average of the single-homing pecuniary utilities of the cards in their wallet.[24] Thus

$$\log U^w = \pi \log U^{(w_1,0)} + (1-\pi) \log U^{(w_2,0)}, w = (w_1, w_2) \in \mathcal{J}_1 \times \mathcal{J}, w_1 \neq w_2 \tag{16}$$

This specification rules out the possibility that Visa complements AmEx more when Visa is accepted at more stores that do not accept AmEx. Appendix F.7 shows that an alternative model that captures this acceptance complementarity is inconsistent with the data on consumer multi-homing.

Rewards Sensitivity: Rewards sensitivity differs by income, so that

$$\log \alpha_i = \log \alpha_0 + \alpha_y \times \log y$$

and α_y represents the elasticity of reward-sensitivity with respect to income.

Non-pecuniary Utility: The non-pecuniary utility terms capture variation in preferences with income, unobserved preference heterogeneity, within-wallet complementarities, and adoption costs. Let the characteristics of card j be $X^j = \left(X_k^j\right)_{k=1}^K \in \mathbb{R}^K$. The

[23] I use the approximation $\log(1+f^w) \approx f^w$, which is accurate given that rewards are around 1%. This approach avoids any spurious total surplus gains that could arise due to the discrepancy between consumers' decreasing marginal utility of income and the networks' objective of profit maximization.

[24] The pecuniary utility for multi-homing agents differs from the micro-founded solution because it incorporates the weighted sum of the single-homing price indices rather than the true price index of the multi-homing consumer P^w. While the modifications introduce a discrepancy between pecuniary utility and the true maximized utility from the consumption problem for multi-homing agents, the two values differ only when card acceptance varies across networks. Since card acceptance across credit card networks is symmetric in all of the counterfactuals, the modification does not affect the equilibrium welfare numbers.

mean non-pecuniary utility for consumer i is

$$\Gamma_i^w = \omega\left(\Xi^{w_1} + \beta_i X^{w_1}\right) + (1-\omega)\left(\Xi^{w_2} + \beta_i X^{w_2}\right) + \sum_{l=1}^{K}\sum_{m=1}^{K} \chi_{lm} X_l^{w_1} X_m^{w_2} \tag{17}$$

where Ξ^j is the mean unobserved utility for a given card, β_i is consumer i's value from the characteristics, ω is the weight put on the characteristics of the primary card, and χ_{lm} are various interaction terms that capture potential within-wallet complementarity or substitution effects. I also let the consumer-specific preferences be distributed normally with a mean that depends on income and a fixed covariance matrix $\beta_i \sim N\left(\beta_y \cdot \log y, \Sigma\right)$. Payment preferences thus depend on income, and consumers substitute more between products with similar characteristics.

Appendix C.7 develops a two-stage model with adoption and usage as in Koulayev et al. (2016) to microfound these parameters. In such a model, the β_i and the intercepts Ξ capture the benefit of using a card of a given type net of adoption costs. A positive value of χ captures the possibility that consumers may multi-home on credit and debit cards to take advantage of their distinct transaction services or that consumers may receive complementary rewards from holding multiple credit cards. A negative value of χ can capture incremental adoption costs of carrying two cards instead of one.

Choice Probabilities: The parametric assumptions on the random coefficients yield the following expressions for choice probabilities. Let μ_i^w denote the probability that consumer i chooses wallet w and μ_y^w denote the probability that a consumer with income y chooses wallet w. These are:

$$\tilde{\mu}_i^w = \frac{\exp\left(\alpha_i \log U^w + \Gamma_i^w\right)}{\sum_{m\in\mathcal{W}} \exp\left(\alpha_i \log U^m + \Gamma_i^m\right)} \tag{18}$$

$$\tilde{\mu}_y^w = \int \tilde{\mu}_i^w \, \mathrm{d}H\left(\beta_i\right), \beta_i \sim N\left(\beta_y \cdot \log y, \Sigma\right) \tag{19}$$

IV.D Stage 1: Network Competition

In the first stage of the game, multiproduct payment networks maximize profits, anticipating consumer and merchant actions.

IV.D.1 Profits

Network profits equal transaction fees charged to merchants minus costs and the rewards paid to consumers. Profits from transaction fees T_j equal the transaction margin multiplied by the total dollars spent

$$T_j = \left(\tau_j - c_j\right) d_j \tag{20}$$

$$d_j = \sum_{w \in \mathcal{W}} \tilde{\mu}^w \times \int \frac{(1+\gamma)\, \pi^w_{M^*(\gamma),j}}{1 + \gamma \pi^w_{M^*(\gamma)}} q^{w*}(\gamma)\, p^*(\gamma)\ \mathrm{d}G(\gamma) \tag{21}$$

where c_j is the cost of processing \$1 on method j. The total cost of rewards is:

$$S_j = f^j \left(\tilde{\mu}^{(j,0)} + \sum_{k>0, k \neq j} \pi \tilde{\mu}_y^{(j,k)} + (1-\pi)\, \tilde{\mu}_y^{(k,j)} \right) \tag{22}$$

where f^j is the reward paid to a consumer that single-homes on j. The terms inside the parentheses capture the rewards paid to single-homers, those paid to multi-homers who primarily use j, and those who use j as a secondary card.

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

$$\Psi_n = \sum_{j \in \mathcal{O}_n} \left(T_j - S_j\right) \tag{23}$$

IV.D.2 Conduct and Equilibrium Determinacy

Networks maximize profits by setting transaction fees τ_j and consumers' pecuniary benefits A_j from payment adoption, given the actions other networks take. Equivalently, networks set consumers' expectations of merchant acceptance, fees, and rewards of their own network given consumers' expectations for other networks' acceptance and rewards. The pecuniary adoption benefit A_j compares rewards as well as increased payment convenience relative to the option of only paying with cash:

$$A_j = \log U^{(j,0)} - \log U^{(0,0)} = f^j - \left(\log P^{(j,0)} - \log P^0 \right) \tag{24}$$

Networks then set promised benefit levels A_j^* and transaction fees τ_j^* for the cards that they own $\mathcal{O}_n$ to maximize expected profits assuming small trembles in all networks' actions:

$$\left(A_j^*, \tau_j^*\right)_{j \in \mathcal{O}_n} = \underset{\left(\overline{A}_j, \overline{\tau}_j\right)_{j \in \mathcal{O}_n}}{\operatorname{argmax}} \ \mathbb{E}\left[\Psi_n\left(A_j, \tau_j, A_{-j}, \tau_{-j}\right)\right] \tag{25}$$

$$A_j \sim N\left(\overline{A}_j, \nu_x^2\right), \tau_j \sim N\left(\overline{\tau}_j, \nu_x^2\right), A_{-j} \sim N\left(A^*_{-j}, \nu_x^2\right), \tau_{-j} \sim N\left(\tau^*_{-j}, \nu_x^2\right)$$

Small trembles help pick an equilibrium when profits are not differentiable in merchant fees (Teh et al. 2022). I set $\nu_x = 10^{-4}$ in my simulations. The trembles can be interpreted as arising from small amounts of fee heterogeneity across merchants. Appendix C.8 discusses the details of my conduct assumption.

IV.E Equilibrium

Equilibrium is characterized by fees τ^*, adoption benefits A^*, market shares $\tilde{\mu}_y^w$, merchant prices $p^*(\gamma)$, merchant adoption strategies $M^*(\gamma)$, consumption $q^{w*}(\gamma)$ such that consumption across merchants is optimal for every wallet type (5), merchant pricing and acceptance maximize profits (10 and 13), consumers choose the optimal payment methods to reflect their preferences (18), and private networks maximize their profits (25). Appendix C.9 contains details on how to solve the model.

IV.F Discussion of Key Assumptions

In this section, I discuss the key assumptions and model predictions.

IV.F.1 Issuers and Acquirers

My model abstracts from issuers and acquirers; networks directly set merchant fees and consumer rewards. This assumption is accurate for proprietary networks like AmEx or fintechs like PayPal, for whom there are no issuers or acquirers. In the case of Visa and MC, this abstraction requires that Visa, the issuers, and acquirers internalize each others' profits. In practice, Visa pays around one-fifth of its gross revenue in incentive payments to issuers and acquirers (Visa 2020). By excluding issuers and acquirers, I cannot model how issuers, acquirers, and Visa split profits.

IV.F.2 Pass-through of Merchant Fees into Prices

Merchants fully pass on merchant fees to higher prices because consumers have CES preferences. Appendix F.6 extends the model to allow for an arbitrary degree of pass-through. Incomplete pass-through means that reductions in merchant fees benefit merchants rather than cash and debit card consumers. Otherwise, the predictions for merchant fees, rewards, market shares, and total welfare are largely unchanged.

From a theoretical perspective, full pass-through is consistent with the macro literature that shows firms fully pass through sector-level cost shocks (Amiti et al. 2019). Since almost all merchants accept cards, increasing merchant fees affects all firms and pass-through should be complete. My results with full pass-through also understate consumers' losses from less variety if merchants instead absorb the merchant fees in the form of lower profits and subsequently exit. The extra losses follow from the fact that entry and pricing are efficient under CES demand and inelastic labor supply (Dhingra and Morrow 2019).

IV.F.3 Price Coherence

I assume price coherence: merchants in the model charge the same price to consumers who use different payment methods. Appendix D discusses the history, empirics, and theory of price coherence. Fewer than 5% of transactions in the U.S. feature payment-specific pricing even though discriminatory pricing is largely legal, and observed discounting and surcharging behavior does not correlate with the stringency of past state-level laws (Levitin 2005; Stavins 2018; CardX 2023). When I extend my baseline model to incorporate card surcharges, I estimate the typical merchant gives up less than 20 basis points of profits from uniform pricing. Even small reputational costs overwhelm the benefits of surcharging.[25]

IV.F.4 One Dimension of Merchant Heterogeneity

Merchants in the model differ only in how much they benefit from card acceptance. I make this assumption to rationalize why merchant acceptance is hierarchical. A shortcoming of a one-dimensional model of merchant heterogeneity is that it ignores the possibility that cash, debit, and credit card consumers shop at different sets of stores (Joshua S. Gans 2018). I explore this possibility with merchant-level data from Homescan and MRI in Appendix E. Although I find some evidence of sorting, it is quantitatively too small to affect my conclusions about redistribution.

IV.F.5 No Fixed Costs of Card Acceptance

The model abstracts away from any fixed costs of card acceptance so that the only costs of accepting cards are the merchant fees τ. Practically, machines are cheap, and the incremental cost of accepting an additional network is zero.[26] When merchants do not have fixed costs of accepting cards, this weakens the effect of consumer adoption on merchant acceptance. [27] A model in which consumer adoption had greater effects on merchant acceptance would likely generate even more intense rewards competition than

[25] Caddy et al. (2020) document that even though surcharging has been legal in Australia since 2003, around one-quarter of consumers report that they avoid merchants who surcharge.

[26] The widely used Clover service charges around \$100 / month with 2.3% fees for card transactions. In 2019, census statistics find that the average annual sales of a small business with between 1-9 employees is around \$600,000. For such a business, around \$1,200 of the costs are fixed, whereas around \$14,000 would be from the variable fee.

[27] Intuitively, since merchant fees scale with transaction volume, merchants are still willing to accept payment methods that few consumers use. Appendix C.4.1 verifies this model implication.

my model. In such a model, networks would face fewer fee-sensitive merchants if they increased consumer adoption by raising rewards.

IV.F.6 No Price Discrimination

In the model, networks set one fee and reward per card. In reality, networks engage in extensive price discrimination on both sides of the market. The main concern with ignoring consumer price discrimination is that debit card consumers may be unable to obtain the same quality of credit cards that high credit score consumers can. I mitigate this by using an average rewards level of 1.4%, which is around the rewards rate on many mid-tier credit cards. For example, the Capital One Quicksilver pays 1.5% in rewards and is targeted at consumers with fair to good credit, and the Citi Double Cash card targets a similar credit score range and offers 2% cash back.

IV.F.7 Credit Cards as a Borrowing Instrument

I assume that the non-rewards characteristics of credit cards for consumers do not change when rewards change. I do this because when Australia regulated merchant fees, there were no effects on the borrowing features of credit cards, such as interest rates or annual fees (Appendix Figure A.12). Credit drives some modeling choices and model estimates. Credit may explain why consumers do not substitute between credit and debit cards at the point of sale. Consumption smoothing benefits of credit show up in the unobserved product characteristics Ξ of credit cards. Profits from interest charges show up as lower marginal cost estimates for credit card payments (Agarwal et al. 2022).

IV.F.8 Identical Sales Benefits For All Consumers

The sales benefit γ depends only on the merchant, not the consumer. A common γ across consumers means I rule out the mechanism for multiple equilibria in Ambrus and Argenziano (2009), in which one network charges high fees and rewards, while the other charges low fees and rewards. Asymmetric competition does not describe competition in the U.S. empirically, as AmEx, Visa, and MC now charge similar merchant fees (Figure 2). If consumers differed in their γ, then consumers with high γ would be more likely to multi-home. However, in Appendix Figure A.21, I do not find evidence that credit card acceptance by the large grocer in Section III.B.1 resulted in larger sales increases from credit card multi-homers. Figure A.22 also shows that high and low-income consumers responded similarly when the large grocer started accepting credit cards.

IV.F.9 Payment Choices Reflect Revealed Preferences

I assume consumers' payment choices reflect preferences, not constraints. Thus, I rationalize the choice of many consumers to use debit cards as revealing that the average consumer has a strong distaste for credit cards, which I term "credit aversion." Around 80% of consumers who prefer to pay with debit own a credit card (Table 1). Appendix B.6 shows survey evidence that some consumers choose not to use credit cards due to a fear of overspending, adoption costs, and a general dislike of debt.

To the extent that some consumers may be constrained, that does not affect my estimated total welfare results. While constraints can explain why many consumers choose debit cards, constraints alone would not be able to match the Durbin evidence on the relationship between rewards and payment choice. As long as the marginal debit card user that switches is indifferent between debit cards and credit cards, then each consumer that switches from debit to credit incurs credit aversion. In that case, any estimated model that matches the Durbin amendment evidence would deliver the same total welfare result.

V Estimation

Estimating the model connects the reduced-form facts to quantitative predictions about how regulation and competition affect the market. The key primitives to recover are (1) consumers' preferences over the different payment options, (2) the distribution of merchants' benefits from payment acceptance, and (3) the networks' marginal cost parameters.

V.A Estimation Procedure

Although all parameters are estimated jointly, estimation is most easily understood as a three-step process. First, I estimate consumer demand by matching evidence from the Durbin event study, data on consumer multi-homing behavior, and second-choice surveys. Second, I recover networks' marginal costs by inverting the networks' first-order conditions with respect to consumer rewards. Third, I recover merchants' profit margins and the distribution of merchant types from data on card acceptance, the effect of credit card acceptance on sales, and networks' first-order conditions with respect to merchant fees. I obtain standard errors by bootstrapping the joint distribution of data moments with 100 draws. I briefly describe how the key parameters are identified below. Appendix F contains the details.

V.A.1 Consumer Demand

I estimate consumer demand using a combination of natural experiments, a novel second-choice survey, data on consumers' card holdings, and aggregate payment statistics. The key consumer demand parameters are the price-sensitivity parameter (α_0), the distribution of random coefficients (Σ), how preferences relate to income $\left(\alpha_y, \beta_y\right)$, the complementarity parameters (χ), and the unobserved characteristics (Ξ).

I estimate the price-sensitivity coefficient α_0 by matching the simulated effects of the Durbin Amendment with my difference-in-difference estimates. Starting from the baseline equilibrium, I increase debit rewards by 25 bps while holding fixed merchant acceptance. I then match the model's implied change in log debit card volumes with minus one times the difference-in-difference estimate. I hold fixed merchant actions because my difference-in-difference estimates remove any equilibrium effects of merchant actions.

I recover the distribution of random coefficients Σ with variation from a second-choice survey (Berry et al. 2004). Appendix B.4 presents evidence from a second-choice survey that consumers view credit and debit cards as two separate categories and that cash substitutes more effectively for debit cards than credit cards. I set the characteristic vector X_j to have an indicator for an inside good and an indicator for being a credit card. The responses to the second-choice questions identify the covariance matrix of the random coefficients.

The relationship between consumers' payment preferences and income is an important driver of the distributional effects of merchant fees and rewards. I model income as log-normally distributed with a mean normalized to 1. I identify the relationship between income and rewards-sensitivity (α_y) through a question on the second choice survey asking credit card consumers whether they would switch if their current bank cut their rewards. Higher-income respondents report being more likely to switch, identifying a positive relationship between income and reward sensitivity. I recover the relationship between mean preferences and income (β_y) through the data in the DCPC, shown in Table 1, on income differences across consumers with different preferred payment methods.

The remaining parameters come from Homescan and aggregate data. I estimate the complementarity parameters χ by matching the multi-homing probabilities shown in Figure 6b. I recover the unobserved characteristics Ξ by matching aggregate statistics on the share of spending on different payment methods (Figure 2).

V.A.2 Network Costs and Merchant Types

After identifying consumer demand, I recover the marginal costs of processing transactions c and the merchant type distribution. I also calibrate the cost of cash.

First, I identify networks' costs from optimal pricing. High rewards are profitable only when networks earn profits from merchants. Therefore, marginal costs must be low relative to observed merchant fees.

Next, I recover the CES substitution parameter σ from the reduced-form evidence on card acceptance and sales. At the time of the event discussed in Section III.B.1, most merchants accepted credit cards. Thus, I interpret the grocer that I study as the lowest-type merchant that chooses to accept credit cards. My reduced form evidence thus suggests that the grocer has a value of $\gamma \approx 15\%$. I solve for a value of σ (which governs margins) so that the sales benefit of 15% is exactly offset by the increase in costs from paying the credit card merchant fee.

To recover the distribution of merchant types G, I rely on acceptance data from the DCPC and the assumption that networks optimally set credit card merchant fees. I model G using a Gamma distribution, with an average sales benefit $\overline{\gamma}$ and standard deviation ν_γ. A higher average sales benefit $\overline{\gamma}$ increases the profitability of accepting cards and the share of merchants that accept cards. Both forces push networks to raise fees. On the other hand, greater dispersion ν_γ lowers the share of merchants that accept cards and pushes networks to lower fees. By adjusting the shape of the Gamma distribution, I can explain high equilibrium merchant fees and why most merchants accept credit cards.

My estimation captures the idea in Rochet and Tirole (2003) that platforms tax the price-insensitive side of the market to subsidize the price-sensitive side. The fact that payment networks subsidize consumers and tax merchants is prima facie evidence that consumers are relatively reward-sensitive, whereas merchants are relatively fee-insensitive. After estimating consumers' reward sensitivity, optimal pricing is informative about networks' costs and merchants' fee sensitivity.

An important cost I cannot estimate is the cost of cash. Thus, I take the baseline 30 bp estimate in Felt et al. (2020) for the U.S. and bootstrap from a distribution centered at that value with a standard deviation of 10 bps. This uncertainty about the cost of cash propagates to the standard errors of other parameters.

V.B Estimated Parameters

I precisely estimate that consumers are reward-sensitive, whereas merchants are fee-insensitive. The high consumer and low merchant sensitivity generate the model pre-

Table 2: Estimated parameters

Panel A: Consumer Parameters

Parameter	Est	SE
S.D. of Card R.C.	0.92	0.21
S.D. of Credit R.C	2.30	0.53
Correlation of R.C.	-0.72	0.05
S.D. of T1EV	0.12	0.03
$\chi_{\text{Card, Card}}$	-0.26	0.58
$\chi_{\text{Card, Cred}}$	4.44	0.79
$\chi_{\text{Cred, Card}}$	3.85	0.73
$\chi_{\text{Cred, Cred}}$	-4.46	0.95
Visa Debit Ξ	-3.41	0.39
Visa Credit Ξ	-5.37	0.34
MC Debit Ξ	-3.59	0.42
MC Credit Ξ	-5.62	0.38
Amex Ξ	-5.69	0.38
Income Elasticity α_y	0.20	0.06
Log Income Vol. ν_y	0.73	0.01
Card β_y	-0.86	0.20
Credit β_y	0.55	0.30
Primary Weight ω	0.61	0.01
Primary Usage Rate π	0.83	0.00

Panel B: Network Cost Parameters (bps)

Parameter	Est	SE
Cash	30	10
Visa Debit	36	8
MC Debit	51	4
Visa Credit	79	7
MC Credit	81	5
Amex	79	5

Panel C: Merchant Parameters

Parameter	Est	SE
Merchant CES	6.40	1.51
Average γ	0.25	0.07
S.D. of γ	0.08	0.02

Notes: S.D. refers to the standard deviation, and R.C. refers to the random coefficients for having a credit function and not being cash. The Ξ are the unobserved characteristics, and the χ^{lm} is the complementarity parameter for a bundle with a primary card with a characteristic l and a secondary card with characteristic m. The standard deviation of R.C. and T1EV shocks, χ, Ξ are all measured in terms of percentage points of pecuniary utility for a consumer with an average income of 1. Merchant types γ are distributed according to a Gamma distribution.

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

Instrument	Visa Debit	Visa Credit	MC Debit	MC Credit	AmEx
Cash	-0.9	-0.3	-0.3	-0.1	-0.1
Visa Debit	2.9	-0.3	-1.6	-0.1	-0.1
Visa Credit	-0.6	3.6	-0.2	-1.3	-1.2
MC Debit	-4.0	-0.3	5.3	-0.1	-0.1
MC Credit	-0.5	-3.2	-0.2	5.5	-1.4
AmEx	-0.5	-3.2	-0.2	-1.6	5.7

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.

diction that competing networks raise merchant fees to fund rewards. The negative preference against credit cards, on average, contributes to my welfare results on how reductions in credit card use can raise welfare. Table 2 contains all the parameter estimates. I interpret these coefficients below.

The consumer substitution matrix highlights how consumers are reward-sensitive but view credit cards, debit cards, and cash as distinct product segments. The second column of Table 3 shows that a 1-bp shock to Visa credit rewards[28], holding fixed merchant fees, raises the share of Visa credit transactions by 3.6% (S.E. 0.8%). The new consumers mostly come from MC credit, which declines by 3.2%. In contrast, MC debit only declines by 0.3%. The difference reflects that consumers treat debit and credit cards as worse substitutes than different networks' credit cards. Cash use declines by 0.3%, indicating cash is also a poor substitute. Consumers are highly willing to substitute between payment methods, especially those with similar characteristics.

In contrast, merchant acceptance is fee-insensitive. A 1-bp increase in Visa's merchant fees, holding fixed consumer adoption decisions, leads to only a 0.5% decrease in the share of merchants who accept that card (S.E. 0.04%). This semi-elasticity is roughly one-seventh of what I estimate for consumers.

The parameters suggest that the average consumer would pay with debit cards if credit cards did not pay rewards. I estimate that a consumer with an average income of 1 is indifferent between a Visa debit card and a Visa credit card that pays 1.2% in rewards.[29] In Appendix B.6, I present survey evidence suggesting that this aversion towards credit cards arises because some consumers face self-control problems when using credit. This preference drives my result that increases in credit card use relative to debit card use reduce welfare.

V.C Goodness of Fit

My estimates of consumer and merchant demand for payments are consistent with a wide range of external facts.

V.C.1 Merchant Parameters

Even though my estimates of the merchant parameters rely heavily on the networks' optimal pricing conditions, they are consistent with several sources of direct evidence on merchants' fee sensitivity and sales benefits from accepting payments.

[28] I model a 1 bps increase in adoption utility. However, given that merchant acceptance largely does not respond to changes in rewards when the networks charge symmetric fees, a 1 bps increase in adoption utility is largely equivalent to an increase in rewards.

[29] The penalty can be computed as $\omega \times \left(\Xi^{\text{V Debit}} - \Xi^{\text{V Credit}}\right)$

First, I validate my merchant fee sensitivity with AmEx's 2016–2019 OptBlue program that cut merchant fees to increase acceptance (Andriotis 2019). In Section B.3.1, I show that during this period, AmEx cut its merchant fee by 20 bps relative to Visa. Appendix B.3.1 shows that the share of Visa merchants that did not accept AmEx shrunk from around 9–14 pp. to almost zero. When I simulate this shock in the model, the gap shrinks by 12.2 pp.[30]

Second, my estimated average sales effect of 25% is consistent with experimental evidence on the effects of payment technologies. For example, Higgins (2022) shows that debit card adoption by corner stores increased sales to different groups of debit card consumers by $20-60\%$. Berg et al. (2022) use a randomized experiment at a merchant to show that accepting Buy Now, Pay Later raises sales by around 20%.

Third, my estimated retail margin of 15.6 percent is also similar to the aggregate markups of 15–20% used in macro studies of misallocation (Edmond et al. 2022; Sraer and Thesmar 2023). The close match shows that my model reasonably approximates firms' profitability in reality.

V.C.2 Consumer Parameters

My consumer demand parameters match cost data and untargeted moments about multi-homing behavior.

First, I validate my estimated consumer sensitivity with accounting data on debit costs.[31] I estimate debit marginal cost parameters for the combination of issuers, acquirers, and the network that average around 45 bps with a standard error of 6 bps. Accounting estimates of issuer costs are around 20–40 bps, acquirer costs are around 5–10 bps and network costs are around 5 bps (Lowe 2005; Mukharlyamov and Sarin 2024; NACHA 2017; Visa 2020). My cost estimates validate my conduct assumption. If

[30] The close match for the merchant fee-sensitivity and network costs suggests that alternative approaches to estimating the model would have arrived at similar results. If I had microdata to estimate the merchant fee sensitivity and estimated a number consistent with the above AmEx case study, the model would have led me to recover a similar consumer reward sensitivity α.

[31] The close match between estimated and accounting costs highlights the benefits of using variation in interchange to identify consumers' relative demand for different payment products. The Durbin Amendment affected the relative attractiveness of debit cards through more channels than just rewards. For example, Chase stopped paying employees bonuses for signing up debit card customers after the Durbin Amendment was announced (Johnson 2010). Thus, my estimate of consumers' reward sensitivity likely overstates consumers' pure sensitivity to rewards and likely includes indirect effects of the change in interchange on banks' strategies. Including these additional effects is desirable when modeling Visa's incentives to raise merchant fees to fund consumer adoption. To the extent that interchange increases card adoption because it funds steering that consumers do not value, my model understates the harms of rewards competition. Had I used the much smaller elasticities that exploit only variation in rewards as in Arango et al. (2015), I would have needed negative marginal costs to rationalize observed levels of credit card and debit card rewards.

Table 4: Baseline Equilibrium

	Cash	Debit	Credit
Market Share (%)	25	42	33
Share of Spending (%)	18	38	44
Merchant Fees (bps)	30	72	225
Rewards (bps)	0.0	0	145

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

Visa and MC were colluding, marginal costs would need to be -37 bps to rationalize the observed fees and rewards for debit cards.

Second, my model closely matches the joint distribution of primary and secondary cards in consumers' wallets. Appendix Figure A.27 compares the market share of different wallets in the Homescan data on the x-axis against the model implied share on the y-axis. Most points are on the 45-degree line. The model over-states the share of AmEx consumers relative to the Homescan data because the share of AmEx transactions in the aggregate data is greater than its share in the Homescan data. The close match validates a key assumption of the demand model that the unobserved characteristic of a wallet can be decomposed into the weighted sum of the characteristics of the primary and secondary cards. That assumption explains why credit cards that are common as primary cards (e.g. Visa) are also the ones that are the most common secondary cards.

V.C.3 Baseline Equilibrium

The baseline equilibrium also yields market shares of cash, debit, and credit consumers that mirror the DCPC's. Table 4 shows prices and shares in the baseline equilibrium. Just as in the DCPC data (Table 1), debit cards are the most popular primary payment method, as 42% of consumers have a primary debit card. Around 33% of consumers have a primary credit card, and the remaining use cash for all their transactions. The share of primary card-holders understates the share of credit cards in total spending (which equals 44%) because credit card consumers tend to have higher incomes. The close match of the market shares is not mechanical because I target the share of spending in my estimation. Thus, recovering correct market shares relies on accurately estimating the correlation between payment preferences and income.

Credit cards charge merchants high fees of around 225 bps and pay generous rewards of 145 bps of spending. In contrast, debit cards charge 72 bps and pay no rewards. Cash is the cheapest, with a cost of only 30 bps.

VI Counterfactuals

My counterfactual results indicate that changing merchant fee regulations is progressive and welfare-increasing, while increased competition can have the opposite effect. The welfare results stem from "excess intermediation" as described by Edelman and Wright (2015). Unlike typical markets in which market power results in inefficiently low output, payment markets feature externalities that encourage the excessive adoption of high-fee, high-reward payment methods.

VI.A Capping Merchant Fees

In my main counterfactual, I cap credit and debit card merchant fees at my baseline estimate of the cost of cash, 30 bps. I choose this fee level because it equalizes merchants' costs of accepting different payment methods, which previous work has shown to be optimal in models in which merchants have homogenous costs of cash acceptance (Rochet and Tirole 2011).[32] Capping fees at the cost of cash also simulates the effects of merchants freely surcharging consumers for the cost of card acceptance. Thus, the results of this counterfactual also speak to the effects of repealing no-surcharge rules (Zenger 2011).

When computing the counterfactual, I hold fixed consumers' preferences β_i, baseline income y, and merchants' sales benefits to card consumers γ. Consumer adoption, merchant acceptance, retail prices, and network prices can adjust. Although merchants' types are held fixed, their incentives to accept cards can change as the effects of card acceptance on total sales depend on the merchants' type γ and the share of consumers who choose to use each card.

VI.A.1 Effects on Prices and Shares

Capping credit and debit card merchant fees reduces consumer rewards and credit card use. The first column of Table 5 shows the effects of the regulation. The first section shows the effect on prices. The caps mechanically reduce credit and debit card merchant fees by 194 bps and 41 bps, respectively. The platforms then optimally reduce consumer rewards by 233 and 36 bps, respectively. The fact that rewards fall by more than the reduction in merchant fees is consistent with the rise in network fees in Europe after interchange caps were imposed (PYMNTS 2024). The price changes illustrate the see-saw principle in Rochet and Tirole (2003). When payment platforms can no longer

[32]Across my bootstrap draws, I implement the same fee cap even though the true cost of cash varies across simulations to capture the effect of the uncertainty in the cost of cash on the estimated welfare effects of fee regulation.

earn markups on merchants, they profit from consumers through negative rewards – i.e., consumer fees.

Lower rewards cause consumers to substitute away from credit and debit cards towards cash. Table 5 shows that the market share of credit cards declines by 30 percentage points, which is around 90% of the baseline share of credit cards. The market share of debit cards also declines by 8 percentage points.

Lower card use reduces the total merchant fees paid in the economy and the total rewards paid out. Nilson (2020b) estimates around 10 trillion of consumer purchases in 2019. Given that total income is normalized to 1 in the model, each basis point of spending in the model corresponds to $1 billion in spending in reality. With this normalization, I find that capping fees would reduce annual merchant fees and rewards by $101 and $85 billion, respectively.

VI.A.2 Distributional Effects

The reduction in merchant fees and rewards redistributes consumption towards lower-income consumers. I measure the change in real consumption for an income group as the sum of changes in pecuniary utility for each wallet type weighted by the baseline market share of each wallet. By this measure, low-income consumers with log income 2 standard deviations below the median increase their consumption by 41 bps, whereas high-income consumers with log income that is 2 standard deviations above the median decrease their consumption by 56 bps. At an average level of household purchases of around $50,000 in 2023,[33] this is a $51 gain for each low-income household and a $1304 loss for each high-income household. Intuitively, all consumers benefit from the decline in retail prices. However, because high-income consumers use more credit cards, they are relatively hurt by the decline in rewards. The net effect is that capping credit card merchant fees redistributes consumption towards lower-income consumers.

VI.A.3 Welfare

Even though merchant fee caps also reduce rewards, they ultimately benefit consumers and merchants at the cost of networks. Whereas consumers and merchants gain $36 and $2.7 billion in aggregate, networks lose $7 billion. On net, total welfare increases by $31 billion.

[33] According to the CEX, average household expenditure was around $80,000. However, only around 2/3 of this comprises purchases between a consumer and a merchant. For example, imputed rent is a form of consumption but is not a purchase (Nilson 2020b).

Table 5: Summary of Counterfactual Effects

	Price Controls				Change Competition			
	Cap Fees		Uncap Debit		Monopoly		Public Debit	
Δ Prices (bps)								
Credit Fees	−194	(0)	−3.9	(0.7)	20	(4)	−1.0	(0.3)
Credit Rewards	−233	(3)	−19	(3)	−118	(30)	−10	(1)
Debit Fees	−41	(0)	25	(0)	0.0	(0.0)	0.0	(0.0)
Debit Rewards	−36	(1)	25	(0)	−38	(8)	6	(1)
Δ Shares (pp.)								
Cash	37	(7)	−6	(1)	30	(1)	−2.0	(0.3)
Debit	−8	(6)	17	(4)	−8	(1)	−4.1	(0.5)
Credit	−30	(2)	−11	(2)	−22	(1)	−4.0	(0.6)
Entrant							10	(0)
Δ Fees, Rewards ($Bn)								
Total Fees	−101	(4)	−6	(4)	−54	(3)	−9	(1)
Total Rewards	−85	(5)	−8	(3)	−72	(8)	−8	(1)
Δ Consumption (bps)								
Low Income	41	(7)	8	(2)	7	(9)	8	(1)
Median Income	11	(5)	5	(2)	−9	(14)	6	(0)
High Income	−56	(6)	−2.4	(1.9)	−46	(21)	2.9	(0.5)
Δ Welfare ($Bn)								
Consumers	36	(8)	5	(3)	−4.2	(12.0)	7	(1)
Merchants	2.7	(1.5)	−1.0	(0.4)	−3.4	(1.8)	0.0	(0.1)
Networks	−7	(1)	4.1	(0.5)	28	(6)	−1.3	(0.3)
Total	31	(9)	8	(3)	20	(7)	6	(1)

Notes: Bootstrap standard errors are in parentheses. The "cap fees" scenario caps credit and debit card merchant fees to 30 bps. The "uncap debit" scenario raises the cap on debit card merchant fees by 25 bps. Monopoly refers to merging all three networks. The public debit scenario creates a new product with the same non-price and cost characteristics as Visa debit but with no rewards and a merchant fee equal to the marginal cost. 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.

I use money-metric utility as my measure of consumer welfare. I compute this as:

$$\text{CS} = \int \mathbb{E}\left[\max_{w} \log V_i^w\right] \times y \,\mathrm{d}F(y) \tag{26}$$

Intuitively, the inner expectation measures consumer surplus for individuals of a given income as a percentage of their baseline income. The outer integral then weights these percentages by baseline income to determine the total effect across consumers. Because total consumer purchases are around 10 trillion, each basis point of surplus corresponds to 1 billion of spending.

Even though capping merchant fees reduces rewards, consumer welfare rises by around 36 billion. The magnitude of this increase is much larger than the 16 billion reduction in merchant fees net of consumer rewards and indicates consumer welfare rises for other reasons.

Capping merchant fees increases consumer welfare not only because it increases rewards net of fees but also because it resolves a prisoner's dilemma for consumers. While consumers individually have strong incentives to distort their payment choices to earn rewards, they collectively benefit from a world of greater debit card use and lower retail prices. By revealed preference, the marginal credit card consumer is indifferent between the more generous rewards of credit cards and the lower average non-pecuniary characteristics of the credit card, which I call "credit aversion." But while credit aversion is a social cost, rewards are merely transfers. Total welfare increases when reduced rewards cause consumers to shift from credit to debit. Credit card use creates a form of "pollution" that raises retail prices for other consumers. Capping merchant fees eliminates these externalities and increases consumer welfare.

Merchants also benefit from fee caps, whereas networks lose. Merchant profits rise by only \$2.7 billion, which reflect the small second-order gains from no longer having to charge uniform prices for payments with heterogeneous costs. Merchants do not experience large profit gains in equilibrium because they compete away the gains from lower merchant fees. Network profits fall by \$7 billion because fewer consumers use cards. This profit loss equals roughly one-third of the networks' baseline profits. The net result of these forces is that total welfare rises by \$31 billion.

VI.B Repealing the Durbin Amendment

Although capping both credit and debit card merchant fees raises welfare, the Durbin Amendment reduces welfare by capping only debit card merchant fees but not credit card merchant fees. To study the effect of repealing the Durbin Amendment, I raise the cap on debit card fees by 25 bps.[34]

Repealing the Durbin Amendment moderates rewards competition between credit card networks. Lifting the cap causes debit card merchant fees to rise by 25 bps, and networks pass all of it on as higher debit rewards. Consumers switch to debit. Consumers, especially reward-sensitive ones, switch from credit and cash to debit cards. The reward sensitivity of the marginal credit card consumer then goes down, which reduces networks' incentives to compete on credit card rewards. The see-saw pricing principle means that networks reduce merchant fees. Credit card rewards and fees fall by 19 and 3.9 bps, respectively. The net effect is that repealing the Durbin Amendment reduces total merchant fees and rewards by $6 and $8 billion, respectively.

These changes are progressive and increase welfare. Higher rewards increase the consumption of low-income consumers by 8 bps while having little effect on high-income consumers. Overall, consumers gain $5 billion, largely from lower credit aversion. As higher card use increases networks ' profits, total welfare rises by an even larger $8 billion.

These two counterfactuals show that the current U.S. regulatory regime is worse than either laissez-faire or European-style regulations. The Durbin Amendment exacerbated the excess adoption of credit cards by capping debit merchant fees while leaving credit unconstrained. This result highlights the difficulty of regulating two-sided markets. Even though regulating both debit and credit card merchant fees is beneficial (Rochet and Tirole 2011), regulating debit without regulating credit is not.

VI.C Increasing Competition Between Private Networks

Although a major part of U.S. policy towards payment markets involves increasing competition, competition is generally regressive and welfare-reducing. I model an extreme reduction in competition by modeling a merger to monopoly and setting merchant fees and consumer rewards to maximize industry profits. By reducing competition, credit card rewards fall by 118 bps, and merchant fees rise by 20 bps. Debit card rewards also fall, so consumers now pay fees to use debit cards. Consumers then substitute away from cards and towards cash. Total fees and rewards fall by $54 and $72 billion, respectively. Reducing credit card use lowers retail prices for all consumers, whereas reducing rewards mainly affects high-income consumers. Thus, low-income consumers experience a 7 bp increase in consumption, whereas high-income consumers experience

[34] The Durbin Amendment caused around a 75 basis point decline in interchange but only around a 25 basis point change in rewards. Banks responded to the decline in interchange by also raising fees on checking accounts (Mukharlyamov and Sarin 2024). To obtain an empirically realistic estimate of the effect of Durbin on payment choice, I model the repeal as lifting the cap by 25 bps.

a 46 bp loss.

The merger is approximately neutral for consumers while dramatically increasing network profits. Consumer welfare is subject to two countervailing forces. First, consumers benefit from the reduction in credit aversion. However, consumers are also hurt as networks charge higher markups in the presence of weaker competition. My point estimate is that consumer welfare falls by $4.2 billion (S.E. 12.0). Merchant profits fall by only $3.4 billion. Network profits rise by a significant $28 billion, and so total welfare rises by $20 billion (S.E. 7) from the reduction in externalities between consumers. The gains from the merger do not arise because of returns to scale but because the merger helps reduce the excessive adoption of credit cards. The merger increases total welfare by reducing pecuniary externalities, but the networks internalize the lion's share of these benefits through higher profits.

The risk of consumer harm means that the merger counterfactual does not justify letting the incumbent networks merge. However, the counterfactual highlights how competitive payment markets can be socially inefficient. Whereas mergers without synergies always increase market power and reduce welfare in conventional markets, mergers that increase market power can increase welfare in payment markets.

VI.D Public Options

An alternative strategy to increase competition in payment markets is to introduce a public option, whether through central bank digital currencies (CBDC) (Shin 2021; Usher et al. 2021) or faster payments like FedNow (B. Federal Reserve 2022). However, government entry is unlikely to substantially lower total merchant fees or increase welfare in the U.S. market. I simulate government entry as a new debit network with the same demand and supply characteristics as Visa debit. Unlike Visa debit, the entrant cannot pay rewards and sets merchant fees at cost. Because the platform does not pay rewards, its market share is less than one-third of Visa's baseline market share. The new platform raises welfare primarily because it spurs debit cards to compete on rewards, thereby reducing credit aversion. The total welfare gains are around $6 billion (S.E. 1), which are less than the gains from repealing caps on debit card interchange fees. Since launching such a new platform would also entail large fixed costs, the gains to a public option in the U.S. appear small relative to revising existing price regulations.

VI.E Summary of Counterfactual Results

An important theme from the counterfactuals is that credit card use is currently excessive, and this central fact shapes whether market structure or regulatory changes increase or decrease welfare. Either capping credit card merchant fees or repealing the

Durbin Amendment makes credit cards less attractive and thus raises consumer welfare. Conversely, private competition makes credit cards more attractive, decreasing welfare. Overall, changes in price regulations stand to achieve much larger welfare gains than even large changes in market structure.

VII Conclusion

This paper compares the relative merits of regulating prices versus increasing competition in U.S. payment markets. To study this question, I develop and estimate a two-sided model of network competition and simulate the price and welfare effects of regulation and competition. Payment markets are inefficient because of too much credit card use and not too little competition. High credit card rewards inflate retail prices for all consumers while encouraging excessive credit card use. There are large gains from uniform caps on credit and debit card merchant fees or uncapping debit card merchant fees, whereas encouraging competition between credit card networks has limited or negative effects. The gains from public options are small relative to revising price regulations. Unlike in standard antitrust settings where competition benefits consumers through low prices and high output, payment network competition can cause harm through high merchant fees and high output.

References

Adams, Robert, et al. 2022. *Credit Card Profitability.* Technical report. Federal Reserve Board of Governors, September.

Agarwal, Sumit, et al. 2015. "Regulating Consumer Financial Products: Evidence from Credit Cards *." *The Quarterly Journal of Economics* 130, no. 1 (February): 111–164. Accessed November 10, 2022.

Agarwal, Sumit, et al. 2022. "Who Pays For Your Rewards? Cross-Subsidization in the Credit Card Market." *Working Paper* (May): 51.

Allen, Jason, et al. 2014. "The Effect of Mergers in Search Markets: Evidence from the Canadian Mortgage Industry." *American Economic Review* 104, no. 10 (October): 3365–3396. Accessed April 2, 2023.

Ambrus, Attila, and Rossella Argenziano. 2009. "Asymmetric Networks in Two-Sided Markets." *American Economic Journal: Microeconomics* 1, no. 1 (January): 17–52. Accessed January 19, 2023.

Amiti, Mary, et al. 2019. "International Shocks, Variable Markups, and Domestic Prices." *The Review of Economic Studies* 86, no. 6 (November).

Anderson, Simon P., et al. 2018. "Competition for Advertisers and for Viewers in Media Markets." *The Economic Journal* 128, no. 608 (February): 34–54. Accessed September 16, 2022.

Andriotis, AnnaMaria. 2019. "AmEx Is Paying Up to Get Businesses to Accept Its Cards." *Wall Street Journal* (November). Accessed April 18, 2023.

Arango, Carlos, et al. 2015. "Consumer Payment Choice: Merchant Card Acceptance versus Pricing Incentives." *Journal of Banking & Finance* 55 (June): 130–141. Accessed July 27, 2021.

Armstrong, Mark. 2006. "Competition in Two-Sided Markets." *The RAND Journal of Economics* 37, no. 3 (September): 668–691. Accessed April 19, 2021.

Bakos, Yannis, and Hanna Halaburda. 2020. "Platform Competition with Multihoming on Both Sides: Subsidize or Not?" *Management Science* 66, no. 12 (December): 5599–5607. Accessed August 12, 2022.

Benetton, Matteo. 2021. "Leverage Regulation and Market Structure: A Structural Model of the U.K. Mortgage Market." *The Journal of Finance* 76 (6): 2997–3053. Accessed November 12, 2022.

Benson, Carol, et al. 2017. *Payments Systems in the U.S.: A Guide for the Payments Professional.* 3rd Editiion. Glenbrook Press, August.

Berg, Tobias, et al. 2022. "On the Rise of Payment Firms." *Working Paper* (May): 55.

Bergemann, Dirk, et al. 2024. “How Do Digital Advertising Auctions Impact Product Prices?” *Review of Economic Studies* (August): rdae087. Accessed November 15, 2024.

Berry, Steven, et al. 2004. “Differentiated Products Demand Systems from a Combination of Micro and Macro Data: The New Car Market.” *Journal of Political Economy* 112, no. 1 (February): 68–105. Accessed June 1, 2022.

Buchak, Greg, et al. 2020. “Beyond the Balance Sheet Model of Banking: Implications for Bank Regulation and Monetary Policy.” *Working Paper* (January): w25149. Accessed September 19, 2022.

Caddy, James, et al. 2020. “Consumer Payment Behaviour in Australia: Evidence from the 2019 Consumer Payments Survey.” *RBA DIscussion Paper* (June).

CardX. 2023. *State Laws on Surcharging,* January. Accessed January 29, 2023.

Chen, Daniel. 2024. “The Market for Attention.” *Working Paper* (May). Accessed January 6, 2025.

Cohen, Alma, and Liran Einav. 2007. “Estimating Risk Preferences from Deductible Choice.” *American Economic Review* 97, no. 3 (June): 745–788. Accessed November 12, 2022.

Cohen, Michael Andrew, and Marc Rysman. 2013. “Payment Choice with Consumer Panel Data.” *SSRN Electronic Journal,* accessed March 20, 2025.

Cuesta, José Ignacio, and Alberto Sepulveda. 2021. “Price Regulation in Credit Markets: A Trade-Off between Consumer Protection and Credit Access.” *SSRN Electronic Journal* (September). Accessed April 22, 2022.

Dhingra, Swati, and John Morrow. 2019. “Monopolistic Competition and Optimum Product Diversity under Firm Heterogeneity.” *Journal of Political Economy* 127, no. 1 (February): 196–232. Accessed October 21, 2024.

Durbin, Richard. 2023. *Durbin, Marshall, Welch, Vance Introduce Bipartisan Credit Card Competition Act | U.S. Senator Dick Durbin of Illinois,* June. Accessed August 1, 2023.

Edelman, Benjamin, and Julian Wright. 2015. “Price Coherence and Excessive Intermediation*.” *The Quarterly Journal of Economics* 130, no. 3 (August): 1283–1328. Accessed July 27, 2021.

Edmond, Chris, et al. 2022. “How Costly Are Markups?” *Journal of Political Economy* Forthcoming (August). Accessed July 28, 2022.

Egan, Mark, et al. 2017. “Deposit Competition and Financial Fragility: Evidence from the US Banking Sector.” *American Economic Review* 107, no. 1 (January): 169–216. Accessed November 12, 2022.

Ellickson, Paul B., et al. 2020. “Measuring Competition in Spatial Retail.” *The RAND Journal of Economics* 51, no. 1 (March): 189–232. Accessed October 9, 2024.

European Commission, DG Comp. 2020. *Study on the Application of the Interchange Fee Regulation: Final Report.* Technical report. LU: Publications Office. Accessed September 26, 2022.

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

Federal Reserve, Board of Governors. 2010. *Debit Card Interchange Fees and Routing,* December.

Felt, Marie-Hélène, et al. 2020. *Distributional Effects of Payment Card Pricing and Merchant Cost Pass-through in the United.* Federal Reserve Bank of Boston Research Department Working Papers, Federal Reserve Bank of Boston Research Department Working Papers. Federal Reserve Bank of Boston, December. Accessed July 27, 2021.

Gabaix, Xavier, and David Laibson. 2006. "Shrouded Attributes, Consumer Myopia, and Information Suppression in Competitive Markets." *Quarterly Journal of Economics* 121, no. 2 (May): 505–540.

Gans, Joshua S. 2007. *Evaluating the Impact of the Payment System Reforms.* Technical report. January.

———. 2018. "Are We Too Negative on Negative Fees for Payment Cardholders?" *Working Paper,* accessed June 3, 2022.

GAO. 2009. *Rising Interchange Fees Have Increased Costs for Merchants, but Options for Reducing Fees Pose Challenges.* Technical report 10-45. November.

Greene, Claire, and Joanna Stavins. 2021. *2020 Diary of Consumer Payment Choice.* Technical report 21-2. May.

Guthrie, Graeme, and Julian Wright. 2007. "Competing Payment Schemes." *Journal of Industrial Economics* 55, no. 1 (March): 32.

Hayashi, Fumiko. 2009. "Do U.S. Consumers Really Benefit from Payment Card Rewards?" *Kansas City Federal Reserve Economic Review* (March): 27.

———. 2012. "The New Debit Card Regulations: Initial Effects on Networks and Banks." *Federal Reserve Bank of Kansas City Economic Review,* 38.

Helcim. 2021. *Visa USA Interchange Rates.* Accessed December 3, 2021.

Higgins, Sean. 2022. "Financial Technology Adoption." *Working Paper* (December): 80.

Honka, Elisabeth, et al. 2017. "Advertising, Consumer Awareness, and Choice: Evidence from the U.S. Banking Industry." *The RAND Journal of Economics* 48, no. 3 (August): 611–646. Accessed July 27, 2021.

Huynh, Kim, et al. 2022. "Equilibrium in Two-Sided Markets for Payments: Consumer Awareness and the Welfare Cost of the Interchange Fee." *Bank of Canada Working Paper* (March). Accessed June 2, 2022.

Johnson, Andrew. 2010. "Issuers Now Plan Debit Reward Cuts." *American Banker* (November).

Koijen, Ralph S. J., and Motohiro Yogo. 2015. "The Cost of Financial Frictions for Life Insurers." *American Economic Review* 105, no. 1 (January): 445–475. Accessed November 12, 2022.

Koulayev, Sergei, et al. 2016. "Explaining Adoption and Use of Payment Instruments by US Consumers." *RAND Journal of Economics.*

Lee, Robin S. 2013. "Vertical Integration and Exclusivity in Platform and Two-Sided Markets." *American Economic Review* 103, no. 7 (December): 2960–3000. Accessed September 16, 2022.

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

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

Mukharlyamov, Vladimir, and Natasha Sarin. 2024. "Price Regulation in Two-Sided Markets: Empirical Evidence from Debit Cards." *Working Paper* (October). Accessed September 16, 2022.

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

Nelson, Scott T. 2020. "Private Information and Price Regulation in the US Credit Card Market." *Working Paper,* 63.

Nilson, Report. 2020a. "Merchant Processing Fees in the United States." *Nilson Report* 1176 (May).

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

———. 2020c. "Visa and Mastercard – U.S. 2019." *Nilson Report* 1169 (February).

Orem, Tina. 2016. "Credit Unions Revive Debit Rewards." *Credit Union Times* (January). Accessed September 6, 2022.

PYMNTS. 2024. *Report: EU Questions Retailers in Visa and Mastercard Fee Controversy,* November. Accessed December 14, 2024.

Robles-Garcia, Claudia. 2022. “Competition and Incentives in Mortgage Markets: The Role of Brokers.” *Working Paper* (May).

Rochet, Jean-Charles, and Jean Tirole. 2002. “Cooperation among Competitors: Some Economics of Payment Card Associations.” *The RAND Journal of Economics* 33 (4): 549. Accessed July 28, 2021.

———. 2003. “Platform Competition in Two-Sided Markets.” *Journal of the European Economic Association* 1, no. 4 (June): 990–1029. Accessed April 19, 2021.

———. 2011. “Must-Take Cards: Merchant Discounts and Avoided Costs.” *Journal of the European Economic Association* 9, no. 3 (June): 462–495. Accessed July 27, 2021.

Rosaia, Nicola. 2020. “Competing Platforms and Transport Equilibrium: Evidence from New York City.” *Working Paper* (November): 77.

Rysman, Marc. 2004. “Competition between Networks: A Study of the Market for Yellow Pages.” *Review of Economic Studies* 71, no. 483 (April): 512.

Schneider, James, and S.K. Prasad Borra. 2015. *The Future of Finance: Redefining "The Way We Pay" in the Next Decade.* Technical report. Goldman Sachs Equity Research, March.

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

Song, Minjae. 2021. “Estimating Platform Market Power in Two-Sided Markets with an Application to Magazine Advertising.” *American Economic Journal: Microeconomics* 13, no. 2 (May): 35–67. Accessed November 16, 2023.

Sraer, David, and David Thesmar. 2023. “How to Use Natural Experiments to Estimate Misallocation.” *American Economic Review* 113, no. 4 (April): 906–938. Accessed April 15, 2023.

Stavins, Joanna. 2018. “Consumer Preferences for Payment Methods: Role of Discounts and Surcharges.” *Journal of Banking & Finance* 94 (September): 35–53. Accessed August 5, 2022.

Sullivan, Michael. 2023. “Price Controls in a Multi-Sided Market.” *Working Paper* (December).

Teh, Tat-How, et al. 2022. “Multihoming and Oligopolistic Platform Competition.” *American Economic Journal: Microeconomics* Forthcoming.

Usher, Andrew, et al. 2021. “The Positive Case for a CBDC.” *Bank of Canada Banking and Payments Department Discussion Paper* (July): 20.

Valverde, Santiago Carbó, et al. 2016. “The Role of Interchange Fees in Two-Sided Markets: An Empirical Investigation on Payment Cards.” *Review of Economics and Statistics* 98, no. 2 (May): 367–381. Accessed July 27, 2021.

Visa. 2019. *Visa USA Interchange Reimbursement Fees,* April.

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

Wright, Julian. 2012. "Why Payment Card Fees Are Biased against Retailers." *The RAND Journal of Economics* 43, no. 4 (December): 761–780. Accessed July 27, 2021.

Zenger, Hans. 2011. "Perfect Surcharging and the Tourist Test Interchange Fee." *Journal of Banking & Finance* 35, no. 10 (October): 2544–2546. Accessed March 30, 2023.

Online Appendices: Not for Publication

A Data Details

A.1 Issuer Payment Volumes

I construct an annual panel of issuer payment volumes from the Nilson Report, which collects data on payment volumes through its relationships with individual financial institutions.

I supplement this payment data with bank financials from the FFIEC call reports and credit union financials from the NCUA's call reports. I measure the assets at the bank-holding level and fill assets back for savings trusts with the value of the assets in 2012. Interchange income is reported in the bank call reports. For credit unions, I use non-interest income to proxy for interchange income, as interchange accounts for a little less than half of non-interest income even after the Durbin Amendment.

I exclude issuers with assets below 2 billion and above 200 billion to exclude systemically important issuers like Chase that were subject to other new regulations. I also exclude issuers that made large acquisitions exceeding 50% of equity: First Tech FCU, Firstmerit Bank, BMO Harris, Regions Bank, and Synovus/Columbus B&T. I exclude them because the changes in payment volumes do not reflect changes in consumer choices, but rather mechanical changes due to substantially expanding the customer base.

Coverage in the Nilson Report varies from year to year. Figure A.1 shows the share of missing data for different payment volume measures across years. Banks may not be included in a year both because the Nilson report only covers the largest issuers, and because the Nilson report has changed what it has reported over time. For example, in 2007, the Nilson Reported had signature debit card volumes for the top 200 issuers of signature debit cards. This high coverage of signature debit shapes why I choose signature debit as my main measure of debit card volume.

A.1.1 Robustness to filtering

In this section, I compare event studies on two slightly different samples. One sample includes banks with large portfolio changes, or that made big acquisitions (which I label "Full sample"), while the other excludes these banks (which I label "Restricted sample"). Both samples exclude banks outside the 2-200 billion range in assets.

Figure A.1: Share of panel observations with missing data by year and card type

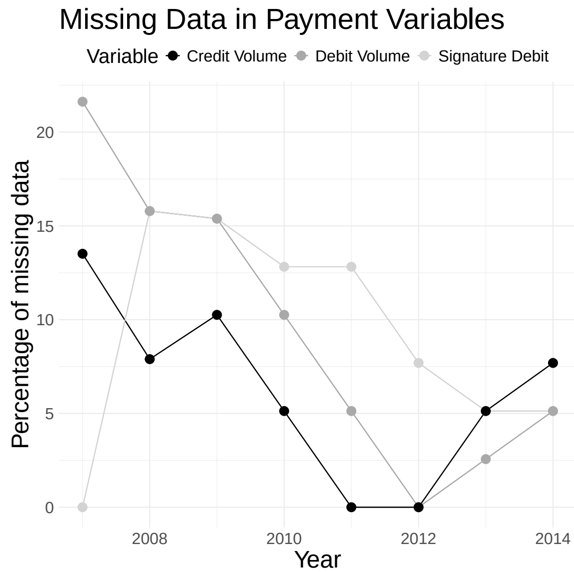
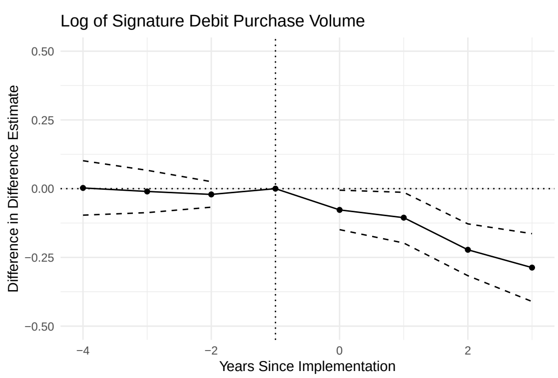


Figure A.2: Signature Debit Volumes

(a) Restricted sample



(b) Full sample

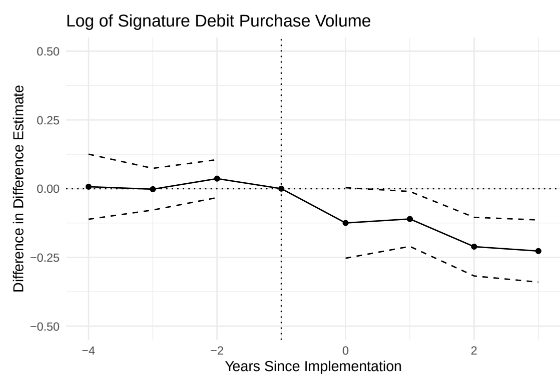
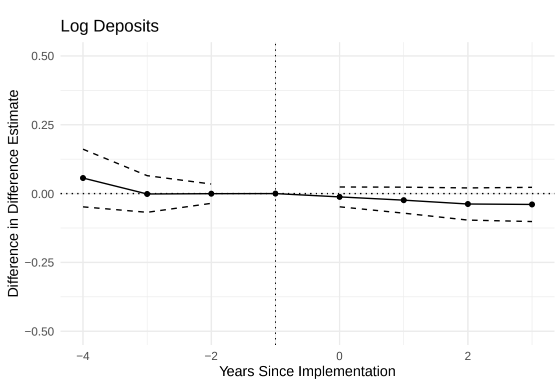
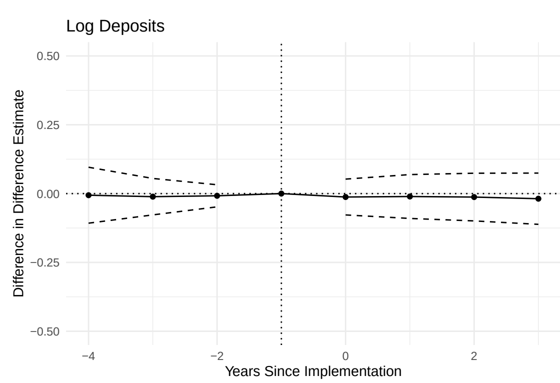


Figure A.3: Deposits

(a) Restricted sample



(b) Full sample



A.2 Aggregate Data

A.2.1 Prices

There are two notions of prices relevant to payments: merchant fees and consumer rewards.

The Nilson Report provides annual measures of total merchant fees split at the level of V/MC Credit, American Express, and V/MC debit. These come from surveys of acquirer firms that help merchants process cards. I then assume that Visa and MC charge the same fees within products (e.g., credit vs. debit).

I collect data on total rewards expense from the annual reports of American Express, Chase, Citi, Bank of America, Capital One, and US Bank. These banks cover around 80% of the total credit card volume in the United States in 2019. I then divide these total rewards expense by the volume of credit card spending from the Nilson Report, discussed in the previous section. This results in a volume-weighted average reward of 1.74% across the non-AmEx banks and then 1.85% at AmEx.

Total rewards expense overstates the amount of benefits credit card consumers obtain because it ignores annual fees. AmEx does report annual fees, and they amount to around 38 bps of payment volumes. For the other banks, I use data from Adams and Bord (2020) showing that over the entire $2014 - 2019$ period, on average, annual fees totaled around 20 bps of purchase volume when aggregated across all consumers. Given that annual fees have roughly doubled from 2015 to 2019 (CFPB 2021), the adjustment for annual fees for the other issuers should subtract around 30 bps from other issuers.

A.2.2 Shares

The Nilson Report publishes its model of consumer purchases every year. Their concept of purchases modifies public consumption data like PCE into different categories, such as bank electronic transfers (e.g., direct deposit), cash, checks, credit cards, and debit cards. The Nilson Report also has network specific payment volumes at the level of Visa Credit, MC Credit, Visa Debit, MC Debit, American Express, and Discover. Other debit includes non-Visa and non-MC PIN debit networks, which are reported in the merchant fee summary tables. These are the data plotted in Figure 2.

When applying the model to the data, I ignore the presence of all networks besides Visa, MC, and AmEx but scale up their volumes within credit and debit cards to match the aggregate volume of credit and debit card transactions. Note that in the estimation, I target the dollar shares of spending, which differ from the share of consumers who use a card because card preferences also depend on income.

A.3 Homescan

The NielsenIQ Homescan panel tracks the payment decisions of over 100,000 households at large consumer packaged goods stores. I use this data to study households' payment preferences and shopping behavior.

A.3.1 Building Payment Choice Data

I first remove all households with more than 1

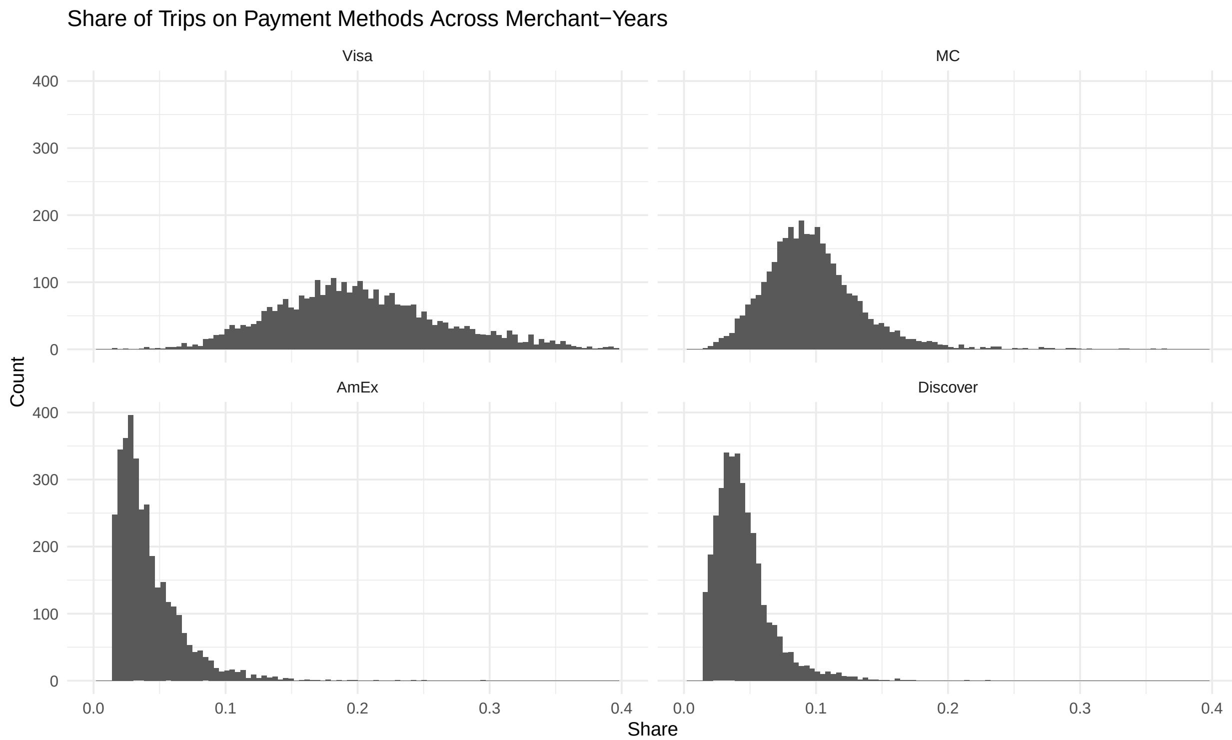
The next step is to use the observed payment decisions across stores to infer the consumers' primary and secondary cards. To avoid confounding merchant acceptance with consumer preferences, I drop store-years below 500 total trips. I base this number roughly on the number of trips needed to have a 99% probability of observing at least one payment with an infrequently used card[35]. This filter drops 0.7% of the sample. On this subsample that excludes the smallest merchants, I further restrict the sample to merchants that accept all cards. However, I do not observe card acceptance but card payments. Thus, I assume a merchant accepts a card in a given calendar year if its payment share is above some threshold. To determine this minimum threshold, I observe how low Visa's share was at a large grocer when we know Visa was not accepted (1.5% of payments). I drop all merchants with a transaction share on any network less than this share. Dropping these firms eliminates an additional 15.7% of the payments sample. I also drop a small merchant that dropped Visa for 6 months (an additional 0.3%).

The histograms below show the distribution of the payment mix across merchant years. Most merchants see meaningful payment activity from all four card networks.

Cash-only consumers I characterize a consumer as a primary and secondary cash user if their Cash payment share is above a cutoff. I define this cutoff to match the share of consumers who prefer cash as their main non-bill payment instrument from the SCPC. This group constitutes 19.7

Primary and secondary cards I characterize first and second payment methods based on the number of card trips and use the amount of spending to break ties. I drop consumers without spending on a primary card. If a consumer has no spending on a secondary card, I define the secondary option as cash. If a consumer is below the cash-only payment share cutoff but has less than 20 trips in total, I set both primary and secondary payment options to NA because of the noisiness of the data.

[35] If the probability of payment with this card is $p = 0.01$, for a Binomial distribution, $P(\text{at least one payment}) = 1 - (1-p)^n = 0.99$. Then, $n = \frac{\log(0.01)}{\log(1-p)} \approx 458$.



A.3.2 Payment acceptance event studies

For the payment acceptance event studies, I use data 24 months before and 24 months after the policy change was implemented. I restrict to payments in grocery stores. For each household, I fill in (with zero payments and zero trips) months with no payment observations within the first and last date the household is observed.

In the case of the large grocer, I restrict the sample to households in zip codes where I observe a store from this large grocer by year $Y-1$, being Y the calendar year in which the policy change was implemented.

I join this data with information on the payment choices of households in year $Y-1$.

A.4 Diary of Consumer Payment Choice

The Survey and Diary of Consumer Payment Choice create a comprehensive picture of US consumers' payment preferences and behavior. Whereas the SCPC collects data on payment ownership and general ratings of different payment methods, the DCPC collects transaction-level data on which payment methods consumers use for specific payments. The surveys are nationally representative and have been conducted by the Federal Reserve Bank of Atlanta since 2016. Questionnaires are sent as a part of the Understanding America Study (UAS) by the University of Southern California. There is a common set of identifiers. It is also possible to use the link with the UAS to identify the state of residence of respondents for every year through 2023.

The diary provides transaction-level data on whether a card is accepted. For card transactions, this evidence is direct. For cash transactions, the diary prompts the consumer whether the merchant would have accepted a card. For check transactions, the diary does not provide evidence. The lack of a question for checks is problematic because some check transactions were likely because the merchant did not accept cards. To estimate the proportion of such transactions, I use the "why not preferred" variable for consumers who report preferring to use debit or credit cards. When I analyze check transactions by consumers who prefer to use debit or credit cards, I find that roughly one-fifth of the time, consumers report that they used check because their preferred payment method was not accepted. Thus, my estimate of the share of transactions that would have accepted cards counts all confirmed cases of the merchant not accepting cards plus one-fifth of the check transactions. When bootstrapping the distribution of this statistic, I resample the "why not preferred" variable to account for the uncertainty in this fraction.

I also characterize transactions with "Likely" and "Sure" card minimums. The former is only defined for the 2017-2020 period and includes the responses "Yes" and "I don't know, but I think so." The latter is defined for the full period and only includes "Yes" responses.

A.5 Yelp Open Dataset

I use Yelp Open Dataset to provide evidence on the verticality of payment options acceptance on the side of merchants. To this end, I download the publicly available data from Yelp's website. I then process the reviews and tips sample in several steps.

I separate reviews into two categories. First, I identify reviews that say a store is cash only by searching for "cash only" or "only...cash" with regular expressions. Then, I define a set of reviews that discuss card acceptance by searching for phrases such as "accept," "take," "took," "bring," "only pay," or "pay only."

Among the acceptance reviews, I then search for payment methods with the strings "american express", "amex", "visa", "master", "debit", "credit", and "discover".

I further split the acceptance reviews into two groups – those that have only one of the aforementioned payment method string, and those that mention two or more.

I then process these remaining acceptance reviews with the ChatGPT API. I prompt this LLM to indicate in each review whether each of the following payment methods is accepted: cash, debit, Visa, Mastercard, American Express, and Discover. If a review says credit cards are accepted but provides no other details, I prompt the LLM to indicate Visa acceptance and not draw any other conclusion. I specifically warn it not to assume

Visa acceptance because of Mastercard acceptance, and not to assume credit acceptance because of debit acceptance. If a store surcharges, I instruct the LLM to include this as acceptance still. I provide it with three concrete examples of how to conduct these instructions. For the reviews that mention multiple payment methods, I use the 4o API. For the ones that only mention one payment method, I use the 4o-mini API.

In Table A.1, I show one random review snippet for each of the categories highlighted in the main paper.

A.6 Second-Choice Survey

I run an online survey designed to understand consumer preferences for debit and credit cards, including their behavior with different choice sets and rewards. Data collection was conducted through an online crowd-sourcing platform, targeting English-speaking adults under 50 years old residing in the United States, who were compensated upon completion of the study.

The study's data was derived from two waves of survey responses. The first wave occurred on June 12-13, 2024, while the second wave took place on August 21, 2024, between 9:20 AM and 11:00 AM.

An Institutional Review Board at Northwestern University approved this study.

A.6.1 Survey Structure

The survey consisted of various blocks of questions, each focusing on specific aspects of payment behavior. The survey's key blocks included:

- **Consent**: Respondents were presented with a consent form detailing the purpose, risks, benefits, and confidentiality of the study.

- **Primary Payment Method**: This block identified the respondents' most frequently used payment method (e.g., debit card, credit card) for in-person transactions.

- **Household Income**: Respondents were asked to place themselves in one of eight annual household income brackets.

- **Primary Bank**: Questions focused on the respondents' primary bank or credit union for their preferred payment method and which banks they considered before selecting their primary payment provider. Respondents were also inquired about other banks used.

- **Second Choice Payment Method**: This block explored alternative payment methods that respondents would consider if their primary payment method or bank

Table A.1: Examples of Yelp reviews

Classification	Review (relevant snippet)
Debit, no Credit	- No credit cards (Cash or debit only) Yet to hit up the hot bar, but I think that is going to happen today!
Debit + Credit	I sent them my one-way plane ticket back to California, proof of disconnection of all my Austin utilities, proof of USPS forwarding mail to my new California address, bank statements and a major credit card showing my updated address, and many other documents to provide proof. They have also tried twice to charge fees because I forgot to update my credit card information on file. I changed debit cards once and it took them a full month to get my membership ""cleared up"" when in fact I just used another debit card to pay that month
Visa and MC	Visa, Mastercard, and American Express accepted. Discover Card not accepted
Visa, no AmEx	They don't take AMEX, so they don't get my business. Seriously, how can a restaurant not take AMEX. A tiny bit of research will let them know they can get the exact same processing costs for AMEX as Visa and Master Card. I'm deeply disappointed in this business, and will spend my money at Minh's, where they take AMEX, and Tabbedout is also accepted.
Credit, no Debit	DEB'S NOW TAKES CREDIT CARDS. No Amex tho and no debit cards, but you can now pay for your delicious and cheap breakfast with Visa, Mastercard, or Discover
Only one: Visa or MC	When I went inside to pay the cashier said they do not take Mastercard. Who doesn't take mastercard. I had to pay with a credit card and with tax I was charged $45.78
AmEx, no Visa	One item that might concern some - American Express is the only credit card they accept.

became unavailable. Specifically, they were asked what they would choose if their primary payment method became unavailable at their preferred bank and what they would choose if their payment method stopped became unavailable at all banks. If respondents used cards for more than one bank, they were asked if they would continue to do so if their primary payment method was no longer offered at their chosen bank.

- **Rewards Programs**: These questions investigated whether respondents receive rewards (e.g., cashback, points) for using their credit or debit cards and how changes in rewards would influence their payment behavior. If they used a credit card with rewards, they were asked what they would use as a primary payment method if their bank halved their rewards. If they used a debit card, they were asked if they were aware that credit cards often offer rewards. If so, they were asked what they would use as a primary payment method if their bank doubled credit card rewards.
- **Attention Check**: This question was designed to ensure that respondents were paying attention to the survey content, requiring them to select specific options.

A.6.2 Data Cleaning

The cleaned dataset included responses only from participants who completed the survey within the designated timeframes for each wave. Respondents who failed this attention check were excluded. The resulting dataset has 788 observations.

Income data were categorized based on self-reported ranges and transformed into continuous variables using geometric means.

A.7 MRI Ultimate Survey of Americans

The MRI-Simmons USA is a nationally representative study on American consumers. It was created from the combination of MRI's Survey of the American Consumer and Simmons Research's National Consumer Study. From 2009–2020, around 25,000 thousand consumers are covered by the survey. Starting in 2021, the sample grew to around 50,000 individuals. For 2009–2022, I use data on consumers' reported financial institutions, the payment methods they own, household income, and bank switching behavior. In the 2022 wave, I collect additional data on shopping behavior. Table A.18 shows summary statistics for the full sample.

A.7.1 Payment method

The data on credit and debit card usage includes the amounts spent with both types of cards, further broken down by the bank and network that issued the card. Unfortunately, the data on cash usage does not provide information on expenditures. To characterize each consumer's payment preference between cash, credit, and debit cards, I proceed as follows. If a consumer reports preferring cash as a payment method, I classify them as having a cash preference. If a consumer reports spending more with a credit (debit) card, I classify them as preferring credit (debit).

A.7.2 Share of consumers across merchants

The shopping behavior data includes whether a consumer has made purchases at specific merchants, either in person or online, across 214 merchants in various sectors (e.g., clothing, food, furniture). For consumers who have made purchases at a given merchant, I can observe their preferred payment method as described earlier. I then calculate the share of consumers preferring each payment method (cash, debit, and credit) declaring making purchases at each store.

B Additional Reduced Form Facts

B.1 Details on Discover's Reward Programs

Discover's *5% Cashback Bonus* program offers a 5% discount on purchases at select stores for customers who use Discover credit cards. This reward is redeemable as a deposit to a bank account or as a discount on the credit card bill, among other options.

The stores at which the reward is active change by quarter, and Discover publishes in advance the reward calendar. As shown in Table A.2, from 2018 to date, grocery stores have had this benefit once a year. I exploit this variation in selected stores and timing to study the effect of the reward on both payment method and store choice.

I focus on customers whom I identify as selecting Discover as either their primary or secondary payment method[36] and track their consumption at grocery stores (periodically offering cash back) and discount and warehouse stores (which don't offer cash back in these periods). Past work has shown that these two categories of stores compete (Ellickson et al. 2020). I exclude merchants that do not accept Discover and household years where I don't observe trips to either of the store categories.

Another explanation for why Discover consumers do not substitute from debit to Discover during the reward periods is that Discover consumers do not have debit cards. However, Figure 6b shows that around one-sixth of Discover credit card users use debit cards as their second most-often used card.

A key part of the Discover experiment is that it shows that consumers have rigid transaction-specific preferences. This requires that consumers do not switch their primary card to Discover during the rewards period. Appendix Figure A.23 shows no spillover of the Discover program on payment decisions at warehouse/discount stores, reinforcing the assumption that the rewards do not induce consumers to adopt Discover as their primary payment method in the affected quarter.

The result in the main text focuses on the effect of Discover's reward program on the number of trips at grocery versus discount/warehouse stores on different methods of payment. Appendix Figure A.24 shows similar charts where the main measure is instead the share of dollars spent at grocery versus discount/warehouse stores on different methods of payment.

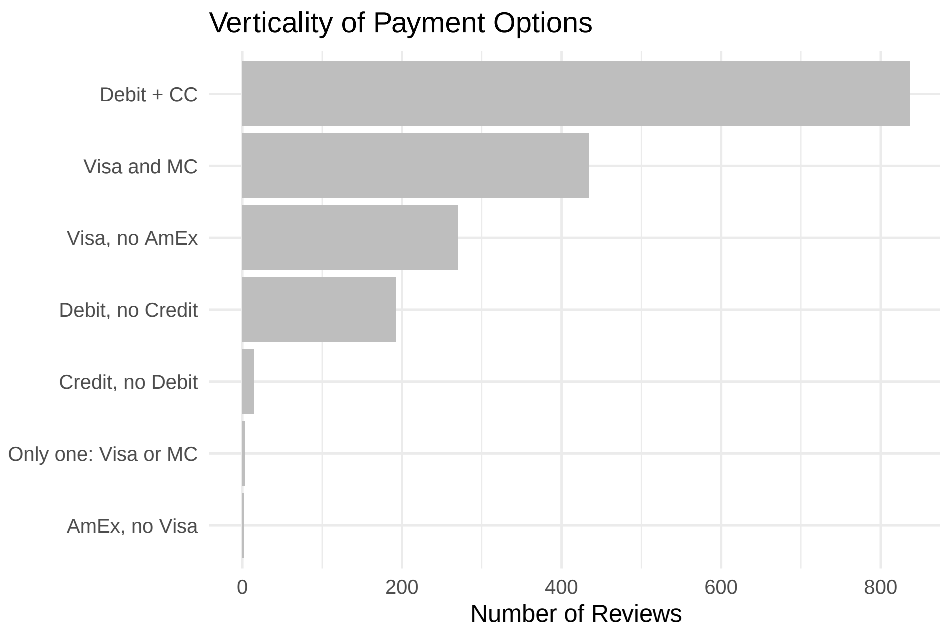
[36] I characterize first and second payment methods based on the number of card trips and use the amount of spending to break ties. I explain this in greater detail in Appendix A.

Table A.2: Discover 5% Cashback Bonus Categories (2017-2022)

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

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

Figure A.4: Multi-homing Behavior in Yelp



B.2 Yelp Evidence on Hierarchical Card Acceptance

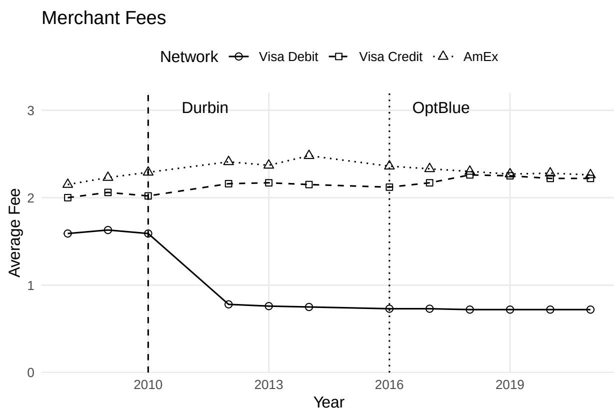
Yelp reviews suggest that variation in merchant acceptance is largely vertical: while some merchants are cash-only, others accept debit, then debit + Visa/MC, then all cards. Using the ChatGPT-4o API, I analyze Yelp reviews that discuss the acceptance of two or more card payment methods. I focus on the approximately $3,000$ reviews that mention at least two payment methods.[37] Figure A.4 shows that some reviews mention debit and credit being accepted together, Visa with MC, Visa without AmEx, and debit without credit. However, almost no reviews mention credit without debit, AmEx without Visa, or accepting only one of Visa or MC. The reviews are mostly from before 2017, which was a period when AmEx acceptance lagged that of Visa's.

These reviews rule out the possibility that some merchants specialize in accepting certain networks while other similar merchants choose a disjoint set of networks. The hierarchical acceptance pattern in payments contrasts with the adoption of food delivery platforms, as that is a market in which merchants frequently are on one platform but not another (Sullivan 2023).

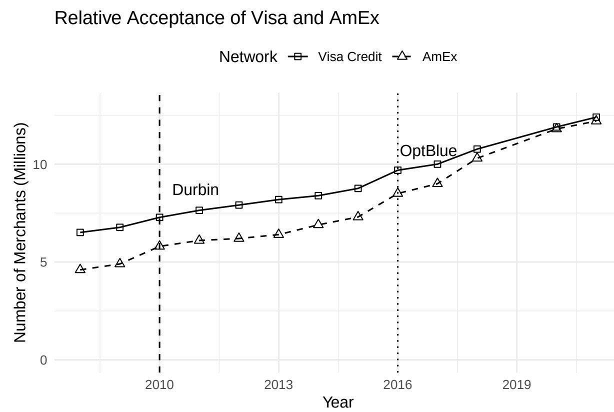
[37] Appendix A.5 discusses how I construct the data.

Figure A.5: Incentives for Merchant and Consumer Multi-homing

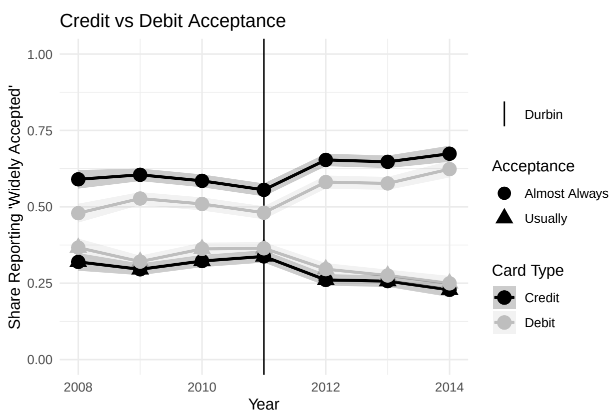
(a) Merchant Fees



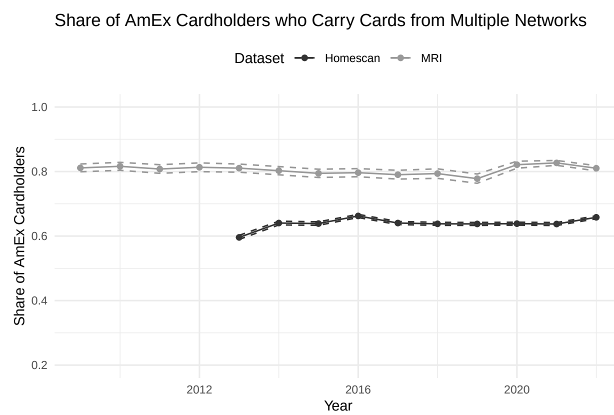
(b) Credit Card Acceptance



(c) Credit and Debit Acceptance



(d) AmEx Multihoming



B.3 Additional Details on Consumer and Merchant Multi-homing Behavior

Merchant multi-homing behavior is consistent with the idea that credit and debit card acceptance are not substitutes. While merchant acceptance of different credit card networks is sensitive to differences in merchant fees between credit card networks, relative acceptance of credit and debit cards is not sensitive to the difference in fees between credit and debit. These findings support the model's assumptions that credit card consumers reduce their purchases from stores that accept only debit cards and not credit cards.

Consumer multi-homing behavior appears to largely reflect incentives to pair differentiated products. It is historically unresponsive to relative differences in card acceptance across networks, supporting the model's assumption that consumers do not internalize acceptance complementarities when choosing credit cards.

B.3.1 Acceptance of Credit Cards is Sensitive to Relative Credit Card Merchant Fees

The decision to accept more or fewer credit cards is sensitive to relative merchant fees. Figure A.5a shows that over the past decade, the gap between AmEx's and Visa's credit card merchant fees has decreased by around 20 bps. The decline in fees has been the result of the OptBlue program, which has reduced merchant fees for small businesses (Glasheen 2020). Figure A.5b shows that as the fee gap has closed, the acceptance gap has also closed by around 14 pp. AmEx's 2019 annual report also reports that its U.S. network went from covering 90% to 99% when measured as a percent of card spending during this period.

B.3.2 Credit/Debit Acceptance is not Sensitive to the Difference Between Credit + Debit Merchant Fees

Even though the Durbin Amendment cut the cost of debit card acceptance by half, credit card acceptance did not decline in response. Figure A.5a shows that the 2010 Durbin Amendment cut debit fees. However, Figure A.5c shows that consumers' ratings of credit and debit card acceptance did not change.

The lack of response is not the result of bundling between credit and debit cards. A 2003 settlement ended Visa's and MC's rules tying debit and credit acceptance (Constantine 2012). Even if Visa debit and credit were tied, that would not explain why AmEx faced no competitive pressure from the decline in debit card merchant fees when around a fifth of AmEx consumers use both a mix of debit and credit (Figure 6b).

One interpretation of the lack of response is that debit and credit cards provide distinct transaction services at the point of sale. If the transactions that benefit from credit card acceptance are distinct from the transactions that benefit from debit card acceptance, the decision of whether or not to accept credit cards is separable from the decision to accept debit cards. Appendix C.4.1 proves that in the model considered in the paper, then the decision to accept credit cards is independent of the level of debit card merchant fees or debit card rewards if credit and debit cards provide distinct transaction services. In contrast, if credit and debit cards are partially interchangeable, then credit card acceptance declines when debit card merchant fees fall.

B.3.3 Consumer Multi-homing Does Not Respond to Relative Acceptance

Consumers multi-home largely to take advantage of product differentiation, not to have a "backup" card in case their primary card is not accepted. As previously seen in Figure A.5b, AmEx acceptance used to lag that of Visa but has closed over time. If consumers multi-home to make sure they always have a card that's accepted, then we should expect the share of AmEx consumers that multi-home to decline over time. However, Figure A.5d uses data from both Homescan and MRI to show that the share of AmEx consumers who use cards from multiple networks has been flat over time.

B.4 Consumer Substitution Patterns from a Second Choice Survey

The results of a second-choice survey suggest that debit cards are more similar to cash than credit cards but that credit and debit cards are nonetheless distinct product categories. Table A.3 shows the results of the survey. The first row shows the results of asking consumers who primarily use credit cards to make everyday purchases what their new primary payment method would be if credit cards did not exist. The vast majority would pay with debit, and only 15% would primarily pay with cash. In contrast, 53% of consumers who primarily pay with debit cards say that they would switch to cash. The greater share of debit users switching to cash suggests that cash and debit are closer substitutes than cash and credit. I next ask consumers how they would pay if their current bank were to no longer offer their primary payment type (i.e., credit or debit). Around 87 percent of credit card consumers and 76 percent of debit card consumers would switch to another bank's card of the same type. The high shares indicate that debit and credit are their distinct categories.

Table A.3: Substitution patterns from a second choice survey

Current Card	Choice Set	Share
Credit	{Cash, DC}	P(Cash) = 0.15
Debit	{Cash, CC}	P(Cash) = 0.53
Credit	{Cash, DC, Other Banks' CC}	P(Other Banks' CC) = 0.87
Debit	{Cash, Other Banks' DC, CC}	P(Other Banks' DC) = 0.76

Notes: The table shows how different types of consumers would pay when faced with counterfactual choice sets. The first column describes the consumer's current primary payment method, the second column is a hypothetical choice set, and the last column denotes the probability of adopting a particular primary payment method. The final respondent pool contains 357 primary credit card users and 383 primary debit card users. Appendix A.6 contains details on the survey design.

The survey also sheds light on consumer heterogeneity in reward sensitivity. The results imply that credit card rewards competition is particularly intense because high-income individuals, who are more likely to use credit cards, are also more reward-sensitive. In the survey, I ask credit card consumers how likely they are to switch credit cards if the rewards on their current credit card were cut by half. I regress an indicator for switching on log income. The first model in Table A.4 shows the results. Evaluated at the dependent variable mean, this regression says that a one percent increase in income is associated with a 19 percent increase in the switching propensity. The second model

Table A.4: Income heterogeneity in rewards sensitivity

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

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

Notes: The first model uses the second-choice survey data, and the dependent variable is an indicator of whether the surveyed credit card consumer is willing to switch if the rewards on their current credit card were to be cut in half. The second model uses the MRI-Simmons data, and the dependent variable is an indicator for whether the consumer says that reward programs are an important factor in their choice of a financial institution. The independent variable in both regressions is log household income.

is a similar regression but uses MRI data from 2009–2022. The dependent variable is an indicator of whether a consumer reports reward programs are an important factor in driving their choice of financial services. The regression provides further support that higher income individuals are more rewards sensitive.

B.5 Comments from Merchants and Networks on the Segmentation Between Credit and Debit Cards

The U.S. Department of Justice's complaints in the Ohio v. AmEx case provide a wide range of comments on why merchants cannot substitute credit card acceptance with debit card acceptance. The bullets below report excerpts from (Conrath 2014). The main mechanism is that credit cards provide a valuable line of credit that allow consumers to make larger purchases.

Evidence from Merchants

- For example, Alaska Airlines views credit and debit as distinct products that do not compete with each other and cannot substitute for each other, while Crate & Barrel regards credit cards and debit cards to be "totally different products." Trial Tr. 252:6-11, 252:25-253:2 (Thiel/Alaska Airlines); Trial Tr. 2322:5-7 (Bruno/Crate & Barrel). (p. 101)

- Even though debit cards are a "much lower" cost for Best Buy than credit cards, Best Buy has never considered accepting only debit cards because "consumers are expecting to pay with credit cards" and for certain individuals "it can be a challenge" to pay with debit for some items. Trial Tr. 1525:9-21 (O'Malley/Best Buy). (p. 102)

- Likewise, given Home Depot's large average ticket size, Home Depot is "almost required to accept credit cards." Trial Tr. 1231:1-5 (Kimmet/Home Depot). Home Depot "customers want to pay with credit when they walk in the store" and "may want to finance" their purchases. (p. 103)

- IKEA accepts credit cards because "our customers have different tendencies and preferences in terms of how they want to pay for their purchases." Trial Tr. 387:8-18 (Robinson/IKEA). Some IKEA customers prefer credit while others prefer debit. IKEA customers who prefer debit "may be people who don't want to carry a balance at the end of the month; they may be people who are budget conscious and simply [do] not want to spend more than what's in their bank account." Certain credit customers "are willing to, basically, carry a balance from month to month." IKEA's "experience has shown us different customers . . . have different preferences, and we have to offer those choices." Trial Tr. 387:21-388:7 (p. 102)

Evidence from AmEx Testimony

- Amex consistently and repeatedly represented to courts and government agencies that it does not compete with debit card networks because of debit's limited substitutability with credit. In its 2004 complaint against Visa and MasterCard, Amex argued that "[t]he 'general purpose card network services market' or 'network services market' is a distinct 'Relevant Product Market'" and that "[c]onsumers do not consider debit cards to be reasonably interchangeable with general purpose credit and charge cards." (p. 90)

- (Amex Senior Vice President for Global Merchant Pricing) Mr. Funda testified that Amex does not compare its prices to a blend of Visa and MasterCard credit and debit prices because credit "is a different enough product with a sufficiently different feature set" than debit and "a sufficiently different cost structure than debit, that it should be priced on its own merits and not combined with debit." Trial Tr. 2730:17-23 (Funda/Amex).365. In seeking to justify its premium over Visa and MasterCard, Amex told one merchant that "we do not compete with debit so we didn't include it in [the rate] analysis." (p.108)

B.6 Survey Evidence on Consumer View of Credit Cards

Survey evidence from the SCPC and external marketing surveys suggests a sizeable fraction of consumers dislike the non-price characteristics of credit cards as a payment instrument so credit card use is crucially supported by the high levels of rewards.

Table A.5: Survey data on why consumers choose their preferred payment instrument

	Cash	Debit	Credit
Budget control	0.15	0.09	0.04
Convenience	0.29	0.43	0.27
Rewards	0.00	0.02	0.30

Notes: Consumers are split into four groups: those who prefer to use cash as their main non-bill payment instrument, those who prefer debit but have a below median utilization of credit cards (relative to all debit card users), those who prefer debit but have an above median utilization of credit cards, and those who prefer credit cards. Each variable is equal to 1 if the consumer reports the feature as the "most important characteristic" of the preferred payment instrument in making purchases. All averages and shares are calculated with individual level sampling weights.

Fear of overspending is a significant concern for many consumers. Table A.5 summarizes data from the DCPC on the reasons consumers choose their primary payment method. Around 15% and 9% of primary cash and debit card users say they pay with cash or debit because it helps them control their budget, compared to 4% of credit card users who report the same response. These responses are consistent with marketing surveys that show around a quarter of consumers report feeling "impulsive," "anxious," or "overwhelmed" when using a credit card, twice the rates from debit card use (Issa 2017).

There is also some evidence that some consumers find debit cards simpler to use. Table A.5 shows that debit card consumers are around 10 percentage points more likely than credit card consumers to choose their primary payment method based on convenience. Given that debit and credit cards have similar physical forms, the convenience here potentially refers to any concerns about making sure to make on-time payments or the simple fact that debit cards come already bundled with checking accounts. An important strand of the household finance literature emphasizes that banks make large profits off of unsophisticated consumers by charging hidden fees (Gabaix and Laibson 2006; Agarwal et al. 2022). If some consumers are sophisticated behavioral agents, they will anticipate these fees, find credit cards less convenient to use, and avoid credit cards.

Some consumers may also be debt averse. Around 37% of consumers who do not have a credit card say they "prefer not to carry any debt" as the reason they do not have a card, whereas only 26% say they do not qualify for a credit card (Boehm 2018).

Behavioral marketing research finds that some consumers prefer to time payments with consumption so that the pain of payment occurs before enjoying the purchase (Prelec and Loewenstein 1998).

The fact that 30% of credit card consumers say that the most important reason they pay with credit cards is for the rewards suggests that these consumers would not use credit cards without the rewards. This response suggests that even many credit card consumers dislike the non-price characteristics of credit cards as a payment instrument.

Many merchants note that consumer credit aversion is an important reason why it's important to accept debit cards in addition to debit cards. For example, IKEA in Conrath (2014) notes that: "IKEA customers who prefer debit "may be people who don't want to carry a balance at the end of the month; they may be people who are budget conscious and simply [do] not want to spend more than what's in their bank account." While not a merchant, Discover also notes that "Consumers with little credit available to them or who are carrying credit balances frequently prefer the discipline of debit cards, particularly for day-to-day purchases such as gas, groceries, or drug stores."

C Model Details

C.1 Deriving the Consumer Demand Function for Merchants

The merchant demand function used in the main text follows from a model in which consumers have symmetric CES preferences over merchants, and payment acceptance affects quality. Let there be a unit continuum of single-product merchants that sell varieties ω. Each merchant is characterized by a type $\gamma(\omega) \geq 0$ that determines the importance of payment availability for consumer shopping behavior at the merchant. Let the elasticity of substitution be σ. The consumer with wallet w has income y and receives lump sum rewards at a rate of f^w. The consumer chooses a consumption vector $q^w(\omega)$ to maximize utility subject to a budget constraint:

$$U^w = \max_{q^w} \left(\int_0^1 \left(1 + \gamma(\omega)\, \pi^w_{M^*(\omega)}\right)^{\frac{1}{\sigma}} q^w(\omega)^{\frac{\sigma-1}{\sigma}} \, \mathrm{d}\omega \right)^{\frac{\sigma}{\sigma-1}} \tag{27}$$

$$\text{s.t.} \int_0^1 q^w(\omega)\, p^*(\omega) \, \mathrm{d}\omega \leq y\,(1 + f^w)$$

The presence of $\pi^w_{M^*(\omega)}$ means that a consumer derives higher utility from consuming at a merchant that accepts a card the consumer wants to use. Consumers only care about *whether* they use a card from their wallet and not about which card is used.

Standard CES results imply that the quantity consumed at a merchant ω depends on the type γ, the price p, the payments accepted M, income y, and an aggregate price index P^w that summarizes the pricing and adoption decisions of all other merchants. The demand from a consumer with wallet w for a merchant of type γ is:

$$q^w(\gamma, p, M, y) = \left(1 + \gamma \pi^w_M\right) p^{-\sigma} \times \frac{y \times (1 + f^w)}{(P^w)^{1-\sigma}} \tag{28}$$

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

In this demand curve, only γ, π^w_M, and p vary across merchants. The price index P^w and the reward f^w are not affected by any one merchant's actions.[38]

Two merchants with the same γ choose the same price and acceptance policy. Therefore, the merchant variety ω can be dropped from the analysis. I can describe merchant actions in terms of an equilibrium price schedule $p^*(\gamma)$ and a set-valued adoption schedule $M^*(\gamma)$. This reparameterization means that the price index can now be expressed

[38] This simplifies the strategic interaction between merchants, who only need to care about other merchants' pricing and adoption decisions through the effect on the price index.

as in Equation 4, where $G(\gamma)$ is the distribution of the γ parameter across merchants.

C.2 Microfounding Merchant Profits

Merchant profits can be built up from quantities purchased by consumers with different income levels and payment preferences, multiplied by margins $L_M^w(\gamma, p)$, and then finally weighted by the masses of these different consumer groups.

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

The margins depend on the price, the fees, and the composition of payments:

$$\underbrace{L_M^w(\gamma, p)}_{\text{Average Margin}} = \underbrace{\frac{1 - \pi_M^w}{1 + \gamma \pi_M^w}}_{\text{Share of Cash}} \times \underbrace{(p-1)}_{\text{Cash margin}} + \sum_{j=1}^{2} \underbrace{\frac{\pi_{M,w_j}^w (1+\gamma)}{1 + \gamma \pi_M^w}}_{\text{Share on Card } j} \times \underbrace{\left(p\left(1 - \tau_{w_j}\right) - 1\right)}_{\text{Post-fee margin}}$$

In this equation, the shares represent the share of total expenditure on card j. The share is not the same as the probability $\pi_{M,j}^w$ that card j is used. They are different because consumers increase their consumption by γ percent when they use their cards. Thus, the per-unit margin not only depends on the merchant's price and acceptance decisions but also the merchant type γ.

To convert to the expression in the main text, note that the margin depends only on the wallet w and not the income y. The homotheticity of CES-demand then allows me to convert from the conditional market shares $\tilde{\mu}_y^w$ to the income-weighted market shares $\tilde{\mu}^w$. The margins can be further simplified to obtain the expression in Equation 6.

C.3 Deriving Merchant Optimal Pricing

The merchant's optimal pricing problem is:

$$\hat{p}(\gamma, M^*(\gamma), \tau) = \underset{p}{\operatorname{argmax}} \, \Pi(\gamma, p, M, \tau) \tag{29}$$

To solve the optimal pricing problem, note that each $\hat{q}^w$ is still a CES demand curve that satisfies the property:

$$\frac{\partial \hat{q}^w}{\partial p} = -\sigma \frac{\hat{q}^w}{p}$$

Let the optimal price for the firm, holding fixed the pricing and adoption decisions of other merchants, be $\hat{p}$. Differentiating equation 6 yields the first order condition

$$\sum_{w\in\mathcal{W}} \tilde{\mu}^w \times \left(-\sigma q^w \left(1-\frac{(1+\gamma)\,\tau_M^w}{1+\gamma\pi_M^w}\right)+\sigma\frac{q^w}{p}+q^w\left(1-\frac{(1+\gamma)\,\tau_M^w}{1+\gamma\pi_M^w}\right)\right)=0$$

$$\sum_{w\in\mathcal{W}} \tilde{\mu}^w \times \left(p\,(1-\sigma)\,q^w\left(1-\frac{(1+\gamma)\,\tau_M^w}{1+\gamma\pi_M^w}\right)+\sigma q^w\right)=0$$

Re-arranging terms yields

$$\begin{aligned}\implies p &= \frac{\sigma}{\sigma-1}\frac{\sum_{w\in\mathcal{W}}\tilde{\mu}^w q^w}{\sum_{w\in\mathcal{W}}\tilde{\mu}^w q^w-\sum_{w\in\mathcal{W}}\tilde{\mu}^w q^w\frac{(1+\gamma)\tau_M^w}{1+\gamma\pi_M^w}} \\ &= \frac{\sigma}{\sigma-1}\frac{1}{1-\frac{\sum_{w\in\mathcal{W}}\tilde{\mu}^w q^w\frac{(1+\gamma)\tau_M^w}{1+\gamma\pi_M^w}}{\sum_{w\in\mathcal{W}}\tilde{\mu}^w q^w}}\end{aligned}$$

By substituting in consumer demand (Equation 28) and the definition of the demand shares μ^w (Equation 9), we get that

$$\tilde{\mu}^w q^w\,(\gamma,p,M,1)=\tilde{\mu}^w\,(1+\gamma\pi_M^w)\,\frac{1+f^w}{(P^w)^{1-\sigma}}p^{-\sigma}=C\mu^w p^{-\sigma}\,(1+\gamma\pi_M^w)$$

In the fraction, the constant C and the prices $p^{-\sigma}$ drop out, hence

$$\frac{\sum_{w\in\mathcal{W}}\tilde{\mu}^w q^w\frac{(1+\gamma)\tau_M^w}{1+\gamma\pi_M^w}}{\sum_{w\in\mathcal{W}}\tilde{\mu}^w q^w}=\frac{\sum_{w\in\mathcal{W}}\mu^w\,(1+\gamma)\,\tau_M^w}{\sum_{w\in\mathcal{W}}\mu^w\,(1+\gamma\pi_M^w)}=\hat{\tau}$$

as desired.

C.4 Linearizing Merchant Profits

In this section, I prove that the merchant profit function $\overline{\Pi}$ is approximately linear in γ, holding fixed the other variables.

Theorem 1. *For any γ, M, P, τ,*

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

where

$$\overline{\Pi}(\gamma, M, \tau) \equiv C \times \left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma} \left\{-a_M + b_M\gamma + \frac{1}{\sigma}\right\} \tag{30}$$

$$a_M = \sum_{w\in\mathcal{W}} \mu^w \tau_M^w$$

$$b_M = \frac{1}{\sigma}\sum_{w\in\mathcal{W}} \mu^w\left(\pi_M^w - \sigma\tau_M^w\right)$$

$$\tau^{\max} = \max_j \tau_j \tag{31}$$

Proof. The profit function $\widehat{\Pi}$ is difficult to compute exactly is because as γ increases, the composition of consumers and the optimal price $\hat{p}(\gamma, M)$ changes for each γ. However, by the envelope theorem, the effect of these price changes has only second-order effects on profits. Formally, start from the optimal payment-specific prices under the assumption that consumers do not switch their payment choices with respect to the prices. These are $p_j = \frac{\sigma}{\sigma-1}\frac{1}{1-\tau_j}$ for payment method j. Any prices that are within an order τ_j adjustment then deliver the same profit, up to second-order terms in τ_j.

It therefore suffices to find a pricing schedule $p(\gamma, M)$ that is within order τ of p_j that generates the above expression for quasiprofits. A natural candidate is $\overline{p} = \frac{\sigma}{\sigma-1}$, i.e. the price that ignores merchant fees.

By plugging in the conversion from market shares to demand shares in Equation C.3, we get that for a general price, profits are:

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

Plugging in $p = \overline{p}$ yields

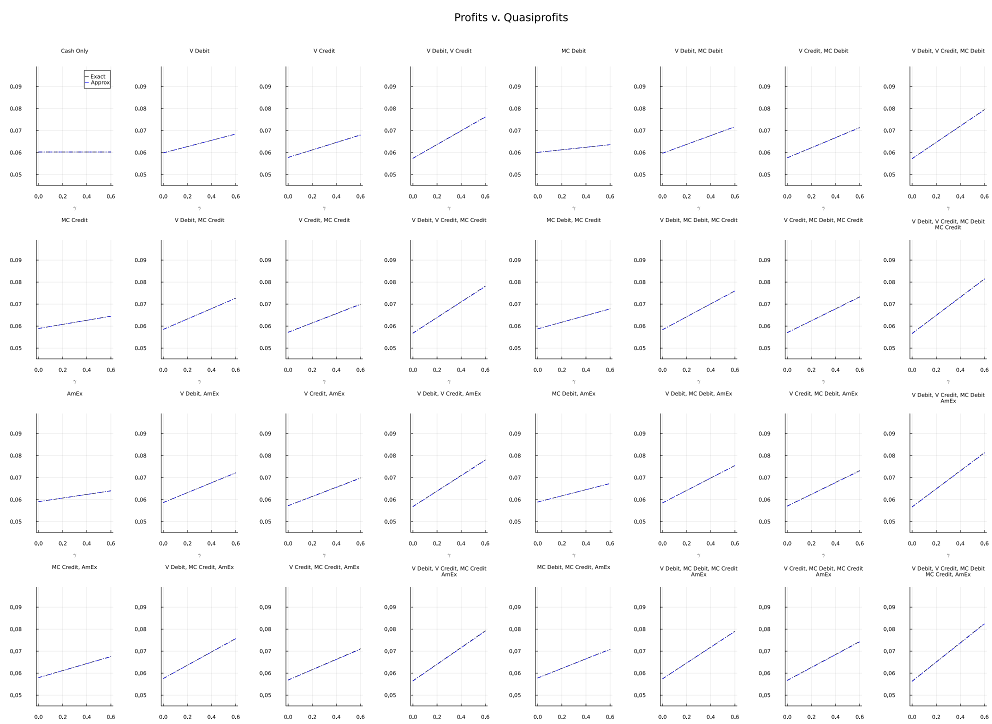
$$\begin{aligned}\Pi(\gamma, p, M) &= C \times \left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma} \sum_{w\in\mathcal{W}} \mu^w\left(1+\gamma\pi_M^w\right) \times \left(1 - \frac{(1+\gamma)\,\tau_M^w}{1+\gamma\pi_M^w} - \frac{\sigma-1}{\sigma}\right)\\ &= C \times \left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma} \sum_{w\in\mathcal{W}} \mu^w\left(1+\gamma\pi_M^w\right) \times \left(\frac{1}{\sigma} - \frac{(1+\gamma)\,\tau_M^w}{1+\gamma\pi_M^w}\right)\\ &= C \times \left(\frac{\sigma}{\sigma-1}\right)^{-\sigma} \left(-\sum_{w\in\mathcal{W}} \mu^w\tau_M^w + \frac{\gamma}{\sigma}\sum_{w\in\mathcal{W}} \mu^w\left(\pi_M^w - \sigma\tau_M^w\right) + \frac{1}{\sigma}\right)\end{aligned}$$

□

The σ^{-1} in b_M term captures that the profitability of card acceptance is decreasing in merchants' demand elasticity, and the $\sigma\tau_M^w$ is the loss from double marginalization between the payment network and merchant.

A natural question is whether the quasiprofit functions are a good approximation of true profits. Figure A.6 compares exact and approximate profits for all 32 potential payment bundles in the baseline equilibrium. The fit is very close for all values of the merchant type γ.

Figure A.6: Comparison of exact profits (which factor in price changes) and quasi-profits (which do not) in the baseline equilibrium for every possible subset of accepted cards.

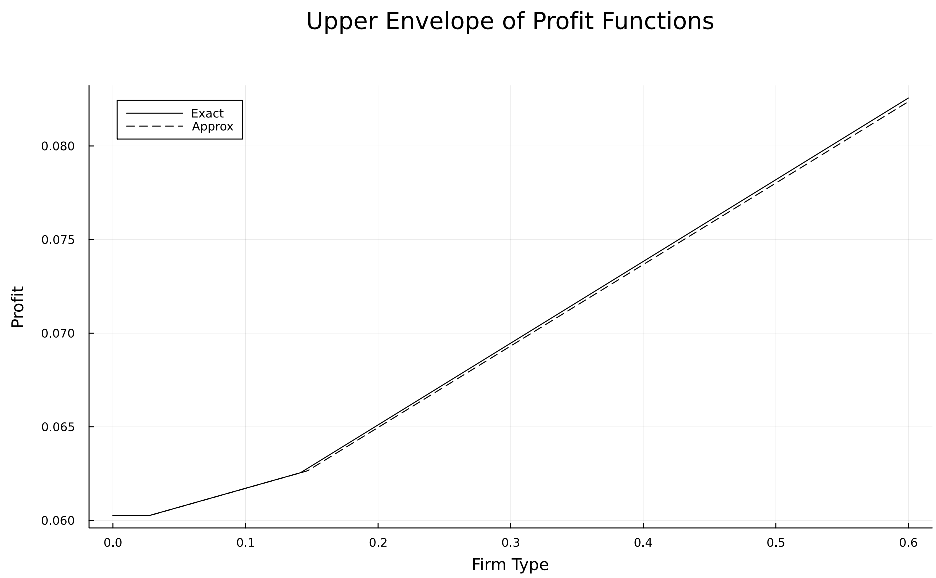


I also plot the upper envelope of the true profit functions and the upper envelope of the approximate profit functions. The points at which the envelope changes slope indicate the areas when the merchants' optimal acceptance strategies change. The close fit indicates I am accurately capturing how optimal acceptance changes with different merchant types.

C.4.1 Comparison of Merchant Acceptance with Rochet and Tirole (2003)

In this section, I analytically characterize the merchant acceptance strategies in a two-card economy. I study both the case when the two cards are of different payment types (i.e., credit and debit) and the case when they are the same type (e.g., two credit cards). The analysis reveals two facts that are useful in interpreting the empirical work.

Figure A.7: Comparison of the upper envelope of profits computed with the exact profit formula versus the quasi-profi approximation.



1. Debit card acceptance does not respond to credit card merchant fees or rewards, and vice versa. The lack of response is because consumers do not substitute between them at the point of sale. This result is consistent with the results in Appendix B.3.2 that indicate that a significant decline in debit card merchant fees had no effects on credit card acceptance.

2. When choosing between different networks' credit cards, acceptance of one network depends on the other network's fees and the relative share of consumers that multi-home versus single-home. This is consistent with the results in B.3.1 that when AmEx's merchant fee fell relative to Visa, AmEx acceptance increased sharply.

Throughout, let there be two cards 1 and 2 that charge merchant fees τ_1, τ_2. Let the insulated shares of different wallets be μ^w, and the merchant elasticity of substitution be σ.

The analysis of merchant acceptance boils down to studying the properties of the quasi-profit function

$$
\begin{aligned}
\overline{\Pi}(\gamma, M; \mu, \tau) &= -a_M + b_M \gamma \\
a_M &= \sum_w \mu^w \tau_M^w \\
b_M &= \frac{1}{\sigma} \sum_w \mu^w \left(\pi_M^w - \sigma \tau_M^w\right) \\
\pi_M^w &= \pi_{M,w_1}^w + \pi_{M,w_2}^w \\
\tau_M^w &= \pi_{M,w_1}^w \tau_{w_1} + \pi_{M,w_2}^w \tau_{w_2} \\
\pi_{M,w_2}^w &= I\left\{w_2 \text{ is not cash}\right\} \times P\left(\text{Pay with } w_2 \text{ if merchant accepts } M\right)
\end{aligned}
$$

A useful fact is that the intercept a_M and the slopes b_M can be decomposed into

$$
\begin{aligned}
a_M &= \sum_w \mu^w \left(\pi_{M,w_1}^w \tau_{w_1} + \pi_{M,w_2}^w \tau_{w_2}\right) \\
b_M &= \frac{1}{\sigma} \sum_w \mu^w \left(\pi_{M,w_1}^w \left(1 - \sigma \tau_{w_1}\right) + \pi_{M,w_2}^w \left(1 - \sigma \tau_{w_2}\right)\right)
\end{aligned}
$$

C.5 Debit Versus Credit

In the first case, let card 1 represent a debit card and card 2 represent a credit card. The first step to solving the merchant acceptance problem is to compute the probabilities of card usage $\pi_{M,j}^w$. Because consumers do not substitute between debit and credit cards at the point of sale, debit card use by those who multihome across credit and debit does not increase when a merchant rejects credit cards. Mathematically, we have that

$$\pi_{M,j}^{(1,0)} = \begin{cases} 1 & j = 1, 1 \in M \\ 0 & \text{o.w.} \end{cases} \qquad \text{(Debit single-homer pays with debit iff it's accepted)}$$

$$\pi_{M,j}^{(2,0)} = \begin{cases} 1 & j = 2, 2 \in M \\ 0 & \text{o.w.} \end{cases} \qquad \text{(Credit single-homer pays with credit iff it's accepted)}$$

$$\pi_{M,j}^{(2,1)} = \begin{cases} 1-\pi & j = 1, 1 \in M \\ \pi & j = 2, 2 \in M \\ 0 & \text{o.w.} \end{cases} \qquad \text{(Primary credit, secondary debit uses both if accepted)}$$

$$\pi_{M,j}^{(1,2)} = \begin{cases} \pi & j = 1, 1 \in M \\ 1-\pi & j = 2, 2 \in M \\ 0 & \text{o.w.} \end{cases} \qquad \text{(Primary debit, secondary credit uses both if accepted)}$$

$$\pi_{M,j}^{(0,0)} = 0$$

Therefore, we have that

$$\begin{aligned}
a_{\{1\}} &= \left(\mu^{(1,0)} + \pi\mu^{(1,2)} + (1-\pi)\,\mu^{(2,1)}\right)\tau_1 \\
b_{\{1\}} &= \frac{1}{\sigma}\left(\mu^{(1,0)} + \pi\mu^{(1,2)} + (1-\pi)\,\mu^{(2,1)}\right)(1-\sigma\tau_1) \\
a_{\{2\}} &= \left(\mu^{(2,0)} + \pi\mu^{(2,1)} + (1-\pi)\,\mu^{(1,2)}\right)\tau_2 \\
b_{\{2\}} &= \frac{1}{\sigma}\left(\mu^{(2,0)} + \pi\mu^{(2,1)} + (1-\pi)\,\mu^{(1,2)}\right)(1-\sigma\tau_2) \\
a_{\{1,2\}} &= a_{\{1\}} + a_{\{2\}} \\
b_{\{1,2\}} &= b_{\{1\}} + b_{\{2\}}
\end{aligned}$$

A key observation is that:

$$\overline{\Pi}(\gamma, \{1,2\}) = \overline{\Pi}(\gamma, \{1\}) + \overline{\Pi}(\gamma, \{2\})$$

That is, the profitability of accepting both cards is separable into two problems of whether to accept debit cards (1) and whether to accept credit cards (2). Any merchant that finds accepting debit cards more profitable than being cash only will find accepting credit with debit more profitable than only accepting credit cards.

This result on the quasiprofit function provides an easy characterization of the merchant acceptance equilibrium. For all $\gamma > \frac{\sigma\tau_1}{1-\sigma\tau_1}$, $\overline{\Pi}(\gamma, \{1\}) > 0$. Similarly, for all $\gamma > \frac{\sigma\tau_2}{1-\sigma\tau_2}$, $\overline{\Pi}(\gamma, \{2\}) > 0$. Without loss of generality, let $0 < \tau_1 \leq \tau_2$. Then:

1. Merchants of type $\gamma < \frac{\sigma\tau_1}{1-\sigma\tau_1}$ accept only cash
2. Merchants of type $\frac{\sigma\tau_1}{1-\sigma\tau_1} \leq \gamma < \frac{\sigma\tau_2}{1-\sigma\tau_2}$ accept only cash and debit
3. Merchants of type $\gamma \geq \frac{\sigma\tau_2}{1-\sigma\tau_2}$ accept cash, debit, and credit

These analytical expressions show that changes in debit card fees do not affect credit card acceptance.

C.6 Two Different Types of Credit Cards

If cards 1 and 2 represent different types of credit cards, then the payment probabilities differ in an important way that changes the merchant acceptance problem. Conditional on the adoption decisions, consumers in the model never increase their use of debit cards if credit cards are not accepted. However, they will increase their use of lower merchant fee credit cards if higher merchant fee cards are not accepted. Without loss of generality, let $0 < \tau_1 \leq \tau_2$, and card 1 can be thought of as "Visa" whereas card 2 is a more expensive "AmEx" card. Mathematically, we have that

$$\pi_{M,j}^{(1,0)} = \begin{cases} 1 & j = 1, 1 \in M \\ 0 & \text{o.w.} \end{cases} \qquad \text{(Visa single-homer pays with Visa iff it's accepted)}$$

$$\pi_{M,j}^{(2,0)} = \begin{cases} 1 & j = 2, 2 \in M \\ 0 & \text{o.w.} \end{cases} \qquad \text{(AmEx single-homer pays with AmEx iff it's accepted)}$$

$$\pi_{M,j}^{(2,1)} = \begin{cases} 1 & j = 1, 1 \in M, 2 \notin M \\ 1 & j = 2, 2 \in M, 1 \notin M \\ \pi & j = 1, M = \{1,2\} \\ 1-\pi & j = 2, M = \{1,2\} \\ 0 & \text{o.w.} \end{cases} \qquad \text{(Multi-homer pays with whichever card is accepted)}$$

$$\pi_{M,j}^{(1,2)} = \begin{cases} 1 & j = 1, 1 \in M, 2 \notin M \\ 1 & j = 2, 2 \in M, 1 \notin M \\ 1-\pi & j = 1, M = \{1,2\} \\ \pi & j = 2, M = \{1,2\} \\ 0 & \text{o.w.} \end{cases} \qquad \text{(Multi-homer pays with whichever card is accepted)}$$

$$\pi_{M,j}^{(0,0)} = 0$$

This results in slopes and intercepts of

$$\begin{aligned}
a_{\{1\}} &= \left(\mu^{(1,0)} + \mu^{(1,2)} + \mu^{(2,1)}\right)\tau_1 \\
b_{\{1\}} &= \frac{1}{\sigma}\left(\mu^{(1,0)} + \mu^{(1,2)} + \mu^{(2,1)}\right)(1 - \sigma\tau_1) \\
a_{\{2\}} &= \left(\mu^{(2,0)} + \mu^{(2,1)} + \mu^{(1,2)}\right)\tau_2 \\
b_{\{2\}} &= \frac{1}{\sigma}\left(\mu^{(2,0)} + \mu^{(2,1)} + \mu^{(1,2)}\right)(1 - \sigma\tau_2) \\
a_{\{1,2\}} &= \left(\mu^{(1,0)} + \pi\mu^{(1,2)} + (1-\pi)\,\mu^{(2,1)}\right)\tau_1 + \left(\mu^{(2,0)} + (1-\pi)\,\mu^{(1,2)} + \pi\mu^{(2,1)}\right)\tau_2 \\
&= a_{\{1\}} + \mu^{(2,0)}\tau_2 + \left((1-\pi)\,\mu^{(1,2)} + \pi\mu^{(2,1)}\right)(\tau_2 - \tau_1) \\
b_{\{1,2\}} &= \frac{1}{\sigma}\left(\mu^{(1,0)} + \pi\mu^{(1,2)} + (1-\pi)\,\mu^{(2,1)}\right)(1 - \sigma\tau_1) + \frac{1}{\sigma}\left(\mu^{(2,0)} + (1-\pi)\,\mu^{(1,2)} + \pi\mu^{(2,1)}\right)(1 - \sigma\tau_2) \\
&= b_{\{1\}} + \frac{1}{\sigma}\mu^{(2,0)}(1 - \sigma\tau_2) - \left((1-\pi)\,\mu^{(1,2)} + \pi\mu^{(2,1)}\right)(\tau_2 - \tau_1)
\end{aligned}$$

The key difference is that accepting the high-fee card in addition to the low-fee card incurs additional fees because multi-homers shift their spending to the high-fee card. However, there is no corresponding increase in sales because consumers would have used the low-fee card and purchased just as much. Thus, the slope and intercept of the bundle does not decompose additively as in the credit and debit card case.

Given these expressions, when the acceptance strategies are characterized by cash-only merchants, Visa merchants, and merchants that accept everything (as in the data), the regions are such that:

1. Merchants with $\gamma < \frac{\sigma\tau_1}{1-\sigma\tau_1}$ accept only cash
2. Merchants with $\frac{\sigma\tau_1}{1-\sigma\tau_1} \leq \gamma < \frac{\mu^{(2,0)}\sigma\tau_2+\sigma\left((1-\pi)\mu^{(1,2)}+\pi\mu^{(2,1)}\right)(\tau_2-\tau_1)}{\mu^{(2,0)}(1-\sigma\tau_2)-\sigma\left((1-\pi)\mu^{(1,2)}+\pi\mu^{(2,1)}\right)(\tau_2-\tau_1)}$ accept only the low-fee card 1
3. Merchants with types $\gamma \geq \frac{\mu^{(2,0)}\sigma\tau_2+\sigma\left((1-\pi)\mu^{(1,2)}+\pi\mu^{(2,1)}\right)(\tau_2-\tau_1)}{\mu^{(2,0)}(1-\sigma\tau_2)-\sigma\left((1-\pi)\mu^{(1,2)}+\pi\mu^{(2,1)}\right)(\tau_2-\tau_1)}$ accept all of the cards

Notice that if $\tau_2 = \tau_1$, then the second zone vanishes and merchants go from being cash-only to accepting all of the cards.

Intuitively, when many American Express holders carry Visa, then $\mu^{(2,1)}, \mu^{(1,2)}$ are large, and fewer merchants will accept American Express if Visa charges a low fee. Merchants become unwilling to accept American Express because doing so would force the merchant to raise higher prices, lowering demand while getting few incremental sales. When fewer merchants accept American Express, Visa is better off and so Visa has strong incentives to compete for merchants if most American Express consumers hold Visa cards. In contrast, if no American Express users carry a Visa, then $\mu^{(2,1)}, \mu^{(1,2)}$ are zero, and the lowest type merchant that accepts American Express is $\frac{\sigma\tau_a}{1-\sigma\tau_a}$. In this case, the set of merchants that accept American Express no longer depends on the fees that Visa charges.

This analysis thus shows that the acceptance of different networks' credit cards are highly sensitive to relative merchant fees because consumers are willing to substitute between them at the point of sale.

C.7 A Microfoundation for Segmentation Between Credit and Debit at the Point of Sale

I derive a microfoundation to explain how payment methods can be substitutes when consumers decide what to adopt but are poor substitutes at the point of sale. I also demonstrate that this microfoundation is empirically supported. This microfoundation is important for the model in the main text because that model assumes that consumers are unwilling to substitute between credit and debit cards at the point of sale. The microfoundation borrows heavily from previous models of adoption and usage, such as Koulayev et al. (2016) and Huynh et al. (2022).

The model below distinguishes usage and adoption to illustrate how segmentation at the usage stage is independent of segmentation at the adoption stage.

C.7.1 Utility at the Point of Sale

Let $\mathcal{J} = \{0, 1, 2, \ldots, J\}$ be the set of all payment methods, where $j = 0$ denotes the outside option of cash. Denote consumers by i. Let M denote the subset of payment methods accepted by the merchant, and W denotes the cards in the consumer's wallet. Denote the characteristics of the payment method j as $X_j \in \mathbb{R}^k$. For example, these characteristics can include whether j is a credit card or whether it is a card at all. Let the reward for using a payment method j be f_j. For a given transaction t, the utility for using a payment method j is

$$\begin{aligned} u_{ijt} &= \alpha f_j + \gamma_{it}' X_j + \epsilon_{ijt} \\ \gamma_{it} &\sim N\left(\overline{\gamma}_i, \Sigma\right) \\ \epsilon_{ijt} &\sim \text{T1EV} \end{aligned}$$

The random shocks to $\gamma_{it} \in \mathbb{R}^k$ encode the idea that for a given transaction, the consumer may value being able to use a credit card more than a debit card or might value using a card far more than using cash. The mean of the distribution $\overline{\gamma}_i \in \mathbb{R}^k$ is consumer-specific, so some consumers might prefer using credit cards in general. The idiosyncratic shocks ϵ_{ijt} encode reasons why different cards of a given type (e.g., different credit cards) have varying values across transactions. For example, some credit cards may give bonuses for travel while others target groceries.

The parametric assumptions mean that we can write the expected utility given the merchant accepts M as

$$V_i\left(M, W_i\right) = \int \log\left(\sum_{j \in M \cap W_i} \exp\left(\alpha f_j + \gamma_{it} X_j\right)\right) \, \mathrm{d}H\left(\gamma_{it}\right)$$

where H captures the distribution of γ_{it}.

C.7.2 Utility at Adoption

At the adoption stage, consumers choose a wallet to maximize their expected utility at the point of sale, less any adoption costs. Thus consumers solve

$$W_i = \underset{W \subset \mathcal{J}}{\operatorname{argmax}} \, V_i \left(M, W \right) - \sum_{j \in W} c^{'} X_j + \phi a_{iW}$$
$$a_{iW} \sim N \left(0, \nu^2 \right)$$

where $c \in \mathbb{R}^k$ is some vector that captures the adoption costs for payment methods of different characteristics.

C.7.3 Mapping Between the Microfounded Model and the Model in the Main Text

The micro-founded model sheds light on the distinction between segmentation at the point of sale versus segmentation at the adoption stage. It also illustrates how different payment methods can either complement or substitute for each other in a wallet.

Distinguishing Segmentation at the Usage Stage Versus Segmentation at the Adoption Stage In the model in the main text, I assume that when a merchant accepts debit cards but not credit cards, consumers who carry both nonetheless do not substitute from credit cards to debit cards at that merchant. However, consumers who carry multiple credit cards readily substitute between them. Mathematically, this is possible if consumers have strong preferences over credit versus debit for any given transaction but are not that heterogeneous in their adoption costs for different cards.

Consumers would strongly prefer one type of card over another if the variances of the transaction-specific shocks $\Sigma \to \infty$. Under this parameterization, any time a consumer wishes to use a payment the method with a credit feature, she obtains very little utility from being able to use a debit card. Economically, this corresponds to the case that there are certain types of transactions (e.g., large ticket sizes) that are more suited for credit than for debit.

At the same time, consumers in the main text are readily willing to substitute between payment methods at the adoption stage. The strong substitution is compatible with the assumption that $\nu^2 \to 0$. More generally, even when the variance Σ of the transaction-specific shocks is large, that does not induce segmentation between payment methods of different types at the adoption stage. At the adoption stage, the consumer cares about the expected utility V_i of different wallets, which integrates over the distribution of transaction-specific shocks γ_{it}. If adoption costs are similar across payment instruments, then consumers may nonetheless be sensitive to rewards in deciding what to adopt.

To take a very extreme example, suppose a consumer has 50 large ticket-size transactions and 50 small ticket-size transactions, and she strongly prefers credit for the large transactions and debit for the small transactions. But at the adoption stage, credit and debit might offer similar adoption utilities because they each cover around half of her transactions. Thus, her choice of whether to adopt credit versus debit might be very sensitive to rewards even though she strongly prefers one card or the other for any one of her transactions.

Complements, Incremental Adoption Costs, and Substitutes at Adoption The micro-founded model also gives a natural reason why consumers who carry debit cards may also want to adopt credit cards. By adopting both payment methods, they can use a credit card when the transaction-specific shock $\gamma_{it}^{'}X_j$ is large for credit and use a debit card when the shock is large for debit. Carrying both raises the inclusive value V_i. This force is captured in the main text by allowing for complementarity parameters $\chi > 0$ for wallets that have both a credit card and a debit card.

The model also captures the fact that consumers face incremental adoption costs. If all cards of a given type pay the same rewards f_j, then the inclusive value V_i is concave in the number of cards of a given type, but the costs are linear. This explains why consumers may not adopt all of the cards on the market. This force can be captured in the main text by allowing for complementarity parameters $\chi < 0$ for wallets with multiple cards.

At the same time, if a consumer highly values credit cards, then she may want to carry multiple credit cards to capture the value of getting more idiosyncratic shocks ϵ_{ijt}. This can happen for consumers for which $\overline{\gamma}_i X_j$ is particularly large for credit cards. I capture this force in the main text by allowing for complementarity parameters $\chi > 0$ for wallets with multiple credit cards.

C.7.4 Empirical Evidence for the Assumption that Debit and Credit are Segmented at the Point of Sale

For consumers to be unwilling to substitute between the debit and credit cards in their wallets at the point of sale, we need the variance Σ of the characteristic-based shocks to be large. An empirical prediction of this assumption is that when consumers are offered rewards for using a certain credit card at the point of sale, they only substitute transactions from other credit cards and not other debit cards. I confirm this prediction when I study the quarterly variation in rewards for Discover credit cards at grocery stores in Appendix B.1.

C.8 Details on the Conduct Assumption

I model competition in pecuniary gains A_j instead of rewards f^j to deal with multiple equilibria arising from the fact that consumer adoption depends on merchant acceptance. Weyl (2010) argues that guaranteeing the utility gains from adoption is a reduced-form way of capturing penetration pricing by which networks subsidize consumer adoption when merchant acceptance is low. By paying more in rewards if acceptance is low, consumers have a dominant strategy in deciding what to adopt, which pins down a unique equilibrium in the subgame. After the networks set A_j, consumer market shares are determined.

I model competition in pecuniary gains A_j rather than utility levels U^j because the utility of the outside option is not fixed. Higher merchant fees raise retail prices and lower utility for all consumers. Thus, a conduct assumption in which networks set U^w would imply that Visa raises its rewards in a deviation when AmEx raises its merchant fees.

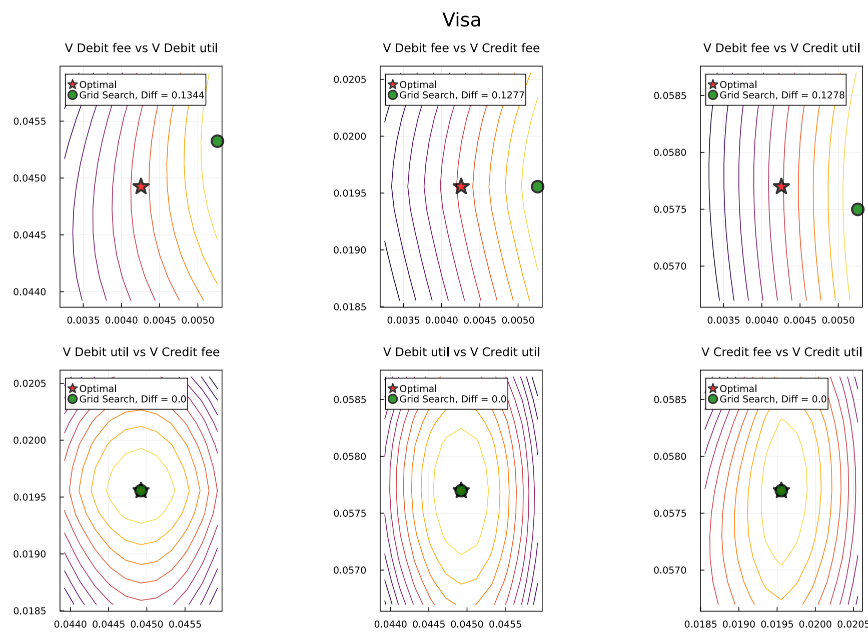
Network profits are not differentiable in the merchant fee. Non-differentiability poses a challenge for equilibrium selection. The assumption of small trembles in the choice variables chooses an equilibrium where networks stand to lose the same profits from raising or lowering merchant fees.

The non-differentiability of profits is a generic problem when merchants do not perceive non-pecuniary reasons to accept cards. Starting from the symmetric equilibrium, a network that raises its merchant fee is now competing with the option to accept all other card networks. A network that cuts its merchant fee is now competing with cash. In these two regions, the marginal revenue from raising fees is very different; therefore, profits are not differentiable in the neighborhood of the original symmetric fee. In their two-network model, Rochet and Tirole (2003) do not encounter this issue. Subsequent theoretical work has shown that problems arise with more networks (Teh et al. 2022).

The non-differentiability of profits means many potential equilibria satisfy the property that networks are maximizing their profits. By introducing noise into the choice variables, I pick an equilibrium in which networks gain equal amounts from raising merchant fees and lowering merchant fees. Mathematically, the profit functions Ψ become differentiable because the convolution of an integrable function (the profit function) and a smooth function (the density of the noise) is smooth. As the amount of noise approaches zero, the smoothed objective function converges uniformly to the original profit function.

To evaluate the approximation error created by the fee trembles ν_x, in Figure A.8, I plot pairwise heatmaps of Visa's total profit (without trembles) in the baseline equilibrium as a function of every pair of control variables that Visa has access to. I then compare the maximizing point that I compute with the maximal point from the grid search. The grid search identifies higher profits when one of the control variables is Visa's debit card merchant fee. The grid search delivers higher profits because the Durbin Amendment constrains fees to be below their profit-maximizing level. Otherwise, the match is essentially exact.

Figure A.8: Comparing the maximum from solving the FOC's of the perturbed profit function with the maximum of the original profit function



C.9 Model Solution Algorithm

Solving the model boils down to two steps:

1. Solving for an allocation given pecuniary benefits A_j and fees τ_j.

2. Jointly solving for the networks' first-order conditions

To solve for the allocation, note that A_j determines the market shares $\tilde{\mu}_y^w$. In effect, consumers' choice of wallets is determined by the pecuniary utilities relative to the outside option and not the level of pecuniary utility (Equation 18). After solving for the market shares, I then use damped iteration to solve for a fixed point to recover the vector of price indices P^w, the individual reward rates f^j, and the merchant acceptance decisions M^*. Given equilibrium merchant actions and consumer actions, it's straightforward to compute network profits from Equations 20 and 22.

When implementing the demand function, I use 1000 draws of random coefficients for the unobserved heterogeneity and then an 11-node Gauss-Hermite quadrature scheme to integrate over the log-normal distribution of income.

I then solve for the equilibrium by jointly solving the networks' first-order conditions, taking into account the structure of the ownership matrix. If a fee is subject to a cap (e.g., Durbin or counterfactual fee caps), I do not enforce the first-order condition of that fee. To handle the normal expectation, I use an N-dimensional Gauss-Hermite quadrature scheme with 2 points per dimension. Two nodes essentially enforce the requirement that each network's profit loss from raising merchant fees by a tiny amount is equal to their profit loss from lowering their merchant fee by a small amount.

After solving for an equilibrium, I verify that the second-order conditions for a local maximum are also satisfied. I also check that the cap is binding for all capped fees.

D Price Coherence

Although merchants in the U.S. can charge discriminatory prices for different payment methods, most do not. This can be rational even assuming small menu costs.

D.1 A Brief History of Price Coherence in the U.S.

While cash discounts have long been legal in the U.S., merchants' ability to apply card surcharges has only gradually increased over time.[39] The Cash Discount Act of 1981 guarantees merchants' right to offer discounts for cash (Chakravorti and Shah 2001; Levitin 2005; Prager et al. 2009). The Durbin Amendment in 2010 also gave merchants the right to offer discounts for debit cards (Schuh et al. 2011; Briglevics and Shy 2014).

The first major change to allow for credit card surcharging was the 2013 settlement between Visa, Mastercard, and the DOJ, which removed no-surcharge rules at the network level. This settlement meant that merchants in the 40 states without state-level no-surcharge rules could now freely charge higher prices for credit card transactions (Blakeley and Fagan 2015). Visa allowed multi-state merchants who operated in states with no-surcharge rules to surcharge in states that allowed them (Visa 2013). Although the settlement technically only applied to Visa and Mastercard, American Express and Discover relaxed their no-surcharge rules at this time to allow merchants to surcharge American Express and Discover credit cards at the same level as the Visa and Mastercard (Merchant 2016).

In the wake of the 2013 settlement, the last remaining barrier to card surcharging in the U.S. were state-level prohibitions in 10 states: California, Colorado, Connecticut, Florida, Kansas, Massachusetts, Maine, New York, Oklahoma, and Texas (Visa 2013; Merchant 2016). Yet, over the subsequent years, many of these states also dropped their requirements against surcharging. As of 2023, only Massachusetts and Connecticut have bans against surcharging (CardX 2023), although the disclosure requirements in New York and Maine render card surcharging impractical.[40]

D.2 Price Coherence in the Data

In this section, I show that around 5% of transactions in the Diaries of Consumer Payment Choice (DCPC) are at a merchant with either card surcharges or cash discounts.

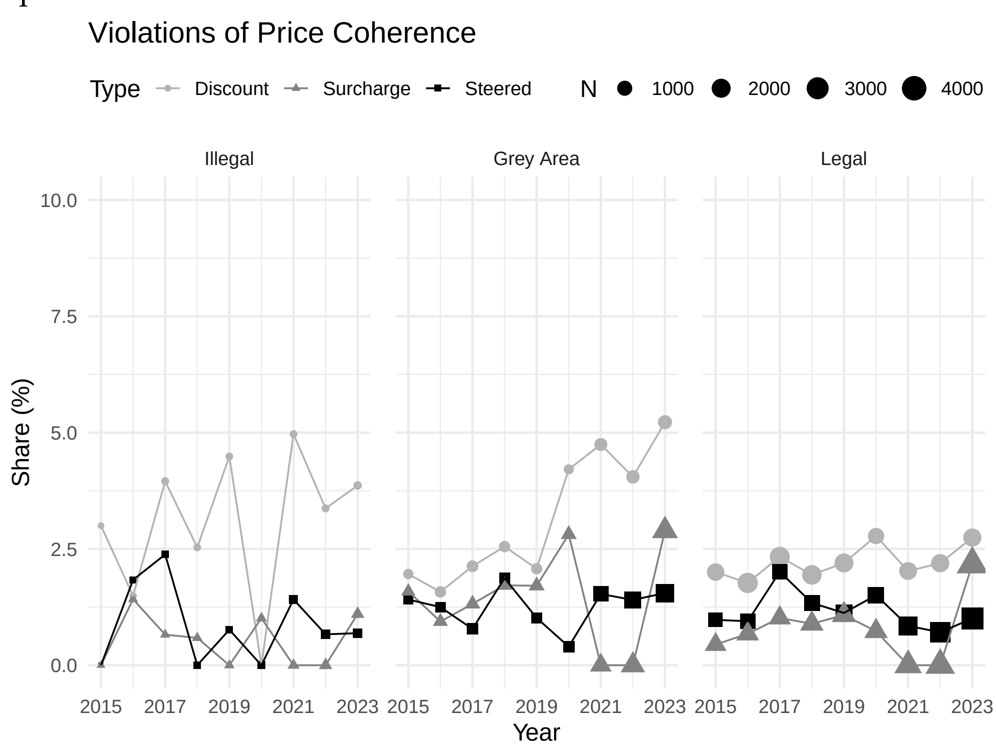
[39] Under complete information, discounts and surcharges are identical. But if the existence of discounts or surcharges is shrouded, then cash discounts are a kind of giveaway, whereas surcharges are an add-on price (Bourguignon et al. 2019).

[40] In New York and Maine, retailers must disclose the dollar and cents value of the credit card price and the cash price in order to surcharge. Satisfying this law would entail posting twice the number of prices. In New York, this requirement is explicitly described as making sure consumers "should not have to do math to figure out whether they are paying the surcharge" (Westchester 2019)

This fact explains why I assume price coherence throughout my paper. I focus on transactions on cash, checks, debit cards, and credit cards. I exclude bank account payments through ACH because it is not covered in the aggregate payment volumes from Nilson (2020). I group cash and check as "cash" and then separate debit and credit. I exclude government or financial transactions to capture the idea of retail purchases.

I identify violations of price coherence in the following way. "Discounts" are cash (or check) transactions in which a discount was applied specifically because of using this payment instrument. "Surcharges" are credit card transactions in which a fee is applied. Note that these fees are not necessarily applied because of the chosen payment instrument; so this includes but is not limited to, all of the transactions applying a fee specifically because of using credit. "Steered" are non-credit card transactions from consumers who prefer using credit cards, in which a discount because of using this payment instrument was applied. Also, note this could include transactions where the consumer would have paid with their non-preferred payment method anyway.

The figure below shows time series of the frequency of surcharges and discounts across three groups of states. I group states into three categories: "Legal" states that never had state-level prohibitions on surcharging, "Illegal" states that still had bans as of 2020, and "Grey Area" states that used to have state-level no-surcharge rules but repealed them at some point in 2013 – 2020. Overall, rates are low across all three groups.



One potential reason surcharging is rare is that it was not always legal. This explanation does not explain why there are so few cash discounts. In addition, the rates of cash discounts and card surcharges across states do not vary with legality.

D.3 Private Incentives to Surcharge

This section outlines the theoretical argument for how small menu costs can support price coherence as an equilibrium outcome. First, I show that merchants are unable to use surcharges to steer consumers between cash and card. Second, by the model assumption that consumers do not substitute between credit and debit at the point of sale, the inability to steer card consumers to cash rules out all kinds of steering between different payment types (e.g., credit vs debit). Third, given this inability to steer, merchants' losses from uniform prices are second order in any type-symmetric equilibrium in which cards of the same type (e.g., Visa/MC/AmEx credit cards) all charge the same merchant fee. Intuitively, price coherence results in merchants charging card consumers a price that is slightly too low and charging cash consumers a price that is slightly too high. By the envelope theorem, neither price deviation has a first-order effect on profits.

I focus on the type-symmetric case because it is a good approximation of the U.S. market structure (See Figure 2). In the estimated equilibrium, these losses from charging uniform prices are less than 20 *basis points* in profits. Thus, even small menu costs, such as upsetting customers (Caddy et al. 2020), can explain why merchants choose not to surcharge.

The previous results concern type-symmetric equilibria. In principle, merchants may find it attractive to surcharge high-fee networks more than others. While a full analysis of this case is beyond the scope of the paper, I discuss some reasons why even this ability may not be enough to motivate merchants to charge different fees.

D.3.1 No Steering

To show that merchants cannot steer consumers between card and cash, I first prove the case when there's a monopoly network. With that result, it immediately follows that in any type-symmetric equilibrium, then merchants are also unable to steer consumers between payment types. Another way of stating the result is that card use is always ex-post efficient in the model, and so passing on merchant fees does not steer consumers between types.

I first extend the baseline model to allow consumers to choose how to pay at the point of sale and to allow merchants to charge payment-specific prices. For simplicity, I ignore variation in baseline income y. I now model the consumption decision in two nests. Consumers choose effective consumption levels of each variety $q(\omega)$, but now effective consumption is a linear aggregate of card $c(\omega)$ and cash consumption $a(\omega)$. Merchants are also allowed to charge different prices for cards versus cash, such that card consumers pay a price that is $1+s(\omega)$ higher. Consumers solve

$$U = \max_{c,a} \left(\int_0^1 q(\omega)^{\frac{\sigma-1}{\sigma}} \, \mathrm{d}\omega \right)^{\frac{\sigma}{\sigma-1}} \tag{32}$$

$$\text{s.t. } q(\omega) = \left(1 + \gamma(\omega)\, v^w_{M(\omega)}\right)^{\frac{1}{\sigma-1}} c(\omega) + a(\omega) \tag{33}$$

$$y \geq \int_0^1 \left(c(\omega)\left(1+s(\omega)\right) + a(\omega)\right) p(\omega) \, \mathrm{d}\omega \tag{34}$$

The linear aggregation corresponds to the idea that card goods are higher quality and perfect substitutes for cash goods. The model assumes that the convenience benefit of using a card is the same on every shopping trip. This assumption is crucial for the result that surcharging is not effective. Note that the original model corresponds to the case of

$$(c(\omega), a(\omega)) = \begin{cases} (0, q^w(\omega)) & v^w_{M(\omega)} = 0 \\ (q^w(\omega), 0) & v^w_{M(\omega)} = 1 \end{cases}$$

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

Proof. Suppress the variety ω. The FOC for the Lagrangian with respect to more card spending c and cash spending a for a card consumer at a merchant who accepts cards is

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

where $I = \int_0^1 q(\omega)^{\frac{\sigma-1}{\sigma}} \, \mathrm{d}\omega$ Both card spending and cash spending are at an interior solution provided that

$$(1+\gamma)^{\frac{1}{\sigma-1}} = 1 + s$$

Because the aggregator for q is linear, for any $s > (1+\gamma)^{\frac{1}{\sigma-1}} - 1$, card spending $c = 0$. For any lower surcharge, cash spending $a = 0$. $\square$

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

Proof. By the expressions for quasiprofits from 1, we have that the lowest type that accepts credit cards in the baseline model satisfies $\gamma^* = \frac{\sigma\tau}{1-\sigma\tau}$. For general $\gamma > 0, \sigma > 1$ we have the inequality that

$$(1+\gamma)^{\frac{1}{\sigma-1}} \geq 1 + \frac{\gamma}{\gamma+1}\frac{1}{\sigma-1}$$

Thus by Lemma 1 the required surcharge exceeds

$$s^* \geq 1 + \frac{\gamma^*}{\gamma^*+1}\frac{1}{\sigma-1} - 1 = \tau\frac{\sigma}{\sigma-1} > \tau$$

□

The result may be surprising. Intuitively, it should be possible to use a surcharge to get a credit card user to switch to a debit card. I have ruled that out by the assumption that consumers only use cards that share the same type as their primary card. I have done this to conform with empirical evidence and antitrust thinking on the topic (Jones 2001). Empirically, debit card incentives do not steer credit card consumers (Conrath 2014).

D.3.2 Magnitude of Losses from Uniform Pricing

When card surcharges do not change the method of payment, then uniform pricing results in only second-order losses. This section quantifies the losses from uniform pricing. Suppose merchants can charge wallet-specific prices p^w. Stack these prices into a vector. Then after dropping the CES price indices and income from the normalization, we get that total profits $\widehat{\Pi}$ are proportional to

$$\widehat{\Pi} \propto \sum_{w \in \mathcal{W}} \mu^w \pi^w$$
$$\pi^w = (1+\gamma v_M^w)(p^w)^{-\sigma}(p^w(1-\tau^w)-1)$$

Let p^* denote the vector of optimal prices, and $\hat{p}$ denote the vector of uniform prices. I use a second-order Taylor expansion of $\log\widehat{\Pi}$ with respect to $\log p$ to derive the losses from uniform pricing:

Theorem 3. *The percentage loss from charging the optimal uniform price instead of optimal payment-specific prices is:*

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

Proof. First, a first-order Taylor expansion gives that

$$\log \widehat{\Pi}\left(p^*\right) - \log \widehat{\Pi}\left(\hat{p}\right) \approx \sum_w \frac{\mu^w \left(1 + \gamma v_M^w\right) \pi^w}{\sum_l \mu^l \left(1 + \gamma v_M^l\right) \pi^l} \times \left(\log \pi^w \left(p^*\right) - \log \pi^w \left(\hat{p}\right)\right)$$

which merely says that the percentage loss in total profits is the weighted sum of the percentage loss in profits from consumers of each different wallet. By Equation 8 the optimal payment specific price is $p^{w*} = \frac{\sigma}{\sigma-1}\left(1-\tau^w\right)^{-1}$. After dropping all terms of order τ and higher, we have that $\pi^w \approx \pi^l$. It then remains to show that

$$\log \pi^w \left(p^{w*}\right) - \log \pi^w \left(\hat{p}\right) \approx \frac{\sigma\left(\sigma-1\right)}{2}\left(\tau^w - \hat{\tau}\right)^2$$

to second order. By the envelope theorem, $\log \pi^w\left(p^*\right) - \log \pi^w\left(\hat{p}\right) = 0$ to first order. We then compute a second-order expansion in $\log p$. Express log profit in terms of the log price

$$\log \pi^w = -\sigma \log p^w + \log\left(\exp\left(\log p\right)\left(1-\tau^w\right) - 1\right)$$

Differentiate twice to obtain

$$\begin{aligned}
\frac{\partial^2 \log \pi^w}{\partial\left(\log p\right)^2} &= \frac{\partial}{\partial \log p} \frac{\exp\left(\log p\right)\left(1-\tau^w\right)}{\exp\left(\log p\right)\left(1-\tau^w\right) - 1} \\
&= \frac{\partial}{\partial \log p}\left(1 - \frac{1}{\exp\left(\log p\right)\left(1-\tau^w\right) - 1}\right) \\
&= \frac{\exp\left(\log p\right)\left(1-\tau^w\right)}{\left(\exp\left(\log p\right)\left(1-\tau^w\right) - 1\right)^2}
\end{aligned}$$

By plugging in the optimal price, we get

$$\begin{aligned}
\exp\left(\log p^{w*}\right)\left(1-\tau^w\right) &= \frac{\sigma}{\sigma-1} \\
\implies \frac{\exp\left(\log p\right)\left(1-\tau^w\right)}{\left(\exp\left(\log p\right)\left(1-\tau^w\right) - 1\right)^2} &= \sigma\left(\sigma-1\right) \\
\log p^{w*} - \log \hat{p}^w &= \tau^w - \hat{\tau}
\end{aligned}$$

Substituting terms into the second-order Taylor expansion then yields the desired result. □

Thus, high fees do not make uniform prices costly. Rather, it is dispersion in fees among the accepted cards that makes uniform prices costly. Thus, increasing the number of competitors does not affect the incentives to surcharge if all networks end up charging symmetric fees regardless. With my estimated value of σ =6.61, the losses from uniform pricing are around 17 *basis points* of profit.

D.3.3 Conditions for Surcharging to be Effective

The above results depend crucially on the assumption that sales decline every time the merchant steers the consumer from card to cash. This assumption may not hold if card acceptance raises sales by γ percent on average, but for any given transaction, some consumers may have lower utility from using a card. In such an extended model, surcharges would be valuable because they would screen out card transactions that bring consumers low utility. However, the gains would only be significant for merchants with intermediate values of γ such that they have a large share of consumers who would change their payment method in response to a surcharge. The core intuition that the vast majority of merchants would see small benefits from surcharging would still apply.

D.3.4 Gains from Charging One Credit Card Versus Another

The above results focus on why surcharges on cards versus cash are ineffective, but in practice, merchants also fight for the right to differentially surcharge cards, e.g., surcharge AmEx higher than Visa or MC (Conrath 2014). One challenge, however, is that the benefits of steering are linear in the difference in fees between the (historically) high fee network (e.g., AmEx) and the low fee network (e.g., Visa). However, the costs of steering are fixed (e.g., the amount of time to tell a consumer or the counter space for a sign). If there are any fixed costs of charging discriminatory prices in a neighborhood of any type symmetric equilibrium, no merchants would surcharge. The networks' first-order conditions would still be satisfied at the original type-symmetric equilibrium even if merchants are allowed to differentially surcharge. While it may be possible for networks to deviate with a non-local fee cut, I leave that analysis for future work.

E Merchant Heterogeneity and Redistribution

In principle, consumer sorting across stores can reduce redistribution among consumers who use different payment methods. If credit card consumers shop at one set of stores and cash consumers shop at a different set of stores, then high credit card merchant fees do not affect cash consumers' consumption.

I find that although there is some sorting of consumers across merchants, the amount of sorting does not have quantitatively significant effects on the amount of redistribution that occurs through merchant fees. I arrive at this conclusion in three steps. First, I measure the distribution of payment shares across stores in two datasets – Homescan and the MRI survey. Second, I derive a sufficient statistic relating the variance-covariance matrix of payment shares to the amount of redistribution. Third, when I compute this sufficient statistic in the data, I find that sorting reduces the amount of redistribution by at most 10%. Intuitively, sorting has limited effects on redistribution because no large merchants exclusively serve consumers with one payment preference.

E.1 Measuring Payment Shares

Homescan: The Homescan database is transaction-level, so I can readily take the value-weighted shares of credit, debit, and cash spending across stores. The advantage of Homescan is that I observe individual transactions. The disadvantage is that it is limited to the grocery sector.

MRI: The second data source, MRI-Simmons, is at the consumer level. The dataset contains both consumer payment choices and consumer shopping behavior. The shopping behavior data includes whether a consumer has made purchases at specific merchants across 214 large merchants in various sectors (e.g., clothing, food, furniture).

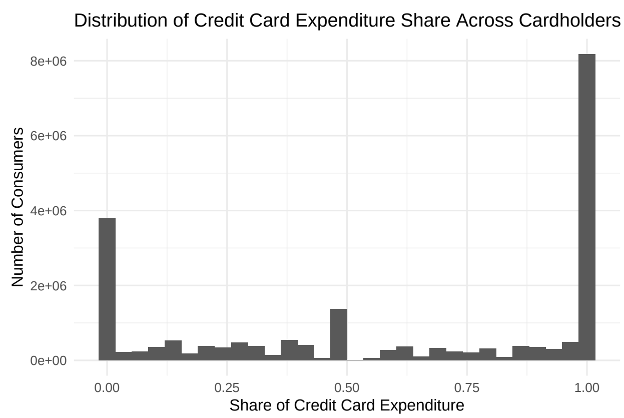
The MRI data on credit and debit card usage includes the amounts spent with both types of cards, further broken down by the bank and network that issued the card. Unfortunately, the data on cash usage does not provide information on expenditures. To characterize each consumer's payment preference between cash, credit, and debit cards, I proceed as follows. If a consumer reports preferring cash as a payment method, I classify them as having a cash preference[41]. If a consumer reports spending more with a credit (debit) card, I classify them as preferring credit (debit).

To build the share of spending at each merchant on each type of card, I assume consumers always use their preferred payment method. This assumption allows me to

[41]Consumers are asked if they agree with the following statement: "I prefer to pay cash for things I buy, whenever I can."

equate the payment mix at a store with the mix of consumers preferring each payment method (cash, debit, and credit) who shop at each store. For such large merchants, all payment methods are accepted, so it is reasonable to expect that a credit card consumer pays with credit. I also calculate the number of consumers at each retailer by summing the population weights of those who reported making purchases from each store. The advantage of the dataset is that I see a broader set of retailers but at the cost of not having transaction-level data. However, given that consumers tend to concentrate their spending on their preferred payment method (see Figure A.9), this is not a significant limitation.

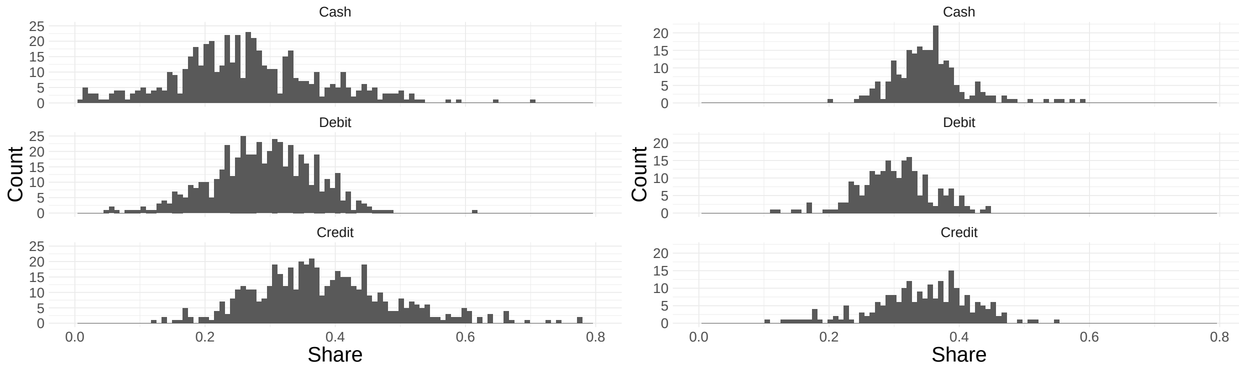
Figure A.9: Distribution of Credit Card Expenditure Share Across Consumers with Cards



Summary of Results: In both datasets, there is substantial dispersion in the share of cash, debit, and credit spending across stores. However, no stores have only one payment method. Figure A.10a and A.10b show the distribution of payment shares across merchants in the Homescan and MRI datasets, respectively. For example, the histogram for credit in the Homescan dataset suggests that credit sales as a share of total sales averages around 40% for the typical merchant but that this can range from around 10 percent to 80 percent.

Larger stores also have less dispersed payment mixes. Figure A.11a shows the relationship between a firm's log revenue in Homescan and the share of transactions on credit cards. In general, the dispersion is higher to the left of the plot among the smaller firms. This firm size relationship is important because it means that the stores at which we see the most sorting are also a small share of the economy. Intuitively, because many consumers all shop at the largest stores, there can be substantial redistribution across consumers. Figure A.11b shows an analogous result for the MRI dataset but with log

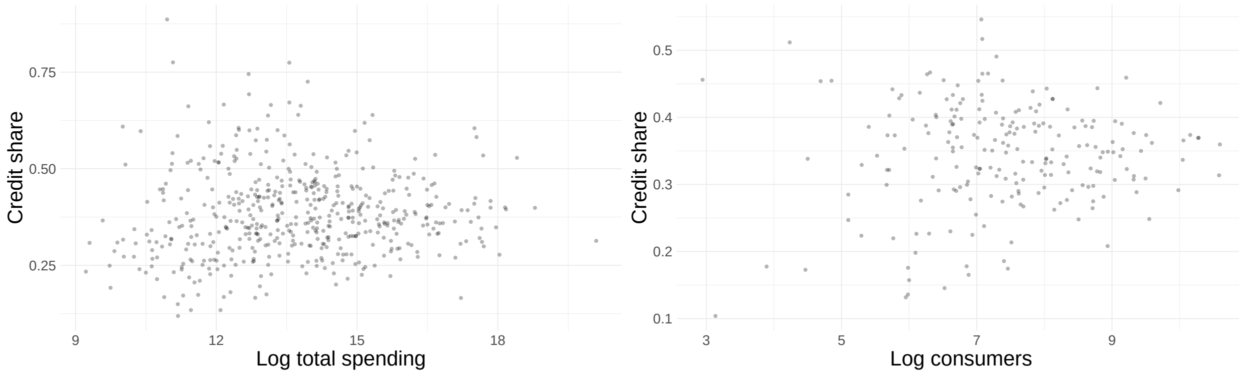
Figure A.10: Share of Spending on Different Payment Methods Across Merchants



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

consumers instead of log revenue.

Figure A.11: Credit card share and firm size



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

In each separate sample, I take the weighted covariances between these shares and the weighted mean share for each payment method. In the Homescan data, I weight these statistics by revenue, measured as the total spending of consumers in the sample at a given store. In the MRI data, I weight them by the number of customers.

I show unweighted and weighted covariances in both samples in Table A.6. Cash-credit and credit-debit covariances are negative, while cash-debit covariance is positive but very small. These covariances reflect the fact that cash and debit card consumers shop at a more similar set of stores when compared to cash and credit card consumers. Every weighted variance is smaller (in absolute terms) than its unweighted analog, which reflects the previously mentioned fact that larger stores see less dispersed payment mixes.

Table A.6: Covariances

(a) Homescan - Unweighted

	Cash	Debit	Credit
Cash	0.0124	-0.0009	-0.0087
Debit		0.0063	-0.0031
Credit			0.0123

(b) Homescan - Weighted

	Cash	Debit	Credit
Cash	0.0058	0.0000	-0.0036
Debit		0.0046	-0.0019
Credit			0.0069

(c) MRI - Unweighted

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

(d) MRI - Weighted

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

As I show in the next section, these negative covariances do mean that consumer sorting reduces the redistributive effect of merchant fees. However, the quantitative effect is ultimately small.

E.2 Sufficient Statistics for Redistribution

In this section I derive a sufficient statistic relating the revenue-weighted variance-covariance matrix of payment shares to the amount of redistribution.

Suppose prices are log-linear in fees, hence

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

where $\mu_{jk} = \frac{q_{jk}}{\sum_l q_{jl}}$ is the share of spending on card k at the merchant and τ_k is the merchant fee for card k. This pricing assumption follows from a CES pricing model.

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

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

This shows that the welfare effect can be broken down into two terms. The first is the revenue-weighted second moment between the share of spending on card l and the share of spending on card m across stores. The second is a revenue weighted second moment between the share of spending on by payment method l and how the shares change in response to changes in fees. By the envelope theorem, there is no direct welfare effect arising from changes in quantity consumed. The changes in the shares μ are of order τ, thus the second expression is of order $O\left(\tau^2\right)$ and is negligible. Hence, we can focus our attention on the first term – the second-moment matrix $\mathbb{E}_R\left[\mu_{jl}\mu_{jm}\right]$.

Normalize this loss in welfare according to the total amount of spending done by consumers of payment method l. This is

$$\int_j q_{jl}p_j = \int_j p_j Q_j \mu_{jl} = \mathbb{E}_R\left[\mu_{jl}\right]$$

Thus, we can think of a complete welfare matrix of the form

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

The interpretation of w_{lm} is that it is the compensating variation required for consumers who pay with l to compensate them for the increase in the fees for m, measured as a percentage of their baseline consumption.

In the homogenous case where all stores have the same payment mix, this equation says that the percentage loss in welfare for a debit consumer from a 1 percentage point increase in credit card fees is simply the share of credit card expenditures in the economy. In the heterogeneous case, if credit and debit card consumers never overlap, then $\mu_{jm} \times \mu_{jl} = 0$ for all j, and the equation says that debit card consumers bear no burden from an increase in merchant fees.

The sufficient statistic also captures the intuition that if consumers with different payment preferences shop at disjoint sets of stores, then there is no redistribution. In such a case, the second-moment matrix is all zeros, and thus w_{lm} is zero for all combinations of l, m.

These sufficient statistics are numerically equivalent to an accounting exercise in which one adjusts merchant-level prices according to the log-linear formula and then weights the price changes across merchants according to each consumer's expenditures.

E.3 Implementing the Sufficient Statistic

Armed with the sufficient statistic, I compute the percentage of welfare lost from fee increases for each dataset. In Table A.7, each entry shows the percentage of welfare lost for consumers of the row payment method from a 1pp change in the fees of the column payment. Focusing on the Homescan results in Table A.7, credit card consumers are more exposed to credit card fees relative to the average expenditure share of credit cards in the dataset. This result is reasonable, as stores where credit (debit) consumers shop most must have a large share of credit (debit) transactions. Therefore, their prices must be highly affected by fees. We see similar effects in both datasets.

The effects of sorting are quantitatively small. Table A.8 shows the ratio of the percentage of welfare lost accounting for consumer sorting across stores (using actual covariances) to the percentage of welfare lost in a model of homogenous merchants. Most ratios are close to 1. If we use the weighted covariances (as prescribed by theory), consumer sorting has the largest effect on reducing the amount of redistribution from cash users to credit users. But even then, the reduction is only 4% of the baseline effect. If we use unweighted covariances, this effect expands to 9% of the baseline effect. The small effects show that sorting of consumers across stores does not change welfare redistribution results substantially.

Table A.7: Percentage of welfare lost from fee increases

(a) Homescan

	Debit	Credit
Cash	0.321	0.360
Debit	0.335	0.369
Credit	0.316	0.394
Mean exp share	0.321	0.375

(b) MRI

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

Table A.8: Ratio of welfare lost with actual covariances to zero covariances

(a) Homescan - Unweighted

	Debit	Credit
Cash	0.988	0.914
Debit	1.075	0.972
Credit	0.972	1.083

(b) Homescan - Weighted

	Debit	Credit
Cash	1.000	0.959
Debit	1.045	0.984
Credit	0.984	1.049

(c) MRI - Unweighted

	Debit	Credit
Cash	0.997	0.975
Debit	1.037	0.971
Credit	0.971	1.051

(d) MRI - Weighted

	Debit	Credit
Cash	1.001	0.989
Debit	1.015	0.986
Credit	0.986	1.023

F Estimation Details

I estimate the model's parameters by matching data and simulated moments. I then conduct inference by bootstrapping the underlying data moments.

F.1 Key Data Moments

I use a wide range of data sources, including a novel second-choice survey, the Durbin event study evidence, Homescan data on usage, aggregate data on total spending, and data from the DCPC on how incomes relate to payment preferences.

F.1.1 Second-Choice Survey: Substitution Patterns

The second-choice survey helps me estimate the distribution of random coefficients, which determines substitution patterns.

The first two questions ask credit card users how they would pay if credit cards did not exist (and analogously for debit cards). From these questions, I estimate the share of credit card consumers who would switch to cash in a world without credit cards and the share of debit card consumers who would switch to cash in a world without debit cards. These two questions have natural model analogs. After taking out credit (debit) cards from the choice set, I can estimate the share that substitute to cash.

The third question asks how consumers switch if their current bank stopped offering their preferred payment type. Interpreting this question is more difficult because I do not explicitly model issuers in my model.

Whereas the model needs to know how consumers would substitute between networks (e.g., Visa, MC), the survey asks consumers how they might substitute between banks (e.g., Chase vs. Bank of America). Because many banks issue Visa cards, second-choice data on bank-to-bank substitution overstates the amount of substitution there would be between networks.

I adjust the answers to that question to account for within-network diversion. I collect data from the Nilson report on the share of cards that banks issue on Visa versus Mastercard. I then assume that when a consumer switches to a new card, their choice set is the list of banks that they already have cards at and from the list of banks that they did in-depth research on the last time that they looked for a payment card. I assume consumers choose randomly off of the list. Based on the network composition of the bank that a consumer currently uses and the composition of the banks in their choice set, I build a person-specific likelihood of moving to a different card network as a result of switching. When computing the diversion ratio, I then take out an expected number

Table A.9: Share of consumers that switch to the same type of card from a different network under different assumptions on whether switching banks (e.g., Chase vs Bank of America) also leads to switching networks (Visa vs. Mastercard)

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

of moves that involve changing banks (e.g., Chase to Bank of America) within the same network.

In practice, the amount of diversion to credit cards does not depend on the assumption of how to model these within network moves. Table A.9 shows the amount of diversion to the same type under different assumptions on the share of between bank moves are also moves from one network to another.

After making these adjustments, I can compute the diversion ratio between card types in response to a consumer's issuer dropping a certain card type.

In the model, I then compute diversion ratios by changing the unobserved characteristics Ξ^w. For example, I can compute the share of primary Visa credit consumers that switch to becoming a primary credit card consumer on a different network in response to a slight decrease in $\Xi^{\text{Visa Credit}}$. This perturbation makes sense because I interpret the Visa product in the model as the best credit card among all Visa credit card issuers. Thus, the mean value of the Visa credit unobserved characteristic reflects the inclusive value after picking the best issuer among all Visa issuers for the consumer. Taking out one issuer is analogous to slightly reducing the inclusive value and the unobserved characteristic.

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

Let $S_{i,1}$ be an indicator for a consumer who would switch to becoming a primary cash consumer if credit cards did not exist. Let $S_{i,2}$ be an indicator for a consumer who would switch to becoming a primary cash consumer if debit cards did not exist. Let $S_{i,3}$ be an indicator for whether a consumer would switch to the same card type (e.g., credit or debit) if their current bank stopped offering their primary payment type.

To adjust from bank-to-bank substitution to network-to-network substitution, for survey respondent i, let the imputed choice set of banks be $\mathcal{C}_i$. Let the current bank for consumer i be b_i, the customer's card type be t_i, and let I_i be an indicator for whether consumer i reports switching to the same card type from a different bank. For each bank j, let the share of type t cards on Visa, MC equal $n_j^{\text{Visa},t}, n_j^{\text{MC},t}$, respectively.

The data moments are then:

$$\hat{g}_1 = \begin{pmatrix} N_c^{-1} \sum_{i,r_i=\text{CC}} S_{i,1} \\ N_d^{-1} \sum_{i,r_i=\text{DC}} S_{i,2} \\ \frac{\sum_i S_{i,3} - \iota}{N - \iota} \end{pmatrix} \tag{35}$$

$$\iota = \sum_{i=1}^{N} S_{i,3} \times \left(1 - \left(\sum_{k \in \{\text{Visa,MC}\}} n_{b_i}^{k,t_i} \times \left(\frac{1}{|\mathcal{C}_i|} \sum_{j \in \mathcal{C}_i} n_j^{k,t_i} \right) \right) \right) \tag{36}$$

To define the model moments, define the sets of wallets $\mathcal{W}_C = w = (w_1, w_2), w_1$ is a CC and $\mathcal{W}_D = w = (w_1, w_2), w_1$ is a DC. Then:

$$g_1 = \begin{pmatrix} \left(\sum_{w \in \mathcal{W}_C} \tilde{\mu}_i^w\right)^{-1} \sum_{w \in \mathcal{W}_C} \underbrace{\int\int \tilde{\mu}_i^w \frac{\tilde{\mu}_i^{(0,0)}}{\sum_{m \in \mathcal{W} \setminus \mathcal{W}_C} \tilde{\mu}_i^m} \, \mathrm{d}H(\beta_i) \, \mathrm{d}F(y_i)}_{P(\text{Second Choice is Cash} \wedge \text{First Choice is Credit})} \\ \left(\sum_{w \in \mathcal{W}_D} \tilde{\mu}_i^w\right)^{-1} \sum_{w \in \mathcal{W}_D} \underbrace{\int\int \tilde{\mu}_i^w \frac{\tilde{\mu}_i^{(0,0)}}{\sum_{m \in \mathcal{W} \setminus \mathcal{W}_D} \tilde{\mu}_i^m} \, \mathrm{d}H(\beta_i) \, \mathrm{d}F(y_i)}_{P(\text{Second Choice is Cash} \wedge \text{First Choice is Debit})} \\ \underbrace{\sum_{w_1 \in \mathcal{J}_1} \left(\sum_{w_2 \geq 0} \tilde{\mu}^{(w_1,w_2)} \right)^{-1} \times \sum_{w_1 \in \mathcal{J}_1} \left(\sum_{w_2 \geq 0} \tilde{\mu}^{(w_1,w_2)} \right)}_{\text{Weighted by market share of each inside option}} \times \underbrace{\frac{\frac{\partial}{\partial \Xi^{w_1}} \left(\sum_{(l_1,l_2) \in \mathcal{W}: l_1 \text{ same type as } w_1} \tilde{\mu}^{(l_1,l_2)} \right)}{-\frac{\partial}{\partial \Xi^{w_1}} \left(\sum_{w_2 \geq 0} \tilde{\mu}^{(w_1,w_2)} \right)}}_{\text{Diversion to same type of primary card}} \end{pmatrix}$$

F.1.2 Durbin Event Study: Overall Rewards Sensitivity

I compute the model analog of the difference-in-difference estimate for debit cards in Figure 3. Holding fixed merchant adoption, I compute new market shares $\tilde{\mu}_y^w$ if debit cards paid 25 bps in additional rewards. Given the new market shares, I can compute the change in dollars spent on each payment method with equation 21 while holding fixed the merchant adoption decision M^*. From this, I can compute the percentage increase in debit card spending. I then target the final difference in difference coefficient from Figure 3.

F.2 DCPC + Second Choice Survey: Variation in Preferences Across Income

Three kinds of parameters vary with income: the average preference for cards, the average preference for credit cards, and consumers' sensitivity to rewards.

To recover how average preferences for cards and credit cards vary with income, I match income differences between different types of primary card holders. In the DCPC data, I regress the log income of the respondent on the preferred payment method. The regression yields the following results:

	DCPC
Prefers Debit	0.20***
	(0.03)
Prefers Credit	0.56***
	(0.03)
Num.Obs.	10332
R2 Adj.	0.091
R2 Within	0.086

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

I then match these log income differences in the model. By Bayes' rule, we have that

$$\text{Log Income of Primary Cash Consumers} = \frac{\mathbb{E}\left[\tilde{\mu}_y^{(0,0)} \times \log y\right]}{\tilde{\mu}^{(0,0)}} \tag{37}$$

$$\text{Log Income of Primary Debit Consumers} = \frac{\mathbb{E}\left[\sum_{w \in \mathcal{W}_D} \tilde{\mu}_y^w \times \log y\right]}{\mathbb{E}\left[\sum_{w \in \mathcal{W}_D} \tilde{\mu}_y^w\right]} \tag{38}$$

$$\text{Log Income of Primary Credit Consumers} = \frac{\mathbb{E}\left[\sum_{w \in \mathcal{W}_C} \tilde{\mu}_y^w \times \log y\right]}{\mathbb{E}\left[\sum_{w \in \mathcal{W}_C} \tilde{\mu}_y^w\right]} \tag{39}$$

To match how reward sensitivity changes with income, I use a question that asks credit card consumers how likely they would be to switch issuers if their current issuers cut credit card rewards in half. As long as individual issuers are small, the probability of switching is proportional to the price-sensitivity coefficient α in a conditional logit model. Fixing the level of income, we would have that

$$\begin{aligned} P\left(\text{Switch}|\text{Credit Card}\right) &= \frac{1}{s_j}\frac{\partial s_j}{\partial f_j} \\ &= \frac{1}{s_j}\int -\alpha s_{ij}\left(1-s_{ij}\right)\, \mathrm{d}H\left(\beta_i\right) \\ &\approx -\alpha \end{aligned}$$

where the last line uses that $1 - s_{ij} \approx 1$. Thus, the elasticity of this switching probability with respect to income then gives the elasticity of reward-sensitivity with respect to income. The data moment that I target is then the data implied elasticity, which I obtain from the slope coefficient in Table A.4 divided by the sample mean switching rate. I then set the model implied coefficient α_y to equal this moment.

F.3 Homescan: Multi-homing Complementarity / Substitution Terms

Given the observed market shares of the different wallets in the Homescan data, I can compute the empirical expectations of the characteristics of the primary wallet and the secondary wallets

$$P_{kl} = N^{-1}\sum_i X_k^{w_{i1}} X_l^{w_{i2}}$$

.

Since the X comprise an indicator for whether a payment method is an inside good and an indicator for whether a payment method is a credit card, these moments capture the probability that consumers multi-home on cards (credit or debit), the probability of observing primary debit card holders with secondary credit cards, the probability of observing primary credit card holders with secondary debit cards, and the probability of observing consumers with multiple credit cards.

I can calculate the same moments in the model data as

$$\hat{P}_{kl} = \mathbb{E}\left[\tilde{\mu}_y^w \times X_k^{w_{i1}} X_l^{w_{i2}}\right]$$

Because the key characteristics are indicators for whether a product is a credit card or an inside good, the products of these characteristics are the joint probabilities of having multiple cards, the probability of having a primary credit card and a secondary card, the probability of having a primary card and secondary credit card, and the probability of having two credit cards.

Non-pecuniary characteristics of the wallet are determined by a weighted average of the characteristics of the primary and secondary cards. To estimate this weight ω, I target the difference between Visa's market share among all primary credit cards and Visa's market share among all secondary credit cards. Intuitively, the fact that the most common secondary cards are also the most common primary cards suggests that ω is close to 0.5. Thus, in the model, I compute

$$g_5 = \frac{\sum_{w_2 \in \mathcal{J}} \mathbb{E}\left[\tilde{\mu}_y^{(\text{Visa Credit}, w_2)}\right]}{\sum_{w \in \mathcal{W}_C} \mathbb{E}\left[\tilde{\mu}_y^{w}\right]} - \frac{\sum_{w_1 \text{is a CC}} \mathbb{E}\left[\tilde{\mu}_y^{(w_1, \text{Visa Credit})}\right]}{\sum_{w=(w_1,w_2), w_1, w_2 \text{ are both CC}} \mathbb{E}\left[\tilde{\mu}_y^{w}\right]}$$

In the data, I can compute

$$\hat{g}_5 = \frac{\sum_i I\{\text{Primary Visa Credit}\}_i}{\sum_i I\{\text{Primary Credit Card}\}_i} - \frac{\sum_i I\{\text{Primary CC and Secondary Visa Credit Card}\}_i}{\sum_i I\{\text{Primary and Secondary Credit Card}\}_i}$$

The model parameter π controls the share of spending that is done on the primary card for those consumers who carry multiple cards. I match this parameter to the average share of primary and secondary card spending on the primary card, summarized in Table A.20.

F.4 Aggregate Dollar Shares: Mean Unobserved Characteristics

From the Nilson data, I can compute the share of spending on each payment network. For my denominator, I use the Nilson Report's concept of total consumer purchases. Purchases include most of PCE but then exclude some items, such as imputed rent, which do not trigger a payment between two parties. I also exclude electronic ACH payments, which are often used for payroll or insurance payments but not for transactions at a merchant.

In the model, I can also compute the share of dollars spent on each payment network, where the expression for dollars is given by Equation 21. I then match the model-implied shares with the data shares. These shares are not quite the same as matching market shares in Homescan or the DCPC because the dollars overweight the spending by high-income individuals.

F.5 Aggregate Prices + Homescan Event Study: Merchant Benefits and Network Costs

In this last section, I search over equilibrium adoption utilities A_j^*, marginal costs c, fees τ for Mastercard Credit and AmEx, and merchant type parameters $(\sigma, \overline{\gamma}, \nu_\gamma)$ to satisfy several conditions.

First, I require that at the equilibrium adoption utilities A_j^*, the first-order conditions are satisfied and that the implied rewards match the aggregate data. Because the rewards f^j in the model are lump-sum, whereas rewards in reality are often paid on a percentage basis, I convert the model implied rewards to rewards rates $r_j = \frac{f^j}{d_j}$. I then match these to the observed reward rate that I derive from financial statements.

Second, I require that the five first-order conditions with respect to the adoption utilities A_j be zero at observed rewards. This requirement helps to identify the marginal costs c.

Third, my estimation recovers the value of σ by matching the lowest γ type of all of the merchants that accept all of the cards to equal the effect of credit card acceptance on sales for the large grocer studied in Section III.B.1. Given the adoption utilities A_j and the observed merchant fees, I can solve the merchant adoption problem in Equation 11 and recover the lowest value of γ^*, above which merchants accept all of the cards. I then minimize the distance between this γ^* and the estimated sales effect shown in Section III.B.1.

In the last step, I recover the parameters $\overline{\gamma}$ and ν_γ and MC and AmEx's fees in order to match Visa Credit's, MC Credit, and AmEx's fee FOCs and data from the DCPC on the share of transactions are conducted at merchants that accept cards (Table 1). Although I do not force MC and AmEx's merchant fees to match those in figure 2, Table 4 shows that the final fees that I recover closely match the symmetric merchant fee equilibrium shown in the figure. In the model, I define a merchant to accept cards if it accepts all credit and debit cards. In the data, almost all merchants that accept debit cards also accept credit cards (Figure A.5c).

F.6 Alternative Estimation with Partial Pass-through

Shutting down merchant pass-through of merchant fees has large effects on the distribution of welfare between merchants and consumers and between high and low-income consumers but minimal effects on changes in fees, rewards, market shares, or total welfare.

To study the case when merchants do not pass-through fees to retail prices, I modify the optimal pricing equation 8 to take out the merchant fees while holding all other equations fixed. I then re-estimate the model under this alternative assumption and re-solve the counterfactuals. Table A.10 shows the parameter estimates.

I compare the counterfactual results in the table below. Since the standard errors are similar with and without pass-through, I focus on the point estimates in the table. The first column for each counterfactual shows the baseline results under full passthrough,

Table A.10: Estimated parameters without passthrough

Panel A: Consumer Parameters

Parameter	Est	SE
S.D. of Card R.C.	0.73	0.25
S.D. of Credit R.C	1.83	0.68
Correlation of R.C.	-0.69	0.06
S.D. of T1EV	0.10	0.03
$\chi_{\text{Card, Card}}$	0.08	0.62
$\chi_{\text{Card, Cred}}$	3.75	0.97
$\chi_{\text{Cred, Card}}$	3.23	0.88
$\chi_{\text{Cred, Cred}}$	-3.63	1.17
Visa Debit Ξ	-3.10	0.43
Visa Credit Ξ	-5.14	0.35
MC Debit Ξ	-3.25	0.47
MC Credit Ξ	-5.34	0.40
Amex Ξ	-5.41	0.41
Income Elasticity α_y	0.20	0.06
Log Income Vol. ν_y	0.73	0.01
Card β_y	-0.80	0.20
Credit β_y	0.34	0.35
Primary Weight ω	0.61	0.01
Primary Usage Rate π	0.83	0.00

Panel B: Network Cost Parameters (bps)

Parameter	Est	SE
Cash	30	10
Visa Debit	43	10
MC Debit	55	5
Visa Credit	84	9
MC Credit	85	6
Amex	82	6

Panel C: Merchant Parameters

Parameter	Est	SE
Merchant CES	6.61	1.42
Average γ	0.25	0.06
S.D. of γ	0.08	0.02

Notes: S.D. refers to the standard deviation, and R.C. refers to the random coefficients for having a credit function and not being cash. The Ξ are the unobserved characteristics, and the χ^{lm} is the complementarity parameter for a bundle with a primary card with a characteristic l and a secondary card with characteristic m. The standard deviation of R.C. and T1EV shocks, χ, Ξ are all measured in terms of percentage points of pecuniary utility for a consumer with an average income of 1. Merchant types γ are distributed according to a Gamma distribution.

whereas the second column shows the results assuming merchants do not pass through merchant fees to retail prices.

The fee cap counterfactual illustrates how pass-through affects the counterfactual results. In the baseline model with full pass-through, capping merchant fees redistributes from high-income consumers towards low-income consumers. It is approximately neutral for merchants while creating gains for consumers. When merchants do not pass-through fees into retail prices, capping merchant fees raises merchant profits at the cost of lowering consumer welfare. Because retail prices do not adjust, lower merchant fees are a windfall to merchants. Consumers then receive fewer rewards without the corresponding relief from lower retail prices. Although high-income consumers are still hurt more by the policy, low-income consumers do not see any benefits because retail prices do not adjust. Ultimately, total welfare still rises by $24 billion even in the absence of

Table A.11: Comparing counterfactual results with and without passthrough

	Price Controls				Change Competition			
	Cap Fees		Uncap Debit		Monopoly		Public Debit	
Passthrough?	Yes	No	Yes	No	Yes	No	Yes	No
Δ Prices (bps)								
Credit Fees	−194	−194	−3.9	−4.5	20	18	−1.0	−1.1
Credit Rewards	−233	−234	−19	−21	−118	−90	−10	−9
Debit Fees	−41	−41	25	25	0.0	0.0	0.0	0.0
Debit Rewards	−36	−36	25	26	−38	−33	6	4.7
Δ Shares (pp.)								
Cash	37	45	−6	−8	30	31	−2.0	−1.9
Debit	−8	−13	17	21	−8	−9	−4.1	−3.7
Credit	−30	−31	−11	−13	−22	−21	−4.0	−4.4
Entrant							10	10
Δ Fees, Rewards ($Bn)								
Total Fees	−101	−101	−6	−10	−54	−53	−9	−10
Total Rewards	−85	−80	−8	−11	−72	−65	−8	−8
Δ Consumption (bps)								
Low Income	41	−62	8	7	7	−36	8	0.2
Median Income	11	−89	5	3.6	−9	−48	6	−1.1
High Income	−56	−159	−2.4	−4.3	−46	−78	2.9	−4.2
Δ Welfare ($Bn)								
Consumers	36	−58	5	4.7	−4.2	−44	7	−0.7
Merchants	2.7	89	−1.0	2.4	−3.4	40	0.0	6
Networks	−7	−8	4.1	3.9	28	22	−1.3	−1.1
Total	31	24	8	11	20	18	6	4.7

Notes: The first number for each counterfactual reports the baseline estimate under full passthrough, and the second number reports the same result under no passthrough. The "cap fees" scenario caps credit and debit card merchant fees to 30 bps. The "uncap debit" scenario raises the cap on debit card merchant fees by 25 bps. Monopoly refers to merging all three networks. Low (high) income consumers are defined as those with log income at -2 (+2) standard deviations relative to the median.

pass-through.

The total welfare gains of merchant fee caps are smaller without pass-through because the baseline economy is less distorted. When merchants raise prices in response to merchant fees, consumers inefficiently divert their spending away from merchants that accept cards. This distortion is costly, and part of the gains from merchant fee caps in

Table 5 come from the removal of this distortion. However, when merchants no longer pass through fees into retail prices, there is no such distortion. Thus, the total welfare gains from capping merchant fees is smaller.

The total welfare predictions for the other counterfactuals, however, are largely unchanged. Repealing the Durbin Amendment still moderates credit card competition, lowers total fees and rewards, redistributes consumption to lower-income consumers, and raises consumer and total welfare. While competition is no longer as regressive, it still lowers total welfare.

F.7 Alternate Estimation with Acceptance Complementarities

When two credit cards are accepted at different sets of stores, then that can create a complementarity for the consumer where adopting the widely accepted card can serve as a backup card when the less widely accepted card is declined. In the baseline model, consumers do not internalize this complementarity. Ignoring the complementarity is not a problem for computing welfare in any equilibrium in which the payment networks charge symmetric merchant fees. Still, it can have important implications on the off-equilibrium path.

I investigate how the model would change if consumers internalized these acceptance complementarities. I implement this change by modifying the definition of pecuniary utility for multi-homing consumers in Equation 16 to

$$\log U^w = \left(\pi f^{(w_1,0)} + (1-\pi) f^{(w_2,0)}\right) - \log P^w \tag{40}$$

The key difference is that P^w factors in the utility gain from the acceptance complementarity, whereas the weighted average in Equation 16 does not.

The key economic consequence of changing the model in this way is that consumers are much more likely to multi-home if a payment method is less widely accepted, which increases merchants' equilibrium fee sensitivity. For example, if AmEx charges a higher merchant fee, then many consumers who adopt AmEx will also choose to adopt Visa in order to make sure to have a backup card. When multi-homing rates increase, this also makes merchants less willing to accept the high-fee card because they know that many consumers who carry the high-fee card also carry the low-fee card. Networks thus face higher merchant fee sensitivity.

After incorporating this change, I re-estimate the model. Different parameters can now rationalize the same equilibrium. Below, I compare the parameter estimates from this version with complementarities against the baseline estimates. The parameters are largely unchanged.

Table A.12: Estimated parameters

Panel A: Consumer Parameters

Parameter	Comp	Baseline
S.D. of Card R.C.	0.91	0.92
S.D. of Credit R.C	2.25	2.30
Correlation of R.C.	-0.74	-0.72
S.D. of T1EV	0.12	0.12
$\chi_{\text{Card, Card}}$	-0.10	-0.26
$\chi_{\text{Card, Cred}}$	4.30	4.44
$\chi_{\text{Cred, Card}}$	3.71	3.85
$\chi_{\text{Cred, Cred}}$	-4.30	-4.46
Visa Debit Ξ	-3.43	-3.41
Visa Credit Ξ	-5.41	-5.37
MC Debit Ξ	-3.61	-3.59
MC Credit Ξ	-5.65	-5.62
Amex Ξ	-5.72	-5.69
Income Elasticity α_y	0.20	0.20
Log Income Vol. ν_y	0.73	0.73
Card β_y	-0.86	-0.86
Credit β_y	0.51	0.55
Primary Weight ω	0.60	0.61
Primary Usage Rate π	0.83	0.83

Panel B: Network Cost Parameters (bps)

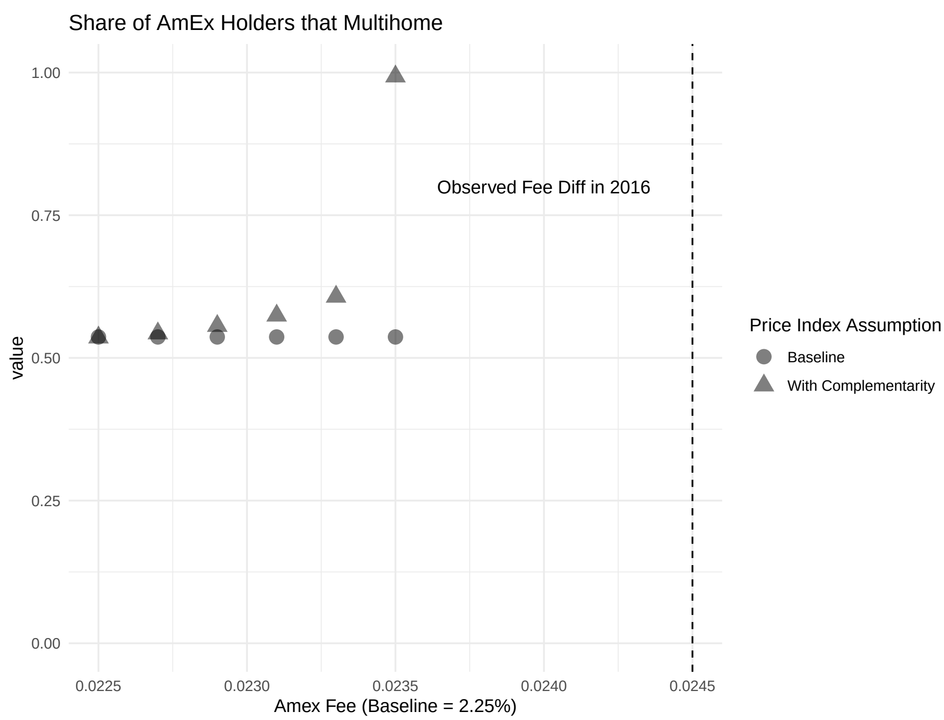
Parameter	Comp	Baseline
Visa Debit	37	36
MC Debit	52	51
Visa Credit	80	79
MC Credit	83	81
Amex	80	79

Panel C: Merchant Parameters

Parameter	Comp	Baseline
Average γ	0.26	0.25
Merchant CES	6.39	6.40
S.D. of γ	0.08	0.08

Notes: S.D. refers to the standard deviation, and R.C. refers to the random coefficients for having a credit function and not being cash. The Ξ are the unobserved characteristics, and the χ^{lm} is the complementarity parameter for a bundle with a primary card with a characteristic l and a secondary card with characteristic m. The standard deviation of R.C. and T1EV shocks, χ, Ξ are all measured in terms of percentage points of pecuniary utility for a consumer with an average income of 1. Merchant types γ are distributed according to a Gamma distribution.

Although the parameters are largely unchanged, this alternative model yields unrealistic predictions for how much fee gaps generate multi-homing differences. In both the baseline and the alternative models, I raise AmEx's merchant fee relative to Visa and plot the share of AmEx consumers who also carry a credit card from a different network. I compute this share with the market share of all secondary AmEx consumers with a primary credit card from a different network plus the market share of all primary AmEx consumers with a secondary credit card, all divided by the sum of all primary or secondary cardholders on AmEx. Whereas this fraction does not depend on the level of AmEx's fees in the baseline model, it dramatically rises in the alternative model with acceptance complementarities. In the data shown in Figure A.5, the rate of multi-homing on AmEx is insensitive to the relative gap in merchant fees, which motivates why I ignore this acceptance complementarity in my baseline estimation.



G Additional Tables

Table A.13: Merchant card acceptance by sector

Merchant Type	Share of Transactions	Card Acceptance	Card Usage
Grocery	0.236	0.973	0.668
Shopping	0.202	0.984	0.785
Fast Food	0.175	0.962	0.574
Gas Station	0.127	0.987	0.682
Restaurant	0.089	0.963	0.662
General Services	0.058	0.865	0.524
Entertainment	0.027	0.755	0.518
Medical	0.021	0.948	0.642
Media	0.019	0.970	0.809
Utilities	0.014	0.898	0.427
Professional Services	0.011	0.814	0.499
Transp + Shipping	0.007	0.932	0.716
Public Transit	0.006	0.842	0.635
Housing	0.005	0.749	0.153
Lodging	0.004	0.920	0.769

Notes: Share of transactions estimates the share of transactions in the given sector relative to all transactions in the DCPC. Card acceptance is measured as the share of card, check, and cash transactions that occurred at merchants that would have allowed the consumer to use a card. Card use is the share of such transactions on credit or debit cards.

Table A.14: Summary statistics of Financial Institutions in the Nilson Panel in 2010

	N	Mean	P25	P50	P75
Assets	39	28704.60	4131.11	9841.50	25562.84
Credit	39	1515.09	365.15	586.38	1500.00
Debit	39	4622.54	1188.69	2334.12	4510.50
Signature Debit	39	2944.55	762.62	1138.75	2638.25
Sig Debit Ratio	39	0.64	0.61	0.68	0.77
Treated	39	0.46	0.00	0.00	1.00

Notes: Treated refers to whether the financial institution had more than $10 billion in assets in 2010. Observations at the institution-year level are aggregated to the institution level by averaging over the years. Assets are measured in millions. Credit, Debit, and Signature Debit all refer to measures of card volumes in millions.

Table A.15: Summary statistics of the Homescan sample

	N	Mean	P25	Median	P75
Years per Household	112823	3.83	1.00	3.00	6.00
Transactions	112823	638.68	146.00	362.00	861.00
Average Tx Size	112823	58.43	36.75	51.23	71.37

Table A.16: Comparing Homescan payment shares to aggregate shares

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

Notes: Homescan payment shares are calculated by summing all the dollars spent on each payment method and dividing by the total spending.

Table A.17: Summary statistics from the second choice survey

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

Notes: Sample of credit and debit card users from the second-choice survey described in Appendix A.6. *Primary Debit* indicates the customer's primary payment method is debit card. *Primary Credit* indicates the customer's primary payment method is credit card. *Switch Rewards* indicates the customer would switch away from their primary credit card if rewards were halved. *Bank Removed Other Debit* indicates the customer would switch to another bank's debit card if their bank stopped offering debit cards (only defined for primary debit card customers). *Bank Removed Other Credit* indicates the customer would switch to another bank's credit card if their bank stopped offering credit cards (only defined for primary credit card customers). *Card Removed Debit* indicates the customer would switch to a debit card if their primary payment type was removed. *Card Removed Credit* indicates the customer would switch to a credit card if their primary payment type was removed. *Card Removed Cash* indicates the customer would switch to cash if their primary payment type was removed. *Female* indicates the customer is female. *Wave 1* indicates the customer participated in the first wave of the survey. *Wave 2* indicates the customer participated in the second wave of the survey. *Additional Cards Used* refers to the number of credit or debit cards used in addition to the customer's primary card. *Age* refers to the customer's age. *Income* refers to the customer's household annual income, which I make continuous by taking the geometric mean of lower and upper bounds in each category.

Table A.18: Summary statistics on payment preferences and bank choice in the MRI survey data

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

Notes: Has Debit Card indicates the customer owns a debit card. *Has Credit Card* indicates the customer owns a credit card. *Debit User* indicates that the consumer is not a cash user and that either the consumer owns a debit card but not a credit card, or that the share of debit expenditure is higher than the share of credit expenditure. *Credit User* indicates that the consumer is not a cash user and that either the consumer owns a credit card but not a debit card, or that the share of credit expenditure is higher than the share of debit expenditure. *Cash User* indicates the consumer agrees completely with the statement "I prefer to pay cash for things I buy, whenever I can". *Multiple Networks* indicates the customer owns credit cards from multiple networks, whereas *Multiple Banks* refers to consumers that own credit cards from multiple issuing banks. *Factor Rewards* indicates the customer deemed rewards programs as very important when choosing a bank, whereas *Rewards* refers to consumers that receive credit card rewards. *Big Banks* indicates the consumer uses Chase, Citibank, Wells Fargo, Bank of America or US Bank. *Small Banks* refers to consumers that use community banks or credit unions. *Switch Banks* indicates the consumer changed banks in the last 12 months (not defined for 2009). *Share of Debit Exp* quantifies the share of card expenditure that is done with debit. *Share of Credit Exp* quantifies the share of card expenditure that is done with credit. *Income* is household income in dollars, which I make continuous taking the geometric mean of lower and upper bounds in each survey.

Table A.19: Correlation between being the card with the top number of trips and the card with the top share of spending.

		Top Card by Spend				
Top Card by Trips		AmEx	Debit	Discover	MC	Visa
AmEx	N	15832	133	95	276	461
	% row	94.3	0.8	0.6	1.6	2.7
Debit	N	538	193878	491	2341	3407
	% row	0.3	96.6	0.2	1.2	1.7
Discover	N	105	107	19074	383	398
	% row	0.5	0.5	95.1	1.9	2.0
MC	N	279	557	300	43495	1139
	% row	0.6	1.2	0.7	95.0	2.5
Visa	N	608	1119	532	1770	93169
	% row	0.6	1.2	0.5	1.8	95.9

Table A.20: The average share of total card spending on consumers' top two cards split by the primary card of each consumer

Primary Card	Primary Share	Secondary Share	Top Two Total
AmEx	0.74	0.19	0.93
Discover	0.76	0.18	0.94
Visa	0.78	0.17	0.95
Debit	0.82	0.14	0.96
MC	0.74	0.20	0.94

Table A.21: Event study estimates for the effect of the Durbin Amendment on interchange fees, signature debit payment volumes, and deposits

	Interchange	Signature Debit	Deposits
Treat, t=-4	-0.023	0.003	0.057
	(0.088)	(0.051)	(0.053)
Treat, t=-3	0.061	-0.010	-0.001
	(0.088)	(0.039)	(0.034)
Treat, t=-2	-0.088	-0.021	0.000
	(0.073)	(0.024)	(0.018)
Treat, t=0	0.006	-0.077*	-0.012
	(0.056)	(0.037)	(0.018)
Treat, t=1	-0.418***	-0.105*	-0.024
	(0.101)	(0.047)	(0.024)
Treat, t=2	-0.318*	-0.222***	-0.038
	(0.119)	(0.048)	(0.030)
Treat, t=3	-0.328**	-0.287***	-0.039
	(0.109)	(0.063)	(0.032)
N	289	280	309
Bank FE	X	X	X
Year FE	X	X	X

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

Table A.22: Event study estimates for the quarterly effects of card acceptance on sales to credit-card consumers

	Trips	Spending
Credit Share at Treated Retailer, t=-8	-0.033	-0.044
	(0.036)	(0.047)
Credit Share at Treated Retailer, t=-7	-0.032	-0.039
	(0.036)	(0.051)
Credit Share at Treated Retailer, t=-6	-0.037	-0.042
	(0.035)	(0.046)
Credit Share at Treated Retailer, t=-5	-0.025	-0.071*
	(0.026)	(0.035)
Credit Share at Treated Retailer, t=-4	-0.001	-0.016
	(0.024)	(0.033)
Credit Share at Treated Retailer, t=-3	-0.009	-0.035
	(0.023)	(0.031)
Credit Share at Treated Retailer, t=-2	-0.020	-0.015
	(0.021)	(0.028)
Credit Share at Treated Retailer, t=0	0.056*	0.039
	(0.022)	(0.030)
Credit Share at Treated Retailer, t=1	0.089***	0.068*
	(0.025)	(0.033)
Credit Share at Treated Retailer, t=2	0.048+	0.078*
	(0.026)	(0.035)
Credit Share at Treated Retailer, t=3	0.065*	0.036
	(0.028)	(0.038)
Credit Share at Treated Retailer, t=4	0.080*	0.088*
	(0.032)	(0.043)
Credit Share at Treated Retailer, t=5	0.081*	0.093*
	(0.033)	(0.043)
Credit Share at Treated Retailer, t=6	0.120***	0.135**
	(0.033)	(0.044)
Credit Share at Treated Retailer, t=7	0.098**	0.152***
	(0.034)	(0.044)
Credit Share at Treated Retailer, t=8	0.132***	0.197***
	(0.039)	(0.052)
N	610570	610570
Credit share by time FE	X	X
Retailer by credit share FE	X	X

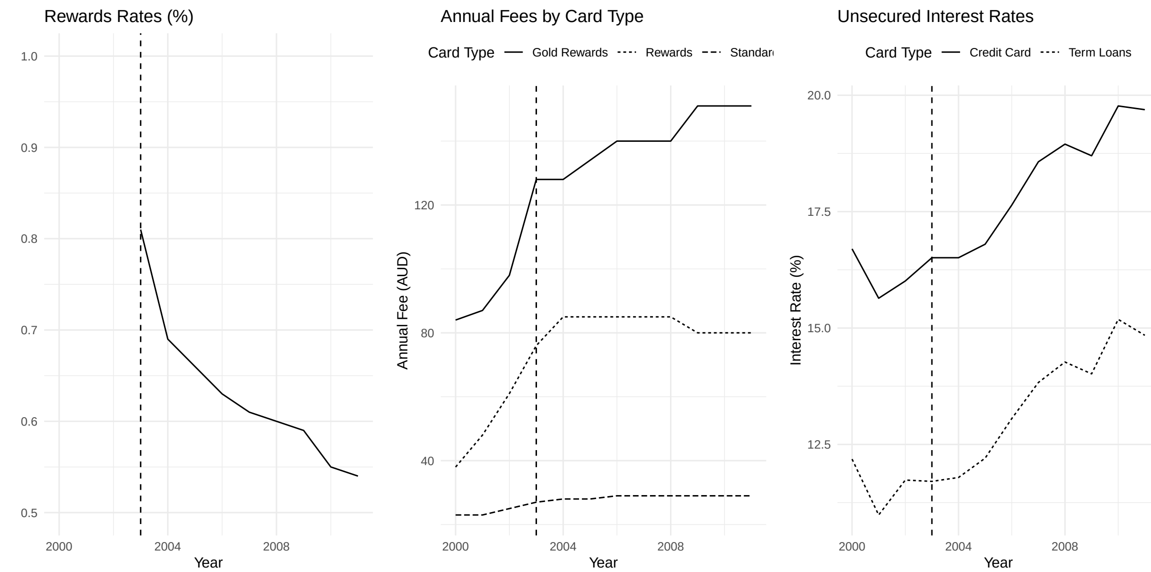
+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.23: Consumer Payment Probabilities π_M^w

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

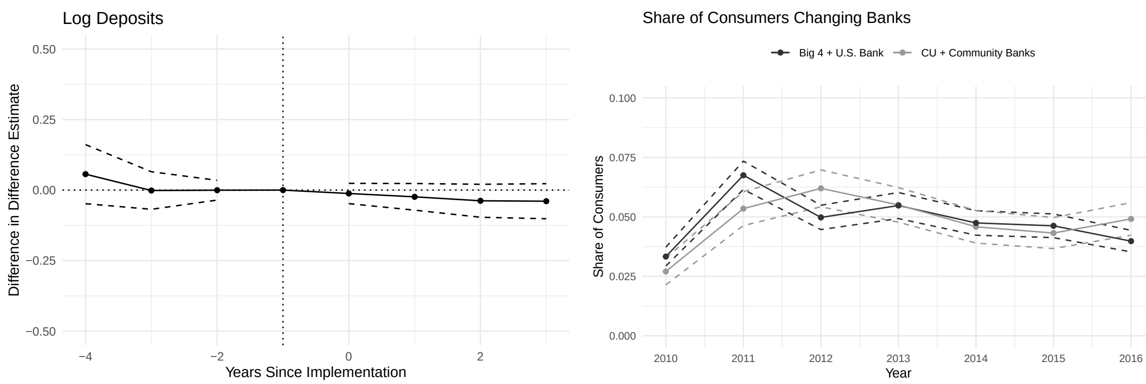
H Additional Figures

Figure A.12: Key changes in the Australian credit card market after interchange regulation



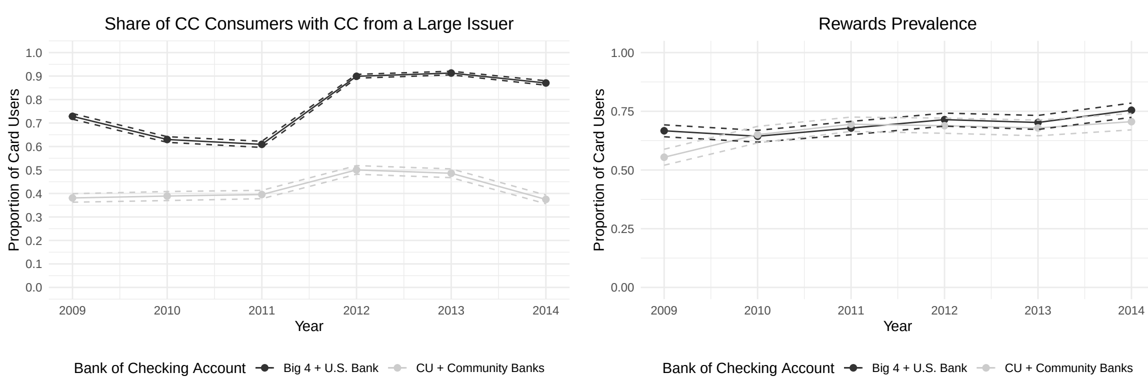
Notes: The vertical line marks the 2003, the start of interchange regulation in Australia. 'Gold' refers to the highest tier of rewards credit cards, whereas 'Rewards' refers to the basic tier of rewards credit cards. 'Basic' refers to credit cards without rewards. Data on rewards comes from Chan et al. (2012). The data on annual fees comes from annual reports on "Banking Fees in Australia". Interest rate data is from the F05 interest rate publication from the Reserve Bank of Australia.

Figure A.13: The effect of the Durbin Amendment on deposits and bank switching behavior



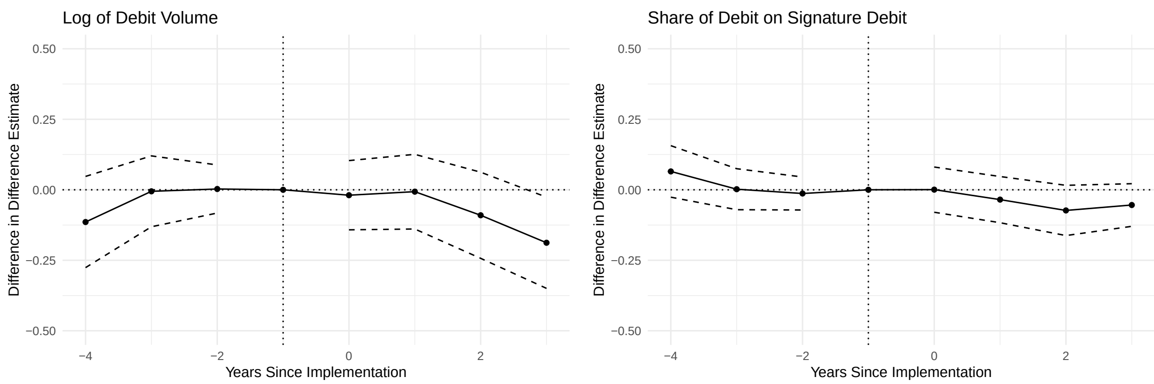
Notes: The left chart shows the estimated effect of the Durbin Amendment on deposits at large banks. The vertical line marks 2010, the year before the policy began to be implemented. The right chart uses data from MRI to show that consumers at small banks did not report being more likely to have recently switched to that bank in the past year when compared to consumers at the largest banks. Small banks are defined as a credit union or community bank as these institutions were largely exempt from the Durbin Amendment.

Figure A.14: Credit card rewards for consumers who use large and small deposit institutions after the Durbin Amendment



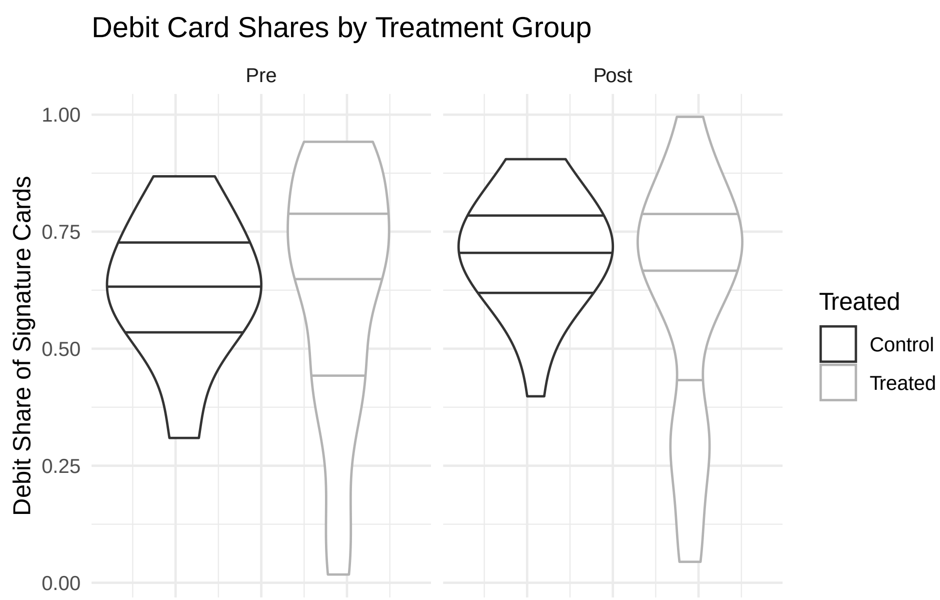
Notes: The left chart shows the conditional probability that a consumer has a credit card from a large credit card issuer, conditional on whether a consumer exclusively has deposit accounts at small or large deposit institutions. The right chart shows the conditional probability of receiving credit card rewards conditional on whether a consumer has a deposit account at a small or large deposit institution. Consumers at small deposit institutions are those who only use deposit accounts at credit unions or community banks. Consumers at large deposit institutions are those who use deposit accounts at Chase, Bank of America, Citibank, Wells Fargo, or U.S. Bank. The large credit card issuers are Chase, Bank of America, Citibank, Wells Fargo, Capital One, Discover, and American Express.

Figure A.15: The effect of the Durbin Amendment on overall debit volumes



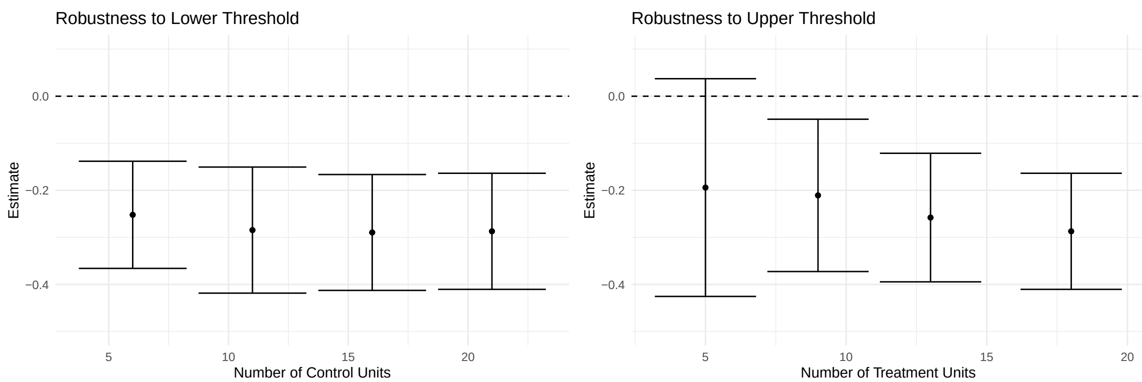
Notes: The vertical line marks 2010, the year before the policy began to be implemented.

Figure A.16: Comparing debit versus credit shares at treatment and control banks



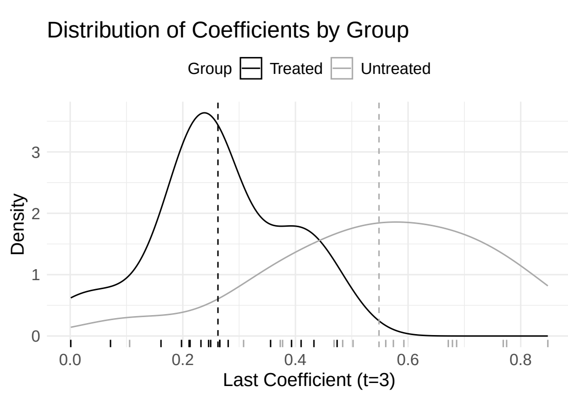
Notes: Each panel shows a violin plot illustrating the distribution of signature debit as a share of total card transactions by value for the control (<$10 billion in assets in 2010) and treatment banks (>$10 billion) in the pre and post periods. The dashed lines show the 25th, 50th, and 75th percentiles of each distribution. The distributions exhibit substantial overlap.

Figure A.17: Robustness of the effect of the Durbin Amendment on debit card volumes to varying asset size cutoffs



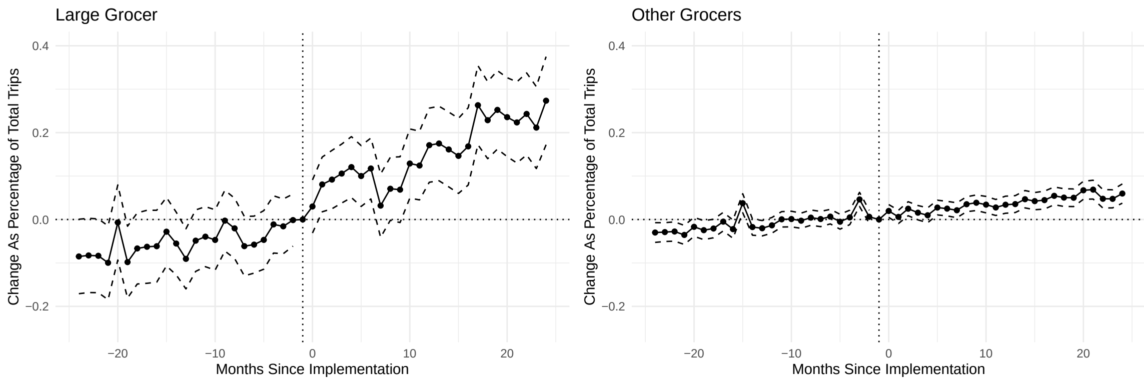
Notes: The panels show the results of the difference-in-difference estimates of the effect of Durbin on signature debit card volumes as I increase the minimum asset requirement up towards $10 billion (for the control group) or as I decrease the maximum asset size down towards $10 billion (for the treatment group) until the treatment or control group is of the desired size. Each dot represents the point estimate, and the error bars provide 95% confidence intervals.

Figure A.18: Distribution of institution-level estimates in the Nilson analysis



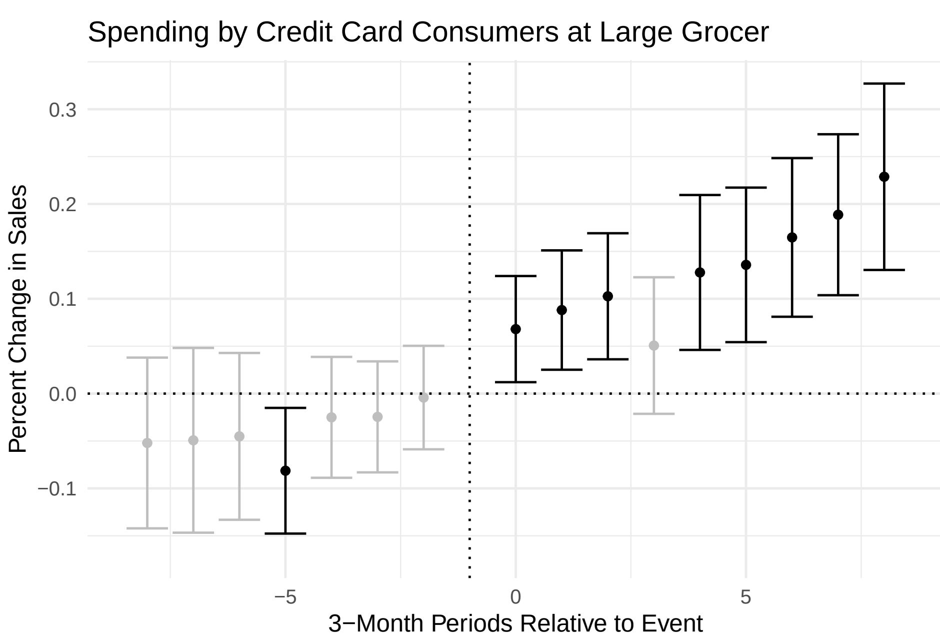
Notes: The density plots show the distribution of institution-level event study estimates the effect of the Durbin Amendment on signature debit card volumes for both the treated and control groups. Each observation is a financial institution. The coefficient estimate in the main text is approximately equal to the difference between the average estimate in the treated group minus the average of the control groups.

Figure A.19: Double differences for the large grocer (left) and all other grocers (right)



Notes: The left panel shows the dynamic estimates of the effect of card acceptance on the number of trips of credit card consumers versus non-credit-card consumers at the large grocer that started accepting credit cards. The right panel shows the same dynamic estimate for all non-treated grocers. The trend in the non-treated grocer sample suggests that credit card consumers are on a different spending trajectory. The triple-difference estimate in the main text effectively subtracts the right estimate from the left.

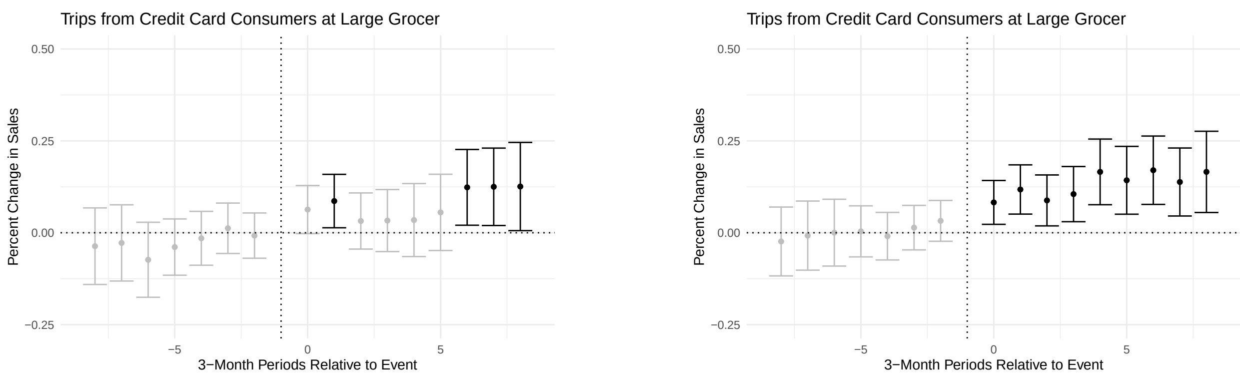
Figure A.20: Spending instead of trips for the large grocer



Notes: The graph shows the dynamic estimates of the estimate of credit card acceptance on sales to credit card consumers. This graph differs from the main text by focusing on dollars spent rather than just trips.

Figure A.21: Triple-difference specifications for the effect of card acceptance on total trips, split by multi-homing status

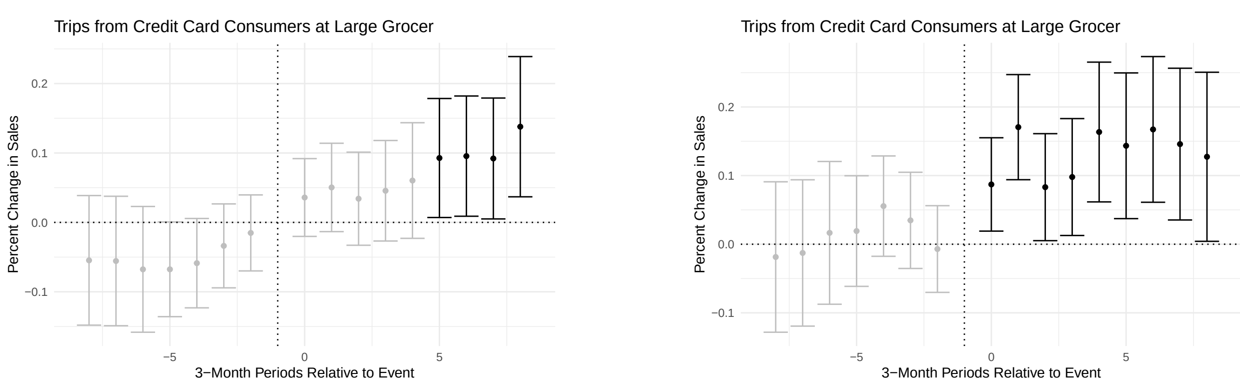
(a) Single-homing Credit Card Users **(b)** Multi-homing Credit Card Users



Notes: The left panel shows the dynamic estimates of the effect of card acceptance on the number of trips by credit card consumers for consumers that carry credit cards only from one network. The right panel shows the same estimation on a sample of consumers who carry credit cards from multiple networks.

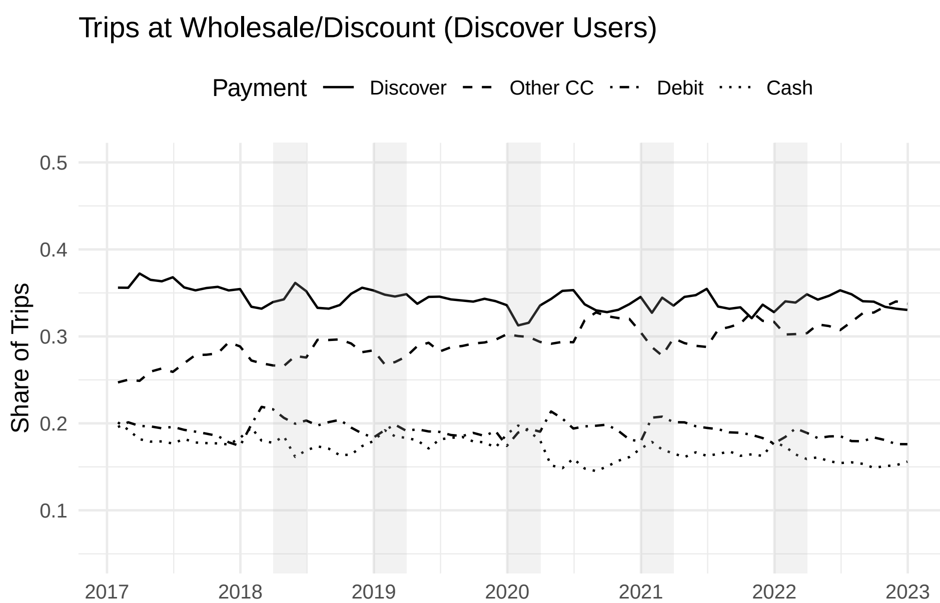
Figure A.22: Triple-difference specifications for the effect of card acceptance on total trips, split by income

(a) High Income **(b)** Low Income



Notes: The left panel shows the dynamic estimates of the effect of card acceptance on the number of trips by credit card consumers for consumers with above median income. The right panel shows the same estimation on a sample of consumers with below median income.

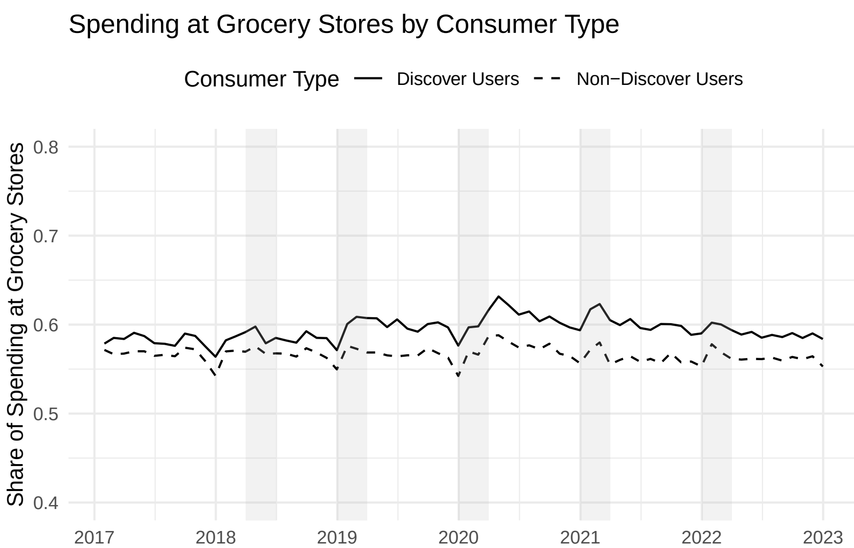
Figure A.23: Effects of Discover's quarterly reward program on the payment mix at warehouse stores



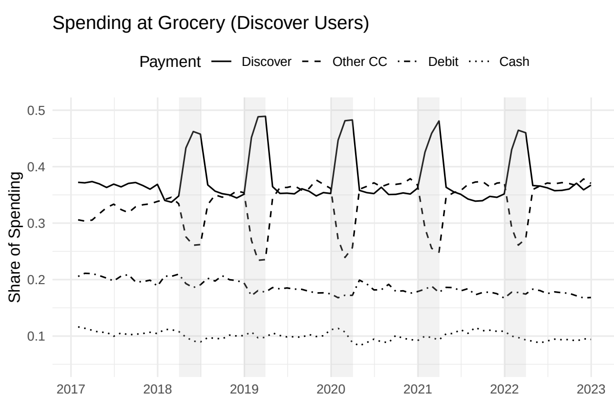
Notes: Grey shaded areas indicate quarters where Discover offers 5% cash back at grocery stores but not at discount retailers, warehouse stores, or other retailers. The figure shows the composition of payments at discount/warehouse stores (control) when measured as a share of all trips at discount/warehouse stores. Data conditions on consumers that use Discover.

Figure A.24: Effects of Discover's quarterly reward program at grocery stores on consumer spending on different payment methods across retailer types

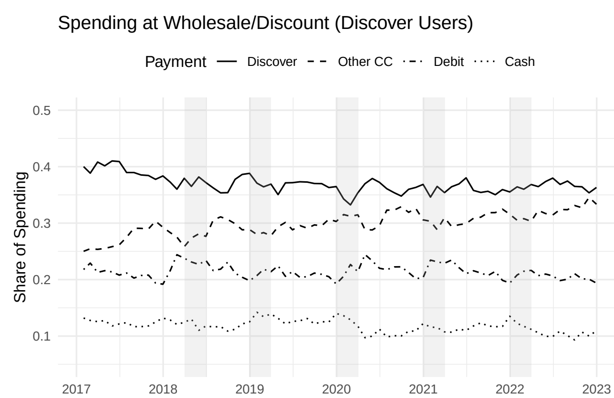
(a) Share of dollars spent at grocery stores



(b) Payment mix at grocery stores

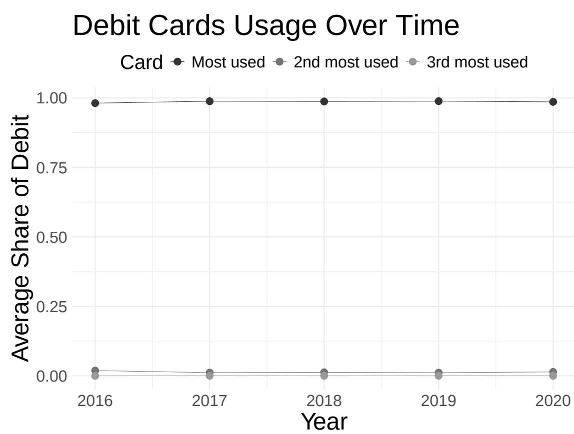


(c) Payment mix at warehouse/discount stores



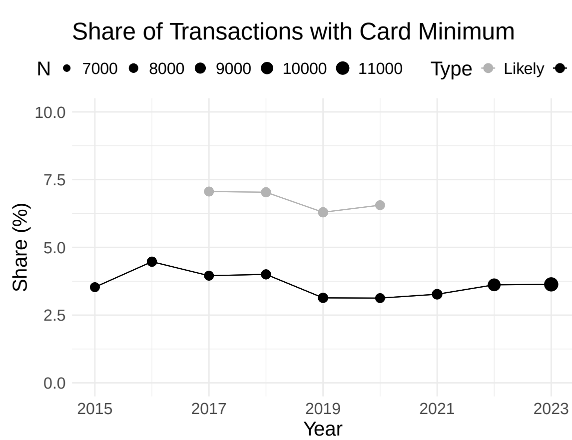
Notes: Grey shaded areas indicate quarters where Discover offers 5% cash back at grocery stores but not at discount retailers, warehouse stores, or other retailers. The first panel shows how shopping decisions across retailer types change in response to the rewards. The second and third panels show the composition of payments at grocery stores (treated) and discount/warehouse stores (control). All samples condition on consumers that have transactions on Discover.

Figure A.25: Share of debit card spending on primary debit card



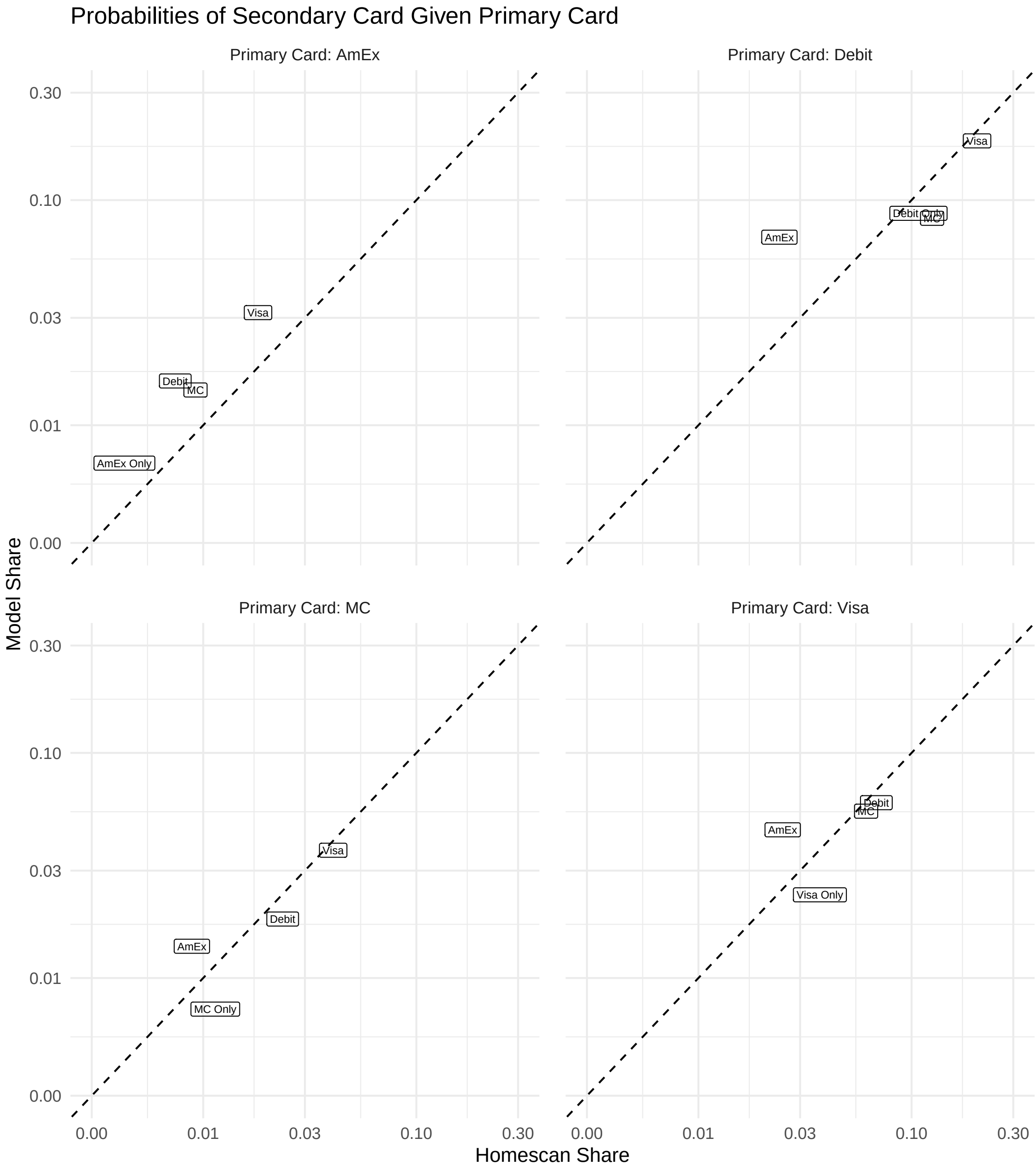
Notes: The graph shows data from the DCPC on the share of debit card spending that consumers allocate to their primary debit card. The primary debit card is defined at the consumer level as the card with the plurality of their debit card spending by counts.

Figure A.26: Share of card subject to a card minimum



Notes: The graph shows data from the 2015–2023 DCPC on the share of transactions for which the consumer reports a "Likely" or "Sure" card minimum. The former is only defined for the 2017-2020 period and includes the responses "Yes" and "I don't know, but I think so." The latter is defined for the full period and only includes "Yes" responses.

Figure A.27: Model fit of the market share of different combinations of primary and secondary cards



Notes: Each observation shows the market share of a combination of primary and secondary cards in both the estimated model and the data. Each facet shows the data for a different choice of primary card. Each point is labeled with the name of the secondary card. The dashed line shows the 45-degree line, indicating that the model shares equal the actual shares.

References

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

Agarwal, Sumit, et al. 2022. "Who Pays For Your Rewards? Cross-Subsidization in the Credit Card Market." *Working Paper* (May): 51.

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

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

Bourguignon, Hélène, et al. 2019. "Shrouded Transaction Costs: Must-take Cards, Discounts and Surcharges." *International Journal of Industrial Organization* 63 (March): 99–144. Accessed January 4, 2023.

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

Caddy, James, et al. 2020. "Consumer Payment Behaviour in Australia: Evidence from the 2019 Consumer Payments Survey." *RBA DIscussion Paper* (June).

CardX. 2023. *State Laws on Surcharging,* January. Accessed January 29, 2023.

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

Chakravorti, Sujit, and Alpa Shah. 2001. "A Study of the Interrelated Bilateral Transactions in Credit Card Networks." *Emerging Payments Occasional Paper Series* (July). Accessed January 29, 2023.

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

Conrath, Craig W. 2014. *Plaintiff's Proposed Findings of Fact.* Technical report 1:10-CV-04496-NGG-RER. United States District Court Eastern District of New York, September.

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

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

Gabaix, Xavier, and David Laibson. 2006. "Shrouded Attributes, Consumer Myopia, and Information Suppression in Competitive Markets." *Quarterly Journal of Economics* 121, no. 2 (May): 505–540.

Glasheen, Jasmine. 2020. *Amex OptBlue: What It Is and How to Lower Your Rates,* November.

Huynh, Kim, et al. 2022. "Equilibrium in Two-Sided Markets for Payments: Consumer Awareness and the Welfare Cost of the Interchange Fee." *Bank of Canada Working Paper* (March). Accessed June 2, 2022.

Issa, Erin El. 2017. *Americans Favor Debit Over Credit for Their Go-To Card.* Technical report. Nerdwallet, September. Accessed October 5, 2022.

Jones, Barbara. 2001. *U.S. v. VISA U.S.A., et Al.,* 98 Civ. 7076 (BSJ), October.

Koulayev, Sergei, et al. 2016. "Explaining Adoption and Use of Payment Instruments by US Consumers." *RAND Journal of Economics.*

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

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

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

Prager, Robin A, et al. 2009. "Interchange Fees and Payment Card Networks: Economics, Industry Developments, and Policy Issues." *Finance and Economics Discussion Series.*

Prelec, Drazen, and George Loewenstein. 1998. "The Red and the Black: Mental Accounting of Savings and Debt." *Marketing Science* 17, no. 1 (February): 4–28. Accessed October 19, 2022.

Rochet, Jean-Charles, and Jean Tirole. 2003. “Platform Competition in Two-Sided Markets.” *Journal of the European Economic Association* 1, no. 4 (June): 990–1029. Accessed April 19, 2021.

Schuh, Scott, et al. 2011. “An Economic Analysis of the 2010 Proposed Settlement between the Department of Justice and Credit Card Networks.” *Public Policy Discussion Papers* (July).

Sullivan, Michael. 2023. “Price Controls in a Multi-Sided Market.” *Working Paper* (December).

Teh, Tat-How, et al. 2022. “Multihoming and Oligopolistic Platform Competition.” *American Economic Journal: Microeconomics* Forthcoming.

Visa. 2013. *Visa Surcharging FAQ.* Accessed January 29, 2023.

Westchester. 2019. *Credit Card Surcharges,* May.

Weyl, E. Glen. 2010. “A Price Theory of Multi-Sided Platforms.” *American Economic Review* 100, no. 4 (September): 1642–1672. Accessed April 19, 2021.