Regulating Competing Payment Networks

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Abstract

Payment markets are two-sided. Card networks like Visa and Mastercard charge merchant fees to fund consumer rewards. I quantify how network regulation and competition affect equilibrium prices, consumption, and welfare. I use data on consumer card holdings, bank payment volumes, and merchant acceptance to estimate a model of how payment networks compete for multi-homing consumers and merchants. Using the estimated model, I compare the effects of capping credit card merchant fees, uncapping debit card merchant fees, and increasing network competition. Either capping credit card merchant fees or repealing caps on debit card merchant fees could raise annual welfare by $38 billion and $11 billion, respectively. However, because consumer adoption is ten times more price-sensitive than merchant acceptance, network competition raises both rewards and fees, lowering welfare.

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Section I Introduction

Card networks dominate consumer payments in most advanced economies, yet regulatory approaches vary widely across countries. European and Australian regulators cap merchant fees, whereas U.S. regulators emphasize increasing competition. Recent U.S. Department of Justice lawsuits against Visa – such as the 2024 monopolization lawsuit or the 2020 challenge to Visa's acquisition of Plaid – reflect a view that network competition is desirable because it pushes down merchant fees (Read et al., 2020).

But because payment markets are two-sided, it's unclear if either approach improves welfare. Networks like Visa, Mastercard, and American Express compete for merchants and consumers by adjusting merchant fees and consumer rewards. While price caps and increased competition are useful remedies against market power in one-sided markets (Cuesta and Sepulveda, 2021), they may reduce welfare in two-sided markets. Supra-competitive merchant fees may fund socially desirable consumer rewards (Rochet and Tirole, 2003; Sullivan, 2023). In other models, competition may induce networks to raise fees to fund more generous rewards (Edelman and Wright, 2015). Despite the diversity in regulatory strategies, there is little empirical evidence for their relative merits.

I quantify how merchant fee caps and network competition affect prices and welfare in U.S. consumer-to-business payments. The central contribution is a quantitative model of how payment networks compete in merchant fees and consumer rewards. 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 and merchant acceptance, retail pricing, and network competition. With the estimated model, I simulate how regulation and competition affect prices, distribution, and welfare.

The U.S. payment system is hamstrung by poorly designed price regulations that additional competition cannot resolve. Regulatory actions, such as capping credit card merchant fees or repealing existing debit card fee caps, could reduce regressive wealth transfers and increase annual welfare by $38 billion and $11 billion, respectively. Unlike in concentrated one-sided markets, I find that reducing competition in this two-sided market structure can improve welfare. For instance, a merger to monopoly decreases total fees and rewards by reducing credit card usage, yielding an annual welfare gain of $25 billion. This outcome reflects the two-sidedness of the market, in which networks compete for consumers with rewards rather than for merchants with lower fees.

My results suggest that a unifying principle for the regulation of payment markets is that optimal regulations reduce pecuniary externalities. Payment markets feature pecuniary externalities 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] Price coherence means that when networks charge high merchant fees to fund consumer rewards, their consumers benefit from the full increase in rewards but only bear part of the cost of higher retail prices. These externalities distinguish payment markets from other important two-sided markets such as food-delivery or ride-hail (Sullivan, 2023; Rosaia, 2020).

The externalities generated by price coherence are regressive and wasteful. Merchant fees fund rewards. When merchants pass on high credit card merchant fees into retail prices, lower-income cash and debit card users ultimately fund high-income credit card users' rewards (Felt et al., 2020).[2] They are wasteful because consumers bear incremental costs to adopt credit cards. I refer to these costs as "credit aversion", and infer its magnitude from the revealed preferece of many debit card consumers to use debit cards despite having access to credit cards. But while credit aversion is a social cost, the rewards are merely transfers. Consumers are thus locked in a prisoner's dilemma. In equilibrium, too many consumers use credit cards because they do not internalize their effects on retail prices. Even though consumers collectively prefer low retail prices and credit card use, they individually benefit from earning rewards from credit cards. Policies that reduce credit card use are thus progressive and welfare-increasing.

To motivate the importance of two-sided competition in payments, I document three reduced-form facts to illustrate how consumer adoption is reward-sensitive, but merchant acceptance should be fee-insensitive. Thus, networks face incentives to charge high merchant fees to fund generous consumer rewards. 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 34%. 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%. Third, I use a combination of industry trade journals and Homescan data to show that while most merchants accept all of the networks, many consumers only carry credit cards from one network. Merchants thus risk large sales declines 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 pay-

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

[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.

ment 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 incremental benefits from higher sales against the incremental cost of merchant fees. Thus, merchant acceptance depends on consumer adoption. 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 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; Gentzkow et al., 2023). Rochet and Tirole (2003); Teh et al. (2022) are flexible models of platform competition that 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. 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 ten 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 4.4%. 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' large benefits from card acceptance.

In my main counterfactual, I cap credit and debit card merchant fees at the cost of cash. Such a policy would reduce credit card use, be progressive, and increase welfare. Lower merchant fees pass through to a 234 bp decline in credit card rewards. The combination of lower merchant fees and lower 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 $42 billion and $38 billion, respectively. For context, the CARD Act was a major piece of credit card legislation that was 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 the gains from regulating issuers.

The same logic justifying caps on credit card merchant fees suggests that the Durbin Amendment's caps on debit card merchant fees were regressive and reduced total welfare by $11 billion. By cutting debit merchant fees, the policy eliminated debit rewards, amplified credit card reward competition, increased credit card use, and reduced welfare. Even if the optimal policy in theoretical models requires capping both credit and debit card merchant fees (Rochet and Tirole, 2011), capping debit card merchant fees while not regulating credit card merchant fees lowers welfare.

In contrast to the large gains from improved price regulation, competition is regressive and potentially welfare-reducing. Consumers are reward-sensitive, whereas merchants are fee-insensitive. Therefore, network competition generates higher rewards that exacerbate the excessive use of credit cards. For example, a merger to monopoly decreases total rewards and fees by $66 and $54 billion. The reduction in rewards redistributes consumption from higher-income consumers to lower-income consumers. Overall consumer welfare rises by $4.8 billion (S.E. 11.2) and total welfare rises by $25 billion (S.E. 7). These estimates show that mergers in payment markets increase market power but can also increase total welfare by correcting the excessive adoption of high-fee, high-reward payment methods. Thus, revised regulation, not just more competition, is necessary to correct the market failure arising from price coherence in payment markets.

More broadly, my paper suggests that the effects of platform pricing on off-platform prices play an important role in determining the welfare effects of platform competition (Bergemann et al., 2024). For example, search engines like Google charge merchants high advertising prices while investing in consumer benefits. Merchants charge the same retail price to consumers who see advertisements and those who do not. Search engine competition can potentially lead to investments in attracting consumers and higher advertising prices, which inflate retail prices and lower welfare.

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). 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; Gentzkow et al., 2023). By modeling a mix of single and multi-homing consumers, I provide a more realistic model of platforms' pricing incentives (Song, 2021).

The closest related empirical work is Huynh, Nicholls and Shcherbakov (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 lets me capture how credit card rewards inflate retail prices, redistribute consumption, and ultimately hurt consumers. Network competition lets me endogenize merchant fees and consumer rewards, enabling me to assess how price controls and competition affect prices and total welfare.

I also contribute to a 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.

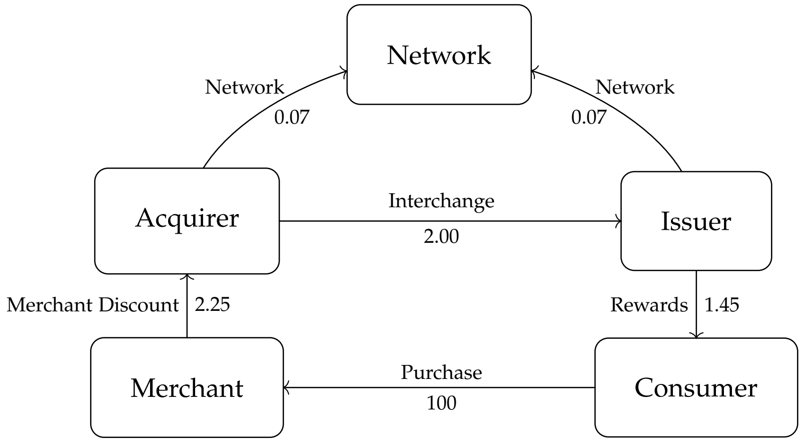
Section II Institutional Details and Data

II.A Network Pricing: Merchant Fees and Consumer Rewards

Payment markets are two-sided. With every card swipe, the merchant pays a fee, and the consumer may receive a reward. This section explains how payment networks compete with each other by adjusting these fees and rewards. 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. 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 will use some of that fee to cover

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 (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.

its costs but must also send around \$2 to the issuing bank (e.g., Chase) in the form of interchange. The issuer and the acquirer collectively then 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.

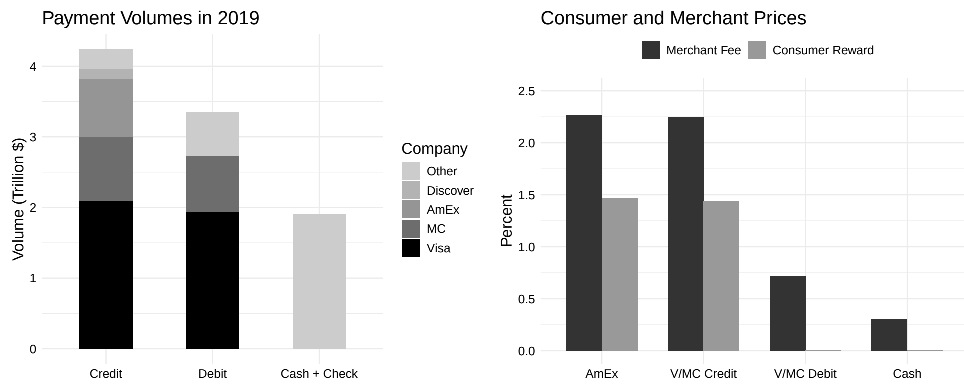
Regulatory shocks are the best evidence for how interchange strongly affects merchant fees and rewards while having limited effects on borrowing. When the E.U. and Australia mandated interchange fee reductions, merchant fees declined roughly one-for-one (Gans, 2007; Valverde et al., 2016; European Commission, 2020). Appendix Figure A.15 shows that after credit card interchange was capped in Australia, rewards fell, annual fees on rewards credit cards rose, whereas annual fees on non-reward credit cards and interest rates were left unchanged.

II.B Data

I use bank-level and aggregate data from the Nilson Report, transaction-level data from the NielsenIQ Homescan panel, and survey data on payments and consumer shopping decisions to estimate consumer and merchant demand for payments. Appendix A contains more details on how the data is constructed.

Aggregate Prices and Shares: I use aggregate shares and merchant fees from the Nilson Report and the average rewards data from the annual reports of the 7 largest banks, which cover 80% of the market. Figure 2 documents payment volumes, merchant fees, and rewards. Visa, Mastercard (MC), and American Express (AmEx) process 85% of all card payments. All three major credit card networks charge similar merchant fees

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



Notes: The left chart shows payment volumes measured in trillions from Nilson (2020b,c). 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 V/MC rewards banks' annual 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)

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 payment volumes. My main difference-in-difference analysis focuses on a subset of 35 issuers, 15 of them above $10 billion in assets and 20 below. My sample excludes issuers that made large acquisitions exceeding 50% of equity or large credit card portfolio acquisitions. Appendix Table A.10 reports summary statistics at the issuer-year 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 over survey data for measuring multi-homing behavior is that I see more transactions. Appendix Table A.11 reports the main summary statistics at the household level. Appendix Table A.12 shows that Homescan slightly overrepresents cash and debit transactions while underrepresenting American Express.

Consumer Payment Surveys: I use three different sources of survey data. 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. These data help me estimate the level of card acceptance at merchants, the share of consumers who prefer cash, and how

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

	Cash	Debit	Credit
Share	0.22	0.45	0.32
Owns credit card	0.68	0.80	1.00
Owns rewards credit card	0.44	0.52	0.89
Owns bank account	0.86	0.98	0.99
Credit utilization	0.22	0.29	0.08
Household income (000's)	67.89	78.91	116.62
Card acceptance	0.94	0.96	0.97
Credit score > 650	0.67	0.70	0.97

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 at merchants that accept cards. All other variables report averages across consumers for each group. Credit share and debit share are shares of transactions on credit cards and debit cards, respectively.

payment preferences relate to income. Table 1 shows summary statistics on consumers' payment preferences. The survey shows that cards are widely accepted at around 95% of merchants, around one-fifth of consumers' preferred payment method is cash, and that credit card users have higher incomes than cash or even debit card users. Second, I field my own 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.

Section 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 that is 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, whereas merchants are fee-insensitive. I then show that whereas almost all merchants accept cards from every network, many consumers concente 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.

III.A Consumers' Sensitivity to Rewards

I use a regulatory shock, the Durbin Amendment, to show that rewards exert a strong effect on 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 (Mukharlyamov and Sarin, 2022). Starting in October 2011, debit interchange fees at covered institutions were reduced by roughly half, whereas debit interchange fees at small institutions and credit interchange fees at all institutions remained unaffected. This law reduced large issuers' revenue from debit card transactions, prompting them, but not small issuers, to end debit rewards (Hayashi, 2012; Schneider and Borra, 2015; Orem, 2016).

To estimate the effect of reward changes on payment volumes, I compare payment volumes at large issuers (defined as those with assets between 10 and 200 billion) and small issuers (with assets between 2.5 and 10 billion). I thus estimate:

$$y_{it} = \sum_{k=-3}^{3} \beta_k I\left\{t = k\right\} \times T_i + \delta_i + \delta_t + \epsilon_{it} \tag{1}$$

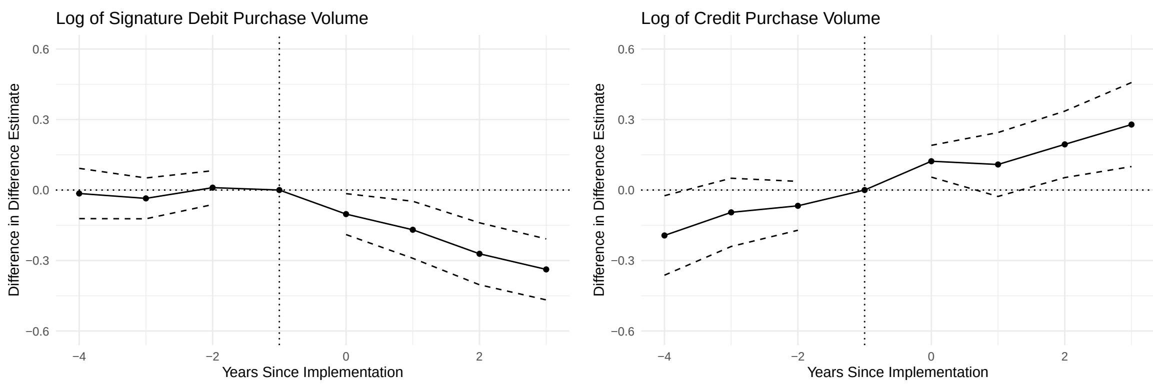
where y_{it} is the log of signature debit or credit card purchase volume at issuer i[3], T_i refers to whether issuer i had more than \$10 billion in assets in 2010, and δ_i and δ_t represent issuer and year fixed effects, respectively. I define $t = 0$ as 2011. By comparing large and small issuers, 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 paid consumers around 25 bps of transaction value. The left panel of Figure 3 plots the estimates and shows that reduced rewards led to a 34% decline in signature debit volumes and an increase in credit card volume at treated banks, although the pre-trend in volumes makes it difficult to quantify the precise effect on credit cards.[4]

[3] 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.17 shows the regression with overall debit volumes and shows that the share of debit transactions on signature cards did not change after Durbin.

[4] In the Appendix, I include additional results and robustness checks. Figure A.16 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. This further suggests 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.13 shows the regression estimates and validates that my estimated decline in interchange is consistent with the effect of Durbin, given that credit interchange was not affected and made up around one-third of total interchange revenue. The pre-trend in credit is hard to evaluate because credit data coverage is lower for the earliest

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



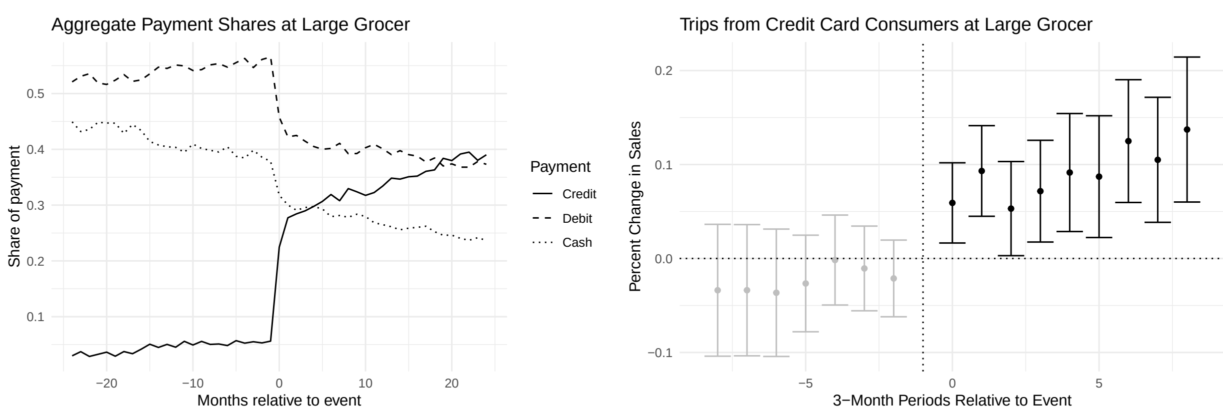
Notes: Data are from the Nilson Report. The vertical line marks the year before the policy implementation in Q3 2011, which is $t = 0$. Standard errors are clustered at the issuer level.

III.B Merchant Benefits from Card Acceptance

When a large U.S. grocer began accepting credit cards in addition to debit cards, it experienced a significant increase in sales from credit card users. Extrapolating from this case, the results suggest that the revenue gains from card acceptance outweigh the incremental costs for most merchants, even at high levels of merchant fees.

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

(a) Payment mix **(b)** Sales effects



Notes: Data is from Homescan. The left panel tracks the evolution of payment methods over time at the grocer that started accepting credit cards. The right panel presents dynamic regression coefficients from a triple-difference model that estimates the impact of credit card acceptance on the number of shopping trips by credit card users. The coefficients reflect percentage changes in trips.

I use a triple-difference approach to estimate how much credit card acceptance in-

period (Figure A.1). Figure A.18 shows that the pre-policy debit versus credit mix at the treatment and control issuers were similar. Figure A.19 shows that the estimates are robust to varying the minimum and maximum asset cutoffs.

creases sales to credit card consumers. Conceptually, I combine two difference-in-differences (DiD) strategies. First, I compare spending patterns between credit card and non-credit card consumers at the treated grocer before and after credit card acceptance. However, to account for the possibility that credit card users may follow different spending trajectories, I refine the estimate by comparing these same consumer groups across all other grocers and subtracting the difference between these two comparisons. To maximize power, I restrict the analysis to three-digit ZIP codes where the grocer was already present in the year before the event.

The estimating equation for the dynamic specification is:

$$y_{ijt} = \delta_{z(i)jt} + \lambda C_i + \phi \times T_j \times C_i + \sum_{k \neq -1} \gamma_k \times C_i \times I(t=k) + \sum_{k \neq -1} \beta_k \times C_i \times T_j \times I(t=k) + \epsilon_{ijt} \tag{2}$$

where y_{ijt} is the number of trips by consumer i at retailer j in quarter t, $\delta_{jtz(i)}$ 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 index $t = -1$ as the quarter before adoption. The coefficients of interest are β_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 β_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 (δ), baseline differences in shopping patterns between credit card and non-credit card consumers (λ, ϕ), and the possibility that credit card users experience higher income growth than other consumers (γ).

After the grocer began accepting credit cards, consumers shifted from cash and debit payments and increased their spending at the store. Figure 4a shows how the share of trips by different payment methods evolved over time, with credit card transactions making up 40% of total payments two years after the change. Figure 4b plots the estimated dynamic coefficients, indicating that sales to credit card users increased by approximately 15% following the grocer's decision.[5]

The increase in sales is driven by the convenience of credit card payments, rather than by credit card users increasing their spending to earn rewards at the grocer. Rewards do little to shift consumers' choices of merchants. In Appendix B.1, I show that when

[5]Appendix Figure A.20 shows the double-difference estimates and shows that credit card consumers have a different trend in the number of trips. Figure A.21 shows the same regression but with dollars spent instead of the number of trips. I use trip frequency as my main result because dollars per trip can exhibit fat tails. Table A.14 shows the estimated coefficients.

Discover turns on rewards for grocery stores —– but not for wholesale or big-box stores —– consumers do not shift their spending between these retail categories. This occurs despite the fact that consumers typically reallocate spending between these categories in response to non-reward-related price fluctuations (Ellickson et al., 2020).

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%.[6] Census statistics indicate gross margins in the grocery industry were around 27% during this time period, suggesting that credit card acceptance is profitable for most merchants. Given that most merchants should expect significant increases in profit from accepting credit cards, increases in credit card fees should have only a small effect on merchant acceptance.

III.C Consumer and Merchant Multi-homing

The effects of platform competition depend not only on reward and fee sensitivities but also on whether consumers and merchants transact across multiple platforms—that is, their multi-homing behavior. Theory provides guidance at the extremes. If consumers regularly use multiple cards from different networks, merchants can afford to limit themselves to accepting only the lowest-fee network. This pushes platforms to compete by lowering merchant fees. On the other hand, if consumers primarily use a single card while merchants accept all networks, merchants must accommodate the consumer's choice. This allows platforms to raise merchant fees, using the additional revenue to fund more generous consumer rewards (Teh et al., 2022).

In practice, both consumers and merchants tend to multi-home, but this behavior exhibits an important asymmetry. 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 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

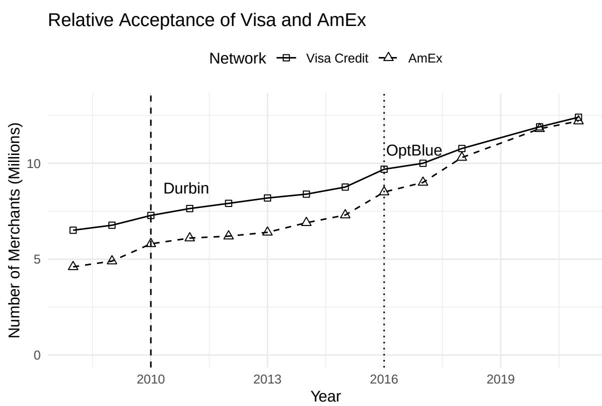
Most merchants accept either all credit cards or none at all. I draw this conclusion from two key observations. First, merchant strategies follow a hierarchical pattern, ranging from cash-only to progressively including debit cards, Visa with Mastercard, and

[6] At such a 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.

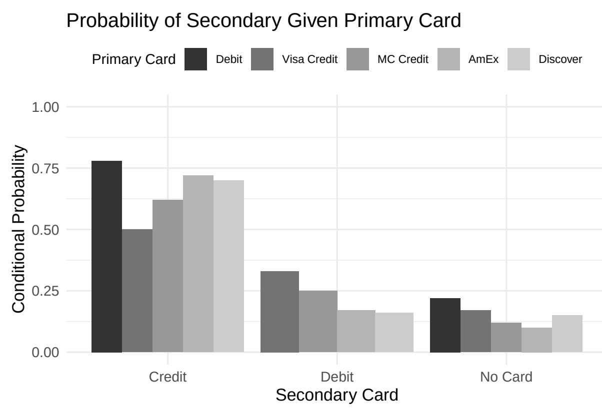
then AmEx. Appendix B.2 presents data from Yelp reviews to confirm this fact. Second, the number of merchants that accept AmEx approximately equals the number of merchants that accept Visa. Figure 5a uses data from the Nilson Report on this point. Since every Visa and Mastercard merchant also accepts AmEx, this shows that almost all credit card merchants accept all three networks.

Figure 5: Consumer and merchant multihoming 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 right panel uses data from Homescan and shows the probability that consumers use a secondary credit card, conditional on different primary cards.

III.C.2 Many Consumers Single-home

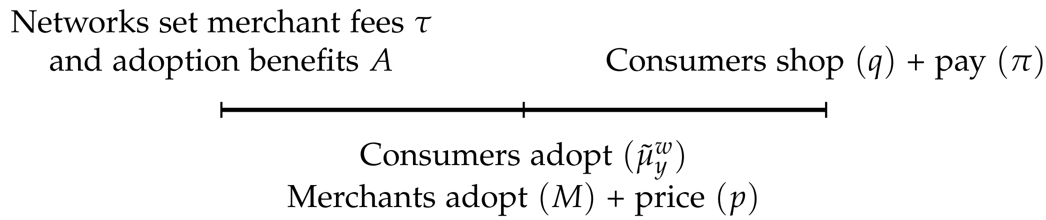
Around 40% of consumers carry credit cards from only one network. Since credit card acceptance tends to incrementally boost sales relative to debit cards, merchants risk substantial sales losses if they reject cards from one network while accepting others. I study consumer multi-homing behavior using the Homescan shopping data. For this analysis, I define a network as Visa credit, MasterCard (MC) credit, AmEx, or any debit card.[7] In Appendix Table A.16, I find that consumers put around 95% of their card spending on two networks.[8] 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.[9]

[7] 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 multiple debit cards for day to day purchases. I show this fact in Figure A.23

[8] A household that spends on five different Visa cards is treated as exclusdively using Visa. The primary network typically covers around 80% of the card spending. Table A.15 shows that the card with the highest number of trips is highly correlated with having the largest amount of spending.

[9] 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

Figure 6: Timeline of the model.



The right panel of Figure 5 shows data on multi-homing behavior. The first set of bars show the probability that different consumers carry a secondary credit card. Among primary credit card users, Visa users have the lowest multi-homing rate of 50% whereas AmEx users have the highest rate around 73%. These measures of multi-homing are conservative because even a consumer who spends 99% on one network and 1% on another is counted as a multi-homing consumer. 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 to lower-fee 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 suggest that merchants who reject cards from high-fee credit card networks risk large declines in sales (Facts 2 and 3). These facts suggest that consumers are reward-sensitive, merchants should be fee-insensitive, and that competition creates only weak incentives for networks to cut merchant fees.

Section IV Model

I develop a model of competing payment networks that captures three key features that are 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.

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.[10] Figure 6 shows the stages. 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 decide how much to consume from each merchant.

The second and third stages micro-found consumers' and merchants' demand for payments, and, 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 their sales increase from card acceptance. The model makes several simplifying assumptions that I discuss in Section IV.F.

IV.B Stage 3: Consumer Shopping and Payment

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 accepted by the merchant. As a consequence of decisions earlier in the game, consumers are either cash-only or carry one or two cards. Consumers who carry one card pay with it if the merchant accepts the card. Otherwise, the consumer pays with cash.

Consumers who carry two cards can potentially substitute between their cards if they are the same type (i.e. both credit or both 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, then 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, but the process is otherwise the same. If the two cards are not the same type, then consumers do not substitute between them. Figure 7(b) illustrates this alternative.

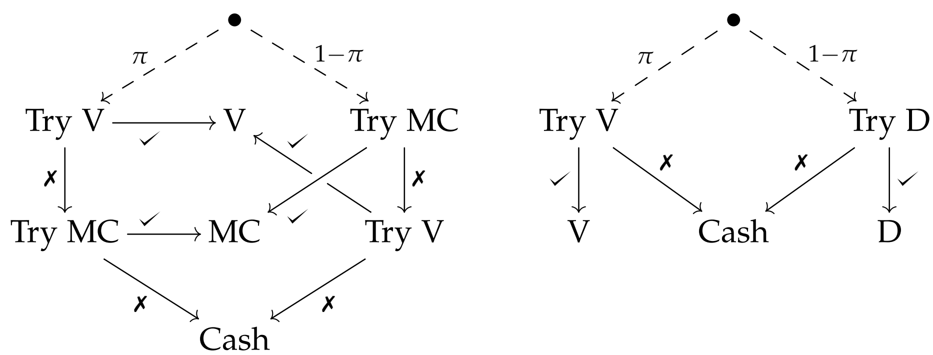
Although simple, this model of payment behavior matches several features of the data. First, when a merchant accepts all of the cards, the model matches the evidence

merchants that have a particularly low share of transactions from any one network. I discuss this in detail in the Data Appendix A.

[10]Because I do not model issuers or acquirers, the Visa network should be viewed as the combination of Visa, the corporation, the issuers of Visa cards (e.g., Chase), and the acquirers who help merchants accept Visa (e.g., Square).

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

(a) Primary Visa/Secondary MC (b) Primary Visa/Secondary Debit



Notes: A ✓ denotes payment acceptance and a ✗ denotes a payment being declined. Dashed lines indicate moves by nature. The left chart shows that with probability π, a primary Visa, secondary MC consumer will first try to pay with Visa, then MC, and then cash. With probability $1 - \pi$ the order of Visa, MC are reversed. The right diagram shows that consumers that multihome on credit and debit cards do not substitute between them when one is not accepted

on how much multi-homing consumers concentrate their spending on one card (Table A.16). Second, the segmentation between debit and credit allows the model to matches the evidence from Section III.B that accepting credit cards in addition to debit cards can increase sales. I find further evidence for this segmentation when I study Discover's quarterly rewards program in Appendix B.1. Point-of-sale incentives to use Discover credit cards induce substitution from other credit cards even though many Discover credit card users use a mix of debit and Discover (Figure 5b).[11] The main weakness of this model is that accepting credit cards at a store does not decrease the amount of debit card transactions at the store. This causes the model to under-estimate the incentive of Visa to raise fees because it knows that some transactions to substitute to Visa Debit. But to the extent the counterfactuals do not change competition between debit card networks,

[11]A more indirect form of evidence can come from looking at the merchant side of the market. Appendix B.3.2 presents evidence that changes in relative credit card merchant fees can have large effects on relative credit card acceptance, whereas lower debit card merchant fees do not reduce credit card acceptance. While this can be hard to interpret given that fee changes can happen with other equilibrium responses, it does suggest that merchants view different credit card networks as much closer substitutes than debit and credit. This perception is naturally justified if consumers do not view debit as a substitute when they want to use a credit card. Appendix B.5 presents merchant and network commentary on the segmentation between debit and credit. This kind of segmentation can be micro-founded with a usage model as in Huynh et al. (2022) in which consumers prefer to use their primary card, cards of the same type have correlated utility shocks at the point of sale, and there are small idiosyncratic utility shocks conditional on the type of card. An example of a correlated utility shock may be that consumers prefer to use credit cards for high ticket sizes. In such a model, even though some consumers may use a mix of credit and debit cards across stores, they are not willing to substitute between credit and debit at any given store.

the quantitative importance of this is small.

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 $M \subset \mathcal{J}_1$. 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 γ varies across merchants. At the same time, consumers also prefer to shop at merchants that set low retail prices. I use a constant-elasticity of substitution (CES) demand curve to model how consumers allocate their spending across merchants subject to a budget constraint. Because card acceptance only increases sales to card consumers, the profitability of card acceptance depends on levels of consumer adoption. [12]

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 $M \subset \mathcal{J}_1$. Then a consumer with wallet $w = (w_1, w_2)$, baseline income y, and percentage rewards f^w buys q^w, where:

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

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

$$\pi^w_M = \pi^w_{M,w_1} + \pi^w_{M,w_2}$$

In this demand function, π^w_M captures the probability that the consumer pays with a card.[13] The price index P^w summarizes the influence of other merchants' actions.

[12] 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. One dimension of heterogeneity matches hierarchical payment acceptance (Appendix B.2).

[13] The definition that $\pi^w_{M,j} = 0$ means that π^w_M captures the probability a single-homing consumer uses the primary card, and it captures the probability that a multi-homing consumer uses either the primary

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.[14] Second, the effect of card acceptance on total sales depends on the extent of consumer payment adoption. Third, consistent with evidence in Appendix B.1 on Discover's quarterly rewards program, rewards do not affect relative consumption choices across merchants. In Appendix D.1, I micro-found this demand function as the solution to a consumer problem with CES utility and a budget constraint, in which payment acceptance increases product quality through convenience and rewards increase income.[15]

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 quantities q^w multiplied by margins, weighted by the mass of different consumers of different payment preferences and income. The margins in turn depend on both the price that the merchant sets and the fees paid to accept different consumers' payments. Appendix D.2 shows that merchant profits can be expressed as

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

where $\tilde{\mu}^w$ is the income-weighted market share of wallet w among consumers, 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 $\gamma = 0$. By letting $\tilde{\mu}_y^w$ equal the market share of wallet w among consumers with baseline income y, the income-weighted market share $\tilde{\mu}^w$ can be computed as

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

or secondary card.

[14] Indifference is a useful assumption to ensure that accepting Visa is a weak substitute to accepting MC for all merchants. A model with three cards gives similar results; Bertrand competition with two or three competitors results in the same equilibrium price.

[15] 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.

where F denotes the distribution of income, which I assume to be log-normal so that $\log y \sim N(-\nu_y^2/2, \nu_y^2)$. The above expressions for profits then 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 on to all consumers. Appendix D.3 shows that the optimal price is

$$\hat{p}\left(\gamma, M, \tau\right) = \frac{\sigma}{\sigma - 1} \times \frac{1}{1 - \hat{\tau}}, \hat{\tau} = \frac{\sum_w \mu^w \tau_M^w \left(1 + \gamma\right)}{\sum_w \mu^w \left(1 + \pi_M^w \gamma\right)} \tag{7}$$

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:

$$\mu^w = \frac{1 + f^w}{\left(P^w\right)^{1-\sigma}} \times \frac{\tilde{\mu}^w}{C}, C = \sum_w \frac{1 + f^w}{\left(P^w\right)^{1-\sigma}} \times \tilde{\mu}^w \tag{8}$$

Demand shares are necessary because the composition of a given merchant's consumer base depends on the acceptance decisions of other merchants.. Relative to cash-only consumers, card consumers direct more of their spending to high γ merchants that accept the consumers' cards. Thus a cash-only merchant faces less demand from card-consumers as more merchants choose to accept cards. 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, and thus retail prices differ.

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

$$\hat{p}\left(\gamma, M^*\left(\gamma\right), \tau\right) = p^*\left(\gamma\right) \tag{9}$$

IV.C.2 Merchant Acceptance

Merchants' acceptance decisions trade off the benefits of additional sales against the costs of paying higher merchant fees. I ingore fixed costs of payment acceptance, which is consistent with the cost of payment terminals being small relative to the per transaction fees. Let $\widehat{\Pi}\left(\gamma, M\right)$ be the profit function from accepting a particular subset of payments $M \subset \mathcal{J}_1$, accounting for the optimal price. In Appendix D.4, I prove that $\widehat{\Pi}$

is approximately proportional to a linear function of γ, which I call quasiprofits $\overline{\Pi}$. [16] Merchants maximize $\overline{\Pi}$, yielding an optimal acceptance strategy $\widehat{M}$:

$$\widehat{M}(\gamma, \tau) = \underset{M \subset \mathcal{J}_1}{\operatorname{argmax}} -a_M + b_M \gamma \tag{10}$$

$$a_M = \sum_{w \in \mathcal{W}} \mu^w \tau_M^w, \; b_M = \frac{1}{\sigma} \sum_{w \in \mathcal{W}} \mu^w \left(\pi_M^w - \sigma \tau_M^w\right) \tag{11}$$

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 want to use 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 if all consumers multi-home across credit card networks, merchants accept only the lowest-fee network. Appendix D.4.1 verifies these intuitions with algebra. The relationship between consumers' card holdings and merchant acceptance means that merchant fee sensitivity is thus not a primitive parameter, but instead depends on consumer behavior.

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

$$\widehat{M}(\gamma, \tau) = M^*(\gamma) \tag{12}$$

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

$$\log V_i^w = \log U^w + \frac{1}{\alpha_i}\left(\Gamma_i^w + \epsilon_i^w\right) \tag{13}$$

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 either in the form of rewards or payment convenience. For single-homing consumers, I define the

[16] Profits are linear because sales are linear in γ. Linearity is useful in quickly computing the optimal acceptance strategy of each type.

pecuniary utility term as

$$\log U^w = f^w - \log P^w, w \in \{(j,0), j \in \mathcal{J}_1\} \tag{14}$$

where f^w represent percentage 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 27 is approximately $\log U^w$.[17] A one percentage point increase in rewards and a one percent increase in retail prices cancel out each others' 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. Thus

$$\log U^w = \pi \log U^{(w_1,0)} + (1-\pi) \log U^{(w_2,0)}, w = (w_1, w_2) \in \mathcal{J}_1 \times \mathcal{J}, w_1 \neq w_2 \tag{15}$$

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. This specification rules out the possibility that Visa complements AmEx when Visa is accepted at stores that do not accept AmEx. I make this modification to match the empirical finding that the share of AmEx cardholders that multi-home has been flat, even as AmEx acceptance has caught up to that of Visa's (Appendix B.3.3).[18] While the modification does 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 equilibrium welfare numbers are not affected by the

[17] 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.

[18] Similar concerns motivates my model of rewards. An alternative model of rewards would be to assume that consumers receive some rewards rate per dollar spent on each network. This would imply that multi-homers can earn strictly more rewards than single-homers. For example, if AmEx is accepted at fewer locations than Visa, and if Visa and AmEx pay the same per dollar rewards rate, then a primary AmEx / secondary Visa consumer would earn strictly more rewards than an AmEx single-homer because the multi-homer uses cards more. But this alternative specification of rewards also predicts consumer multi-homing rates to increase when a network has lower acceptance, which is inconsistent with the data.

modification.

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, consumer substitution patterns, and within-wallet complementarities or substitution effects. Let the characteristics of card j be $X^j = \left(X_k^j\right)_{k=1}^K$. The mean non-pecuniary utility for consumer i is

$$\Gamma_i^w = \omega\left(\Xi^{w_1} + \beta_i X^{w_1}\right) + (1-\omega)\left(\Xi^{w_2} + \beta_i X^{w_2}\right) + \sum_{l=1}^K \sum_{m=1}^K \chi_{lm} X_l^{w_1} X_m^{w_2} \tag{16}$$

where Ξ^j is the mean 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 complementarities or substitution effects. These terms capture the possibility that consumers may carry credit and debit cards to cover different use-cases, or that consumers are less willing to carry multiple credit cards because they serve redundant purposes. I also let $\beta_i \sim N\left(\beta_y \cdot \log y, \Sigma\right)$ so that payment preferences depend on income, and consumers substitute more between products with similar characteristics.

Choice Probabilities: The parametric assumptions on the random coefficients result in 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:

$$\tilde{\mu}_i^w = \frac{\exp\left(\alpha_i \log U^w + \Gamma_i^w\right)}{\sum_{m\in\mathcal{W}} \exp\left(\alpha_i \log U^m + \Gamma_i^m\right)} \tag{17}$$

$$\tilde{\mu}_y^w = \int \tilde{\mu}_i^w \, \mathrm{d}H\left(\beta_i\right), \beta_i \sim N\left(\beta_y \cdot \log y, \Sigma\right) \tag{18}$$

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 total dollars spent

$$T_j = \left(\tau_j - c_j\right) d_j \tag{19}$$

$$d_j = \sum_{w \in \mathcal{W}} \tilde{\mu}^w \times \int \frac{(1+\gamma)\, \pi^w_{M^*(\gamma),j}}{1+\gamma \pi^w_{M^*(\gamma)}} q^{w*}(\gamma)\, p^*(\gamma)\ \mathrm{d}G(\gamma) \tag{20}$$

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

$$S_j = f^j \left(\tilde{\mu}^{(j,0)} + \sum_{k>0, k \neq j} \pi \tilde{\mu}_y^{(j,k)} + (1-\pi)\, \tilde{\mu}_y^{(k,j)} \right) \tag{21}$$

where f^j is the reward paid to a consumer that single-homes on j. The terms inside the parentheses respectively capture the rewards paid to single-homers, the rewards paid to multi-homers who primarily use j, and the multi-homers who use j as a secondary card.[19]

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

$$\Psi_n = \sum_{j \in \mathcal{O}_n} \left(T_j - S_j\right) \tag{22}$$

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, holding fixed the actions taken by other networks. Equivalently, networks set consumers' expectations of merchant card acceptance, fees, and rewards while holding fixed 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:

$$A_j = \log U^{(j,0)} - \log U^{(0,0)} = f^j - \left(\log P^{(j,0)} - \log P^0\right) \tag{23}$$

[19] Although rewards are modeled as a lump-sum transaction that does not depend on whether the consumer uses the card, this is without loss of generality since consumers who adopt a card do not make a separate usage choice.

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:

$$\left(A_j^*, \tau_j^*\right)_{j \in \mathcal{O}_n} = \underset{\left(\overline{A}_j, \overline{\tau}_j\right)_{j \in \mathcal{O}_n}}{\operatorname{argmax}} \mathbb{E}\left[\Psi_n\left(A_j, \tau_j, A_{-j}, \tau_{-j}\right)\right] \tag{24}$$

$$A_j \sim N\left(\overline{A}_j, \nu_x^2\right), \tau_j \sim N\left(\overline{\tau}_j, \nu_x^2\right), A_{-j} \sim N\left(A_j^*, \nu_x^2\right), \tau_{-j} \sim N\left(\tau_j^*, \nu_x^2\right), \nu_x^2 = 10^{-8}$$

Small trembles help pick an equilibrium when profits are not differentiable in merchant fees (Teh et al., 2022). Appendix D.5 and D.6 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 (9 and 12), consumers choose the optimal payment methods to reflect their preferences (17), and private networks maximize their profits (24). Appendix D.7 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 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. Joint profit maximization holds whenever parties bargain under complete information with a complete contract space. In practice, Visa pays around one-fifth of its gross revenue in side payments to issuers and acquirers (Visa, 2020). I interpret these payments as evidence that the contract space is approximately complete. Joint profit maximization is consistent with a wide range of issuer market structures, from perfect competition to network bargaining with a monopoly issuer.

IV.F.2 Price Coherence

I assume price coherence: merchants in the model charge the same price to consumers who use different payment methods. Appendix F 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 their profits from uniform pricing. Even small reputational costs overwhelm the benefits of surcharging.[20]

IV.F.3 Pass-through of Merchant Fees into Prices

Merchants fully pass on merchant fees into higher prices because I assume consumers have CES preferences. 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, an increase in merchant fees affects all firms and pass-through should be complete. Although CES overstates the extent to which firms with an idiosyncratically large share of credit card transactions increase prices in response to merchant fees, CES also understates how much cash-only firms raise prices in response to higher prices from rivals. My results with full pass-through also understate consumers' losses from reduced variety if merchants instead absorb the merchant fees in the form of lower profits and subsequently exit. This follows from the fact that entry and pricing are efficient under CES demand (Dhingra and Morrow, 2019). Section VI.F.1 discusses how my estimated results change if I instead assume merchants do not pass fees through to prices.

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 (Gans, 2018). If true, that would imply merchant fees do not redistribute consumption among consumers because credit card merchant fees would not affect the retail prices cash and debit card users pay. I explore this possibility with merchant level data from Homescan

[20] 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.

and MRI in Appendix C. Although I find some evidence of sorting, it is quantitatively too small to affect my conclusions about redistribution.

IV.F.5 No Price Discrimination

Networks in the model set one fee and reward per card, but in reality networks engage in extensive price discrimination on both sides of the market. Grocers pay lower fees than restaurants, large firms pay lower fees than small firms, and richer, more creditworthy consumers tend to holds cards that earn issuers greater interchange and thus pay out larger rewards. By ignoring price discrimination on the merchant side of the market, I overstate the merchant fees paid by the large grocer in the event study, leading me to overstate the grocer's margins. But although I overstate the grocer's margins, the resulting estimate is more reasonable when modeling an average level of margins for the retail sector. 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 obtain. I mitigate this by using an average rewards level of 1.4% that 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.6 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.15). 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. Potential 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 (Ru and Schoar, 2020; Agarwal et al., 2022).

IV.F.7 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). In principle, consumers of different income levels could vary in how much they increase their purchases when a store accepts cards. However, I find that high and low income consumers responded similarly when the large grocer in Section III.B started accepting credit cards (Appendix Figure A.22).

Section V Estimation

Estimating the model provides a bridge between the reduced-form facts to quantitative statements about how regulation and competition affect market outcomes. 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. I use the estimated model to evaluate the effects of regulation and competition.

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 data from 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. I briefly describe how the key parameters are identified below. Appendix E contains the details.

V.A.1 Consumer Demand

I estimate consumer demand with 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 parameters (α_0), the distribution of random coefficients $(\Sigma,)$, how preferences relate to income $\left(\alpha_y, \beta_y\right)$, the complementarity parameters (χ), the weight ω on the characteristics of the primary card in the utility function, 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 evaluate the effect of a 25 bps increase in debit rewards on the total dollar spending on debit cards, while holding fixed merchant acceptance. I hold fixed merchant actions because my difference-in-difference estimates take out any equilibrium effects of merchant actions.

I recover the distribution of random coefficients Σ with state of the art 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 changes in merchant fees and rewards. I recover 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. I find that higher income respondents report being more likely to switch, which identifies a positive relationship between income and rewards-sensitivity. I recover the relationship between mean preferences and income (β_y) through the data in the DCPC, shown in Table 1, on consumers' card preferences by income.

The remaining parameters come from Homescan and aggregate data. I estimate the complementarity parameters χ and the primary weight ω by matching the multi-homing probabilities shown in Figure 5b. The primary usage share π comes from the share of transactions that multi-homing consumers in Homescan put on their primary card (Table A.16). I recover the unobserved characteristics Ξ by matching aggegate 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 from networks' optimal pricing conditions, the event study evidence on the effects of credit card acceptance on sales, and data on merchant card acceptance. 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, 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 merchant card acceptance data from the DCPC and the assumption that networks set credit card merchant fees optimally. 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 charge higher fees. On the other hand, greater dispersion ν_γ lowers the share of merchants that accept cards. 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 should optimally 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 I estimate merchants' reward-sensitivity, optimal pricing then is informative about networks' costs and merchants' fee-sensitivity.

An important cost I am not able to estimate is the cost of cash. I therefore 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 is thus factored into 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 sensitivity and low merchant sensitivities generate the model prediction that competing networks raise merchant fees to fund rewards. The negative preference against credit cards on average also 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 and debit cards as two different product segments. The second column of Table 3 shows that a 1-bp shock to Visa credit rewards raises the share of Visa credit transactions by 4.4% (S.E. 1.2%). The new consumers mostly come from MC credit, which declines by 3.8%. In contrast, MC debit only declines by 0.4%. The difference reflects that consumers treat debit and credit cards as worse substitutes than different

Table 2: Estimated parameters

Panel A: Consumer Parameters

Parameter	Est	SE
S.D. of Card R.C.	0.75	0.26
S.D. of Credit R.C	1.88	0.69
Correlation of R.C.	-0.69	0.06
S.D. of T1EV	0.10	0.03
$\chi_{\text{Card, Card}}$	0.06	0.64
$\chi_{\text{Card, Cred}}$	3.83	0.99
$\chi_{\text{Cred, Card}}$	3.30	0.90
$\chi_{\text{Cred, Cred}}$	-3.72	1.20
Visa Debit Ξ	-3.14	0.43
Visa Credit Ξ	-5.17	0.35
MC Debit Ξ	-3.29	0.47
MC Credit Ξ	-5.38	0.40
Amex Ξ	-5.45	0.41
Income Elasticity α_y	0.20	0.06
Log Income Vol. ν_y	0.73	0.01
Card β_y	-0.81	0.20
Credit β_y	0.36	0.36
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	42	10
MC Debit	54	5
Visa Credit	83	9
MC Credit	84	6
Amex	82	6

Panel C: Merchant Parameters

Parameter	Est	SE
Merchant CES	6.61	1.47
Average γ	0.26	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.

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

Instrument	Visa Debit	Visa Credit	MC Debit	MC Credit	AmEx
Cash	-1.0	-0.3	-0.4	-0.1	-0.1
Visa Debit	3.6	-0.4	-2.0	-0.1	-0.1
Visa Credit	-0.7	4.4	-0.3	-1.6	-1.5
MC Debit	-4.9	-0.4	6.5	-0.1	-0.1
MC Credit	-0.6	-3.8	-0.2	6.6	-1.7
AmEx	-0.6	-3.9	-0.2	-1.9	6.9

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.

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. Starting from the baseline equilibrium, a 1-bp increase in Visa's fees leads to only a 0.5% decrease in the share of merchants who accept that card (S.E. 0.05%). This is roughly one-tenth 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 the average income level of 1 is indifferent between a Visa debit card and a Visa credit card that pays 2.1% in rewards. 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.

First, I validate my merchant fee sensitivity with AmEx's 2016–2019 OptBlue program that cut merchant fees in order 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. The share of Visa merchants that did not accept AmEx shrunk from around 9–14 pp. to zero. [21] When I simulate this shock in the model, the gap shrinks by 12 pp.[22]

Second, my estimated average sales effect of 26% is consistent with experimental evidence on the effects of payment technologies. For example, Higgins (2022) show that debit card adoption by corner stores increased sales to different groups of debit card

[21] AmEx 10K's report that its U.S. network went from covering 90% to 99% when measured as a percent of card spending. Figure 5a shows data from the Nilson Report suggesting the the gap shrunk by 14 pp. when measured as a share of merchants.

[22] 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.

consumers by $20-60\%$. Berg et al. (2022) use a randomized experiment at a merchant to show that accepting a closely related credit product to credit cards raises sales by around 20%.

Third, my estimated retail margin of 15.1 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).

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 network costs. I estimate debit marginal cost parameters for the combination of issuers, acquirers, and the network that average around 49 bps with a standard error of 8 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, 2022; NACHA, 2017; Visa, 2020). My cost estimates validate my conduct assumption. If Visa and MC were colluding, marginal costs would need to be -20 bps to rationalize the observed fees and rewards for debit cards.

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. This is desirable when modeling Visa's incentives to raise merchant fees to fund the consumer side of the market. 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.

Second, my model closely matches the joint distribution of primary and secondary cards in consumers' wallets. Appendix Figure A.25 compares the actual market share of different wallets in the Homescan data on the x-axis against the model implied share on the y-axis. 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 de-

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 of 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.

mand 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 is what explains why credit cards that are common as primary cards (e.g. Visa) are also the ones that are the most common secondary cards.

Section 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 Baseline Equilibrium

In the baseline equilibrium, credit and debit cards account for 80% of spending but have different fees and rewards. Table 4 summarizes 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 of 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. 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.B 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).[23] The effects of capping fees at the cost of cash also simulates the effects of merchants freely surcharging consumers for the cost of card acceptance, and 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 are allowed to adjust. Although merchants' types are held fixed, their incentives to accept cards can change as consumers' card holdings influence merchants' acceptance decisions.

VI.B.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 234 and 36 bps, respectively. Whereas consumers are paid to use cards in the baseline equilibrium, capping merchant fees results in consumers paying fees to use cards. The price changes illustrate the see-saw principle in Rochet and Tirole (2003). When payment platforms can no longer earn markups on merchants, they instead earn profits from consumers.

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 31 percentage points, which is around 90% of the baseline share of credit cards. The market share of debit cards declines by 13 percentage points as well.

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 $81 billion, respectively.

VI.B.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

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

Table 5: Summary of Counterfactual Effects

	Price Controls				Change Competition			
	Cap Fees		Uncap Debit		Monopoly		Credit Entry	
Δ Prices (bps)								
Credit Fees	−194	(0)	−4.1	(0.7)	17	(3)	−0.2	(0.3)
Credit Rewards	−234	(4)	−20	(3)	−95	(30)	0.3	(2.0)
Debit Fees	−41	(0)	25	(0)	0.0	(0.0)	0.0	(0.0)
Debit Rewards	−36	(1)	25	(0)	−34	(7)	0.8	(0.1)
Δ Shares (pp.)								
Cash	44	(9)	−8	(2)	31	(1)	−1.7	(0.2)
Debit	−13	(7)	21	(5)	−9	(1)	0.8	(0.5)
Credit	−31	(2)	−13	(3)	−22	(1)	−9	(0)
Entrant							10	(0)
Δ Fees, Rewards ($Bn)								
Total Fees	−101	(4)	−9	(5)	−54	(4)	1.8	(1.5)
Total Rewards	−81	(5)	−10	(4)	−66	(8)	2.2	(1.9)
Δ Consumption (bps)								
Low Income	39	(9)	10	(3)	13	(10)	−1.7	(0.8)
Median Income	12	(5)	7	(3)	1.0	(15.1)	−1.6	(0.6)
High Income	−58	(7)	−0.6	(2.5)	−30	(26)	−1.5	(0.4)
Δ Welfare ($Bn)								
Consumers	42	(9)	8	(4)	4.8	(11.2)	1.8	(0.9)
Merchants	3.2	(1.3)	−1.0	(0.3)	−2.4	(1.6)	0.0	(0.1)
Networks	−8	(1)	3.9	(0.5)	23	(6)	−1.2	(0.4)
Total	38	(10)	11	(4)	25	(7)	0.6	(0.6)
No Logit Shocks								
Consumers							−1.3	(0.4)
Total							−2.5	(0.6)

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 30 bps. Monopoly refers to merging all three networks. The credit entry scenario creates a new product that has the same observed and unobserved characteristics as Visa credit. Low (high) income consumers are defined as those with log income at -2 (+2) standard deviations relative to the median. Dollar values are computed by normalizing to $10 trillion of total consumer purchases.

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 39 bps, whereas high-income consumers with log income that is 2 standard deviations above the median decrease their consumption by 58 bps. At a median household income of $\$80,000$, this is a \$71 gain for each low-income household and a \$2020 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.B.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 \$42 and \$3.2 billion in aggregate, networks lose \$8 billion. On net, total welfare increases by \$38 billion.

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

$$\mathrm{CS} = \int \mathbb{E}\left[\max_{w} \log V_i^w\right] \times y \; \mathrm{d}F(y) \tag{25}$$

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

I find that even though capping merchant fees also reduces rewards, consumer welfare rises by around 42 billion. The magnitude of this increase is much larger than the 21 billion reduction in merchant fees net of consumer rewards and indicates consumer welfare rises for other reasons.

Capping merchant fees increases consumer welfare not because it increases rewards net of fees, but rather 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 lower rewards 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". While the marginal consumer is privately indifferent between the two options, a planner is not. Whereas credit aversion is a social cost, rewards are merely transfers. Thus, when reduced rewards cause consumers to shift from credit to debit, welfare increases.

Because merchants pass on merchant fees to all consumers, and not just those who use credit cards, consumers' exert externalities on each other through their payment choices. Credit card use is akin to a form of "pollution" that raises retail prices for other consumers. Capping merchant fees eliminates these externalities and can therefore raise consumer welfare above and beyond the effects on fees and rewards.

Merchants also benefit from fee caps, whereas networks lose. Merchant profits rise by only \$3.2 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 \$8 billion because fewer consumers use cards at all. This profit loss is equivalent to roughly one-third of networks' baseline profits. The net result of all of these forces is that total welfare rises by \$38 billion.

VI.C 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.[24]

Repealing the Durbin Amendment moderates rewards competition between credit card networks. Lifting the cap mechanically causes debit card merchant fees to rise by 25 bps, and networks pass all of it on in the form of higher debit rewards. Consumers switch to debit. Consumers, especially those who are reward-sensitive, switch from credit and cash towards 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 then gives that networks reduce merchant fees. Credit card rewards and fees then fall by 20 and 4.1 bps, respectively. The net effect is that repealing the Durbin Amendment reduces total merchant fees and rewards by \$9 and \$10 billion, respectively.

Repealing the Durbin Amendment is progressive and increases consumer and total welfare. Higher rewards increase the consumption of low income consumers by 10 bps while having little effect on high-income consumers. Overall, consumers gain \$8 billion,

[24]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, 2022). 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.

largely from lower credit aversion. Total welfare rises by an even larger $11 as higher card use increases networks' profits.

The combination of these two counterfactuals shows 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.D Increasing Competition

Although a major part of U.S. policy towards payment markets involves increasing competition, I find that competition is generally regressive and welfare-reducing. I model an extreme reduction in competition by merging all five payment products into one network. By reducing competition, credit card rewards fall by 95 bps and merchant fees rise by 17. Debit card rewards also fall, so that 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 $66 billion, respectively. The reduction in credit card use lowers retail prices for all consumers, whereas the reduction in rewards mainly affects high-income consumers. Thus low-income consumers experience a 13 bp increase in consumption, whereas high-income consumers experience a 30 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. Thus my point estimate is that consumer welfare rises by $4.8 billion (S.E. 11.2). Merchant profits fall by only $2.4 billion. Network profits rise by a significant $23 billion, and so total welfare rises by $25 billion (S.E. 7) from the reduction of externalities between consumers. The merger increases total welfare by reducing pecuniary externalities, but the lions share of these benefits are internalized by the networks in the form of higher profits.

The merger counterfactual is not a justification for letting the incumbent networks merge, as the estimates cannot rule out large consumer harms. However, the counterfactual highlights how even competitive payment markets can be socially inefficient. Whereas mergers always increase market power and reduce welfare in conventional markets, mergers that increase market power can increase welfare in payment markets.

VI.D.1 Credit Card Network Entry

An alternative way to model competition is to introduce a new single-product credit card network with the same characteristics and costs as Visa Credit. This is a relevant counterfactual given that Discover could grow as a network, or other technological entrants such as Buy Now, Pay Later (BNPL) could become more prominent.

Although the new network takes substantial market share, it has minimal effect on equilibrium prices. The new network rises to 10 percent of the market, which is almost one-third of the baseline market share of credit cards. However, entry does not have significant effects on fees or rewards. This is because the merger creates two countervailing pricing incentives. On one hand, networks' reduced market power over consumers incentivizes them to increase rewards and to fund the rewards with higher merchant fees. At the same time, entry increases the share of multi-homing consumers, which incentivizes networks to cut merchant fees. The net result is almost no change in either merchant fees or rewards.

The remaining distributional and overall welfare effects are either small or opposite in sign to the merger. The small change in prices means there are only limited distributional consequences. A notable exception is that when I compute consumer welfare by equation 25, consumer welfare rises by $1.8 billion (S.E. 0.9). However, this welfare increase is largely a mechanical feature of the large number of logit shocks in the model. After I remove the contribution of the logit shocks on consumer welfare, I find that consumer welfare falls by $1.3 billion (S.E. 0.4). If I take out the logit shocks from total welfare, total welfare falls by $2.5 billion (S.E. 0.6). Thus entry fails to robustly improve consumer or total surplus.

VI.E Reconciling Model Predictions with Historical Examples

My counterfactual results on the effects of competition are consistent with historical experience. A major shock to competition was the 2004 *United States v. Visa U.S.A.* Supreme Court case that struck down rules preventing Visa and MC issuers from also issuing AmEx cards. Following that court decision, Visa and MC raised interchange to incentivize issuers to issue cards on their networks instead of switching to AmEx (GAO, 2009). My model and historical evidence therefore suggest that more fundamental changes to how networks compete for merchants, potentially through the repeal of anti-steering provisions, are necessary for network competition to create benefits.

VI.F Discussion of Key Assumptions

The distributional and total welfare results largely revolve around two implications of the model: that merchants pass on merchant fees into higher retail prices and that consumers are credit averse.

VI.F.1 Relaxing the Pass-through Assumption

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 7 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. Appendix Table A.17 shows the parameter estimates and Appendix Table A.18 shows the results. For example, capping merchant fees now 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 less rewards without the corresponding relief from lower retail prices. Consumer welfare thus falls while merchant profits rise significantly. 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. However, ultimately total welfare still rises by $24 billion.[25]

VI.F.2 Credit Aversion

An alternative explanation for why many consumers do not pay with credit cards is that they are credit rationed. However, rationing is inconsistent with the results of a second-choice survey in which around half of debit card users would substitute to credit cards if debit cards were no longer offered (Appendix A.6). In reality, 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 to not use credit cards due to a fear of overspending, adoption costs, and credit aversion.

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

[25]The total welfare gains of merchant fee caps are also reduced as the baseline economy in a model without merchant pass-through 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.

choose debit cards, constraints by themselves would not be able to match the Durbin evidence on the relationship between 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.

VI.G 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, competition tends to makes credit cards more attractive, thereby decreasing welfare. Overall, changes in price regulations stand to achieve much larger welfare gains than even large changes in market structure.

Section VII Conclusion

This paper compares the relative merits of regulating prices versus increasing competition in U.S. payment markets. There are large gains from either capping credit card merchant fees or uncapping debit card merchant fees, whereas encouraging competition between credit card networks has limited or negative effects. 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. Unlike in standard antitrust settings in which competition benefits consumers through low prices and high output, payment network competition can cause harm through high merchant fees and high output.

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Online Appendices: Not for Publication

A Data Details

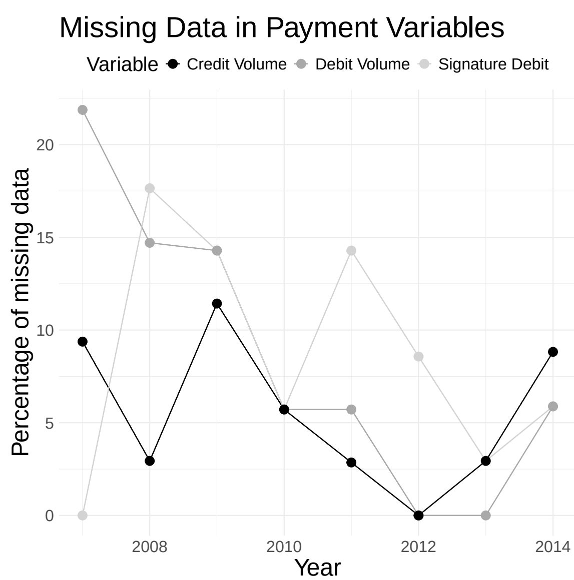
A.1 Issuer Payment Volumes

I construct an annual panel of issuer payment volumes from the Nilson Report. I obtain 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 backwards 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 bellow 2.5 billion and above 200 billion, to exclude systemically important issuers like Chase that were subject to other new regulations[26].

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.

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



[26] I eliminate one outlier observation because signature debit and debit volume was atypically low (BBVA Compass in 2011).

The purpose of the Durbin event study is to examine consumer payment behavior as a result of the Durbin amendment. Thus, I need to exclude banks whose payment volumes changed due to significant corporate changes. I exclude from the analysis some banks that had large changes in their portfolios:

- Associated Bank sold its credit card portfolio to Elan in 2009 (link).
- TD Bank acquired Target credit cards in 2012 (link).
- HSBC sold credit card portfolio to Capital One in 2012 (link).
- First Niagara went from no cards to a large portfolio. Its credit volume increased more than 50% in 2013.
- Bank of the West did two large portfolio acquisitions. Its credit volume more than tripled in 2011.

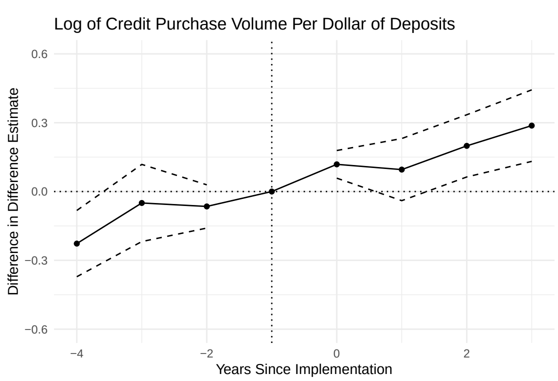
I also exclude issuers that made large acquisitions exceeding 50% of equity: First Tech FCU, Firstmerit Bank, BMO Harris, Regions Bank and Synovus/Columbus B&T.

A.1.1 Robustness to filtering

In this section, I compare event studies on two slightly different samples. One sample includes banks with large changes in their portfolios or that made big acquisitions (which I label "Full sample"), the other excludes these banks (which I label "Restricted sample"). Both samples drop banks outside the 2.5-200 billion range in assets.

Figure A.2: Credit volume

(a) Restricted sample



(b) Full sample

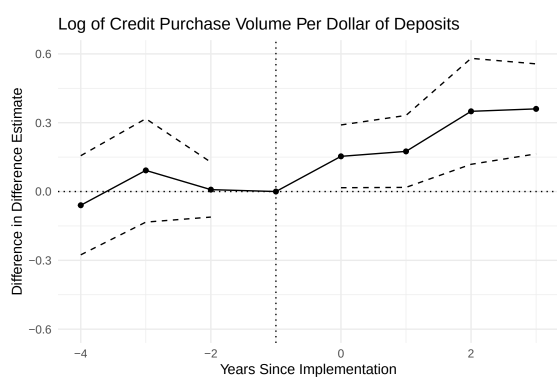
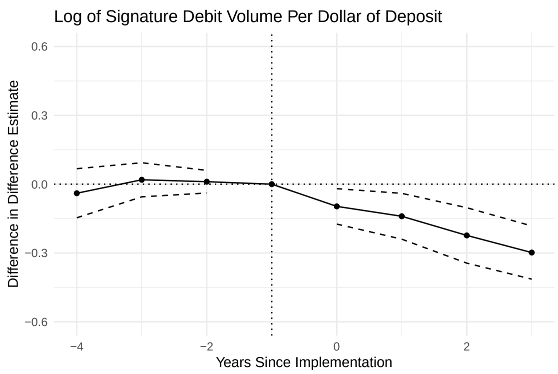
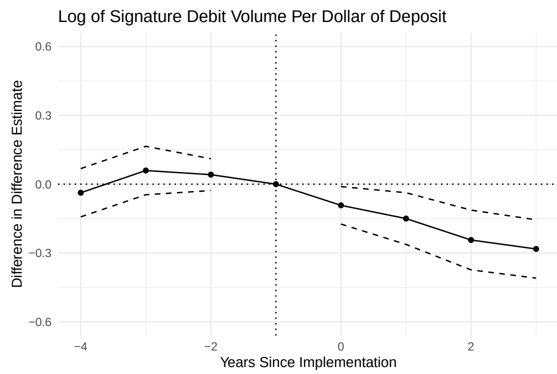


Figure A.3: Debit signature

(a) Restricted sample



(b) Full sample



A.2 Constructing Rewards Rates from Financial Filings

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 totalled 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.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

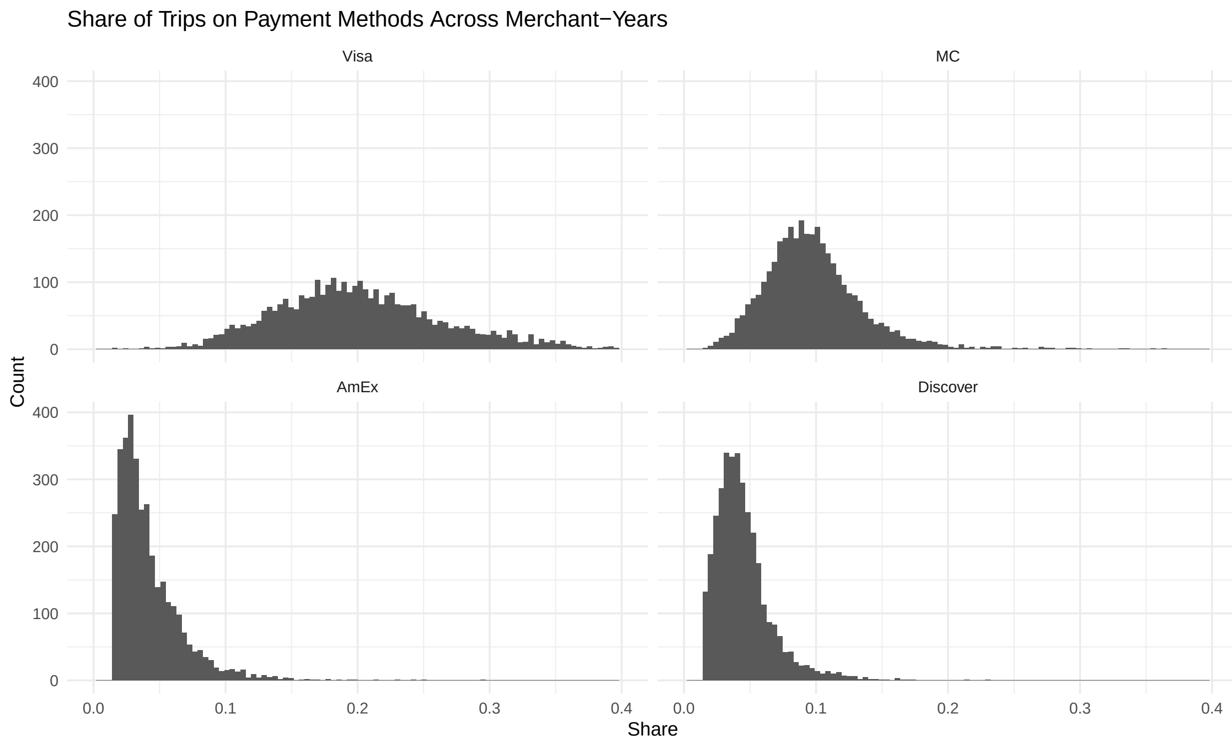
I first drop all households with more than 1% of missing payment information. This effectively drops 28.9% of the payments in the sample.

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[27]. This 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

[27] 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, $n = \frac{\log(0.01)}{\log(1-p)} \approx 458$.

this share. This implies dropping 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 a meaningful amount of 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 some 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% of the sample. I exclude these consumers from payment choice computation.

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.

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 Diary of Consumer Payment Choice (DCPC) is a nationally representative survey conducted by the Federal Reserve Bank of Atlanta since 2016. I merge this dataset to the Understanding America Study by the University of Southern California 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. This 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 card 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 include 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. I first identify reviews that say a store is cash only by searching for "cash only" or "only...cash" with regular expressions. I then 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 are 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 still include this as acceptance. I provide it with three concrete examples on 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.

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.

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.

Data for the study 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.

This study was approved by an Institutional Review Board at Northwestern University.

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. This included transactions through digital wallets.
- **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 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 chose 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 not 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.
- **Mobile Wallet Usage**: Collected information on respondents' smartphone brands and whether they use mobile wallets for contactless payments. Specifically, they were asked what they would do if their primary payment method from their preferred bank was no longer supported at their mobile wallet: switch phones, stop using mobile wallet or switch bank/card.

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.

B Additional Reduced Form Facts

B.1 Evidence from Discover's Reward Programs on Consumer Substitution Between Payments and Between Merchants

I analyze the effects of Discover's quarterly rewards program and find evidence that consumers are unwilling to substitute between credit and debit at the point of sale, and that consumers do not reallocate their spending across stores to earn rewards. The first fact provides evidence for the mechanical usage model used in the text that treats credit and debit cards as segmented markets. The second fact supports the model's assumption that consumers treat rewards merely as an increase an income, and not a price reduction that justifies shifting spending across stores.

Discover *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[28] 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.

Consumers are willing to substitute from other credit cards in order to take advantage of the 5% rewards. In Figure A.4 I plot Discover users' share of trips on Discover and other methods over time, both at grocery and comparable stores. Shaded areas indicate quarters in which the *5% Cashback Bonus* program was active at grocery stores. Time trends suggest rewards have a large effect on payment mix, leading users to increase the share of trips on Discover by 30.4% (10.2 pp) on average at grocery stores. This increase is entirely substituted away from other credit cards. The change in payment behavior reflects the effect of Discover's program, as the effect is not observable at discount / warehouse stores. These substitution patterns are consistent with testimony from IKEA in Conrath (2014). When IKEA offered consumers point-of-sale incentives to use PIN

[28] 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.

Figure A.4: Effect on payment mix (trips)

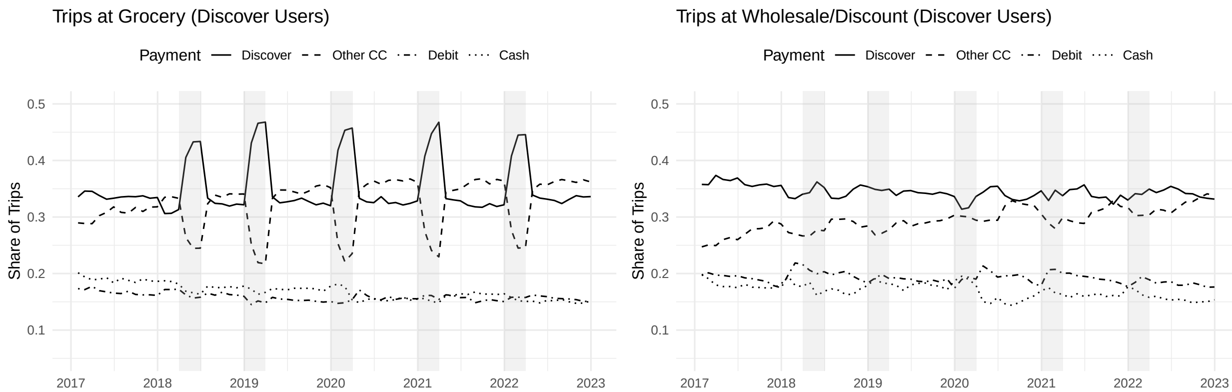
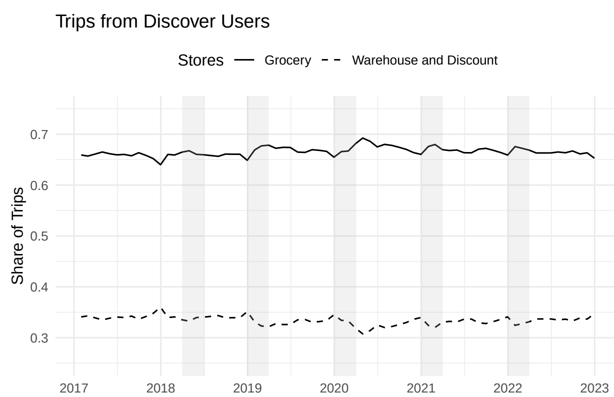


Figure A.5: Effect on sales (trips)



debit cards, it mostly led to substitution from signature debit cards and checks, with no substitution from credit cards.

Consumers do not substitute between merchants in order to take advantage of rewards. In Figure A.5 I plot Discover users' share of trips at grocery and comparable stores over time, and find the discount periods do not trigger substantial store type substitution. Discover users do not seem to change store choice in response to discounts being offered at grocery stores, but not at wholesale and discount stores. The small observed response seems largely due to seasonality. In 2018, when the grocery reward was in Q2 instead of Q1, the share of trips at grocery stores is essentially flat. In Figures A.6 and A.7 I replicate very similar results for spending.

The Discover quarterly rewards experiment thus provides evidence that consumers who carry credit and debit cards are not willing to substitute between them at the store even in response to large pecuniary rewards. Also, consumers are not responsive to rewards-induced changes in relative prices when deciding when to shop.

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.6: Effect on payment mix (spending)

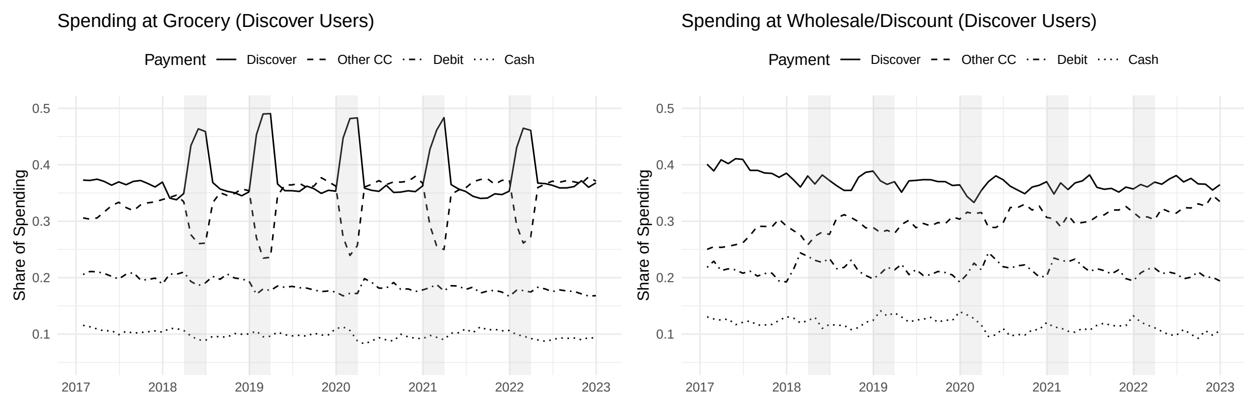
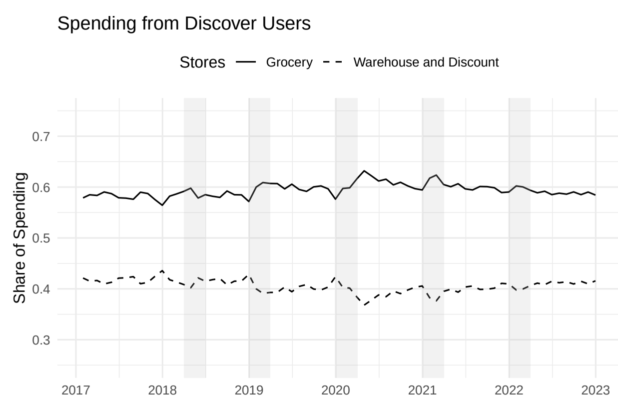


Figure A.7: Effect on sales (spending)



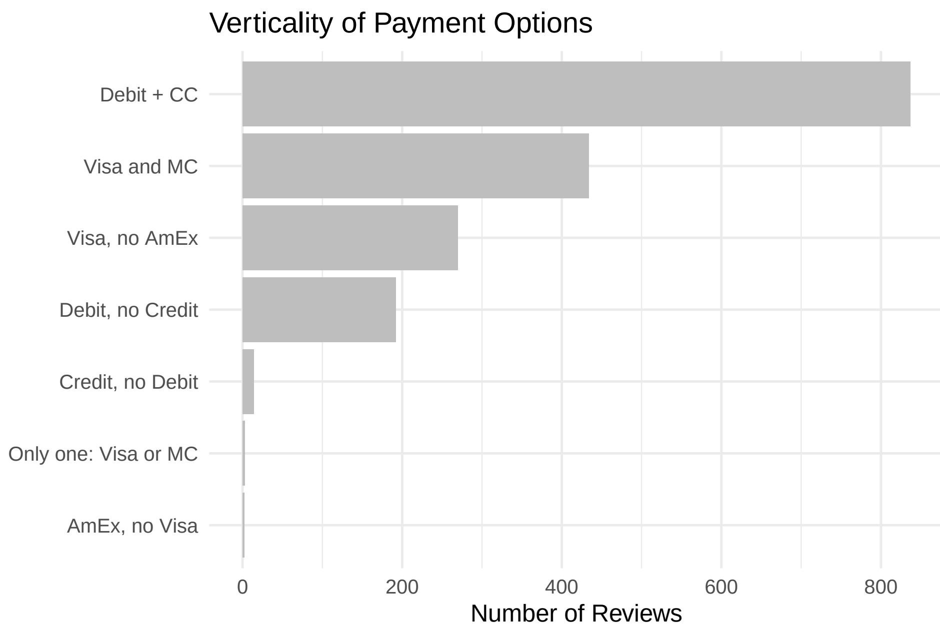
B.2 Yelp Evidence on Hierarchical Card Acceptance

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.[29] Figure A.8 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 of time 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. This

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

Figure A.8: Multihoming Behavior in Yelp



contrasts card acceptance with the adoption of food delivery platform, as that is a market in which merchants frequently are on one platform but not another (Sullivan, 2023).

B.3 Additional Details on Consumer and Merchant Multihoming 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.

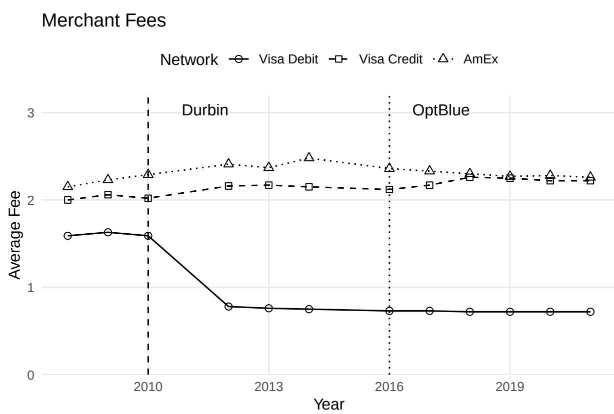
Consumer multi-homing behavior appears to largely reflect incentives to pair differentiated products. It is historically unresponsive to relative differences in card acceptance across networks. This supports the model's assumption that consumers do not internalize acceptance complementarities when choosing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

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

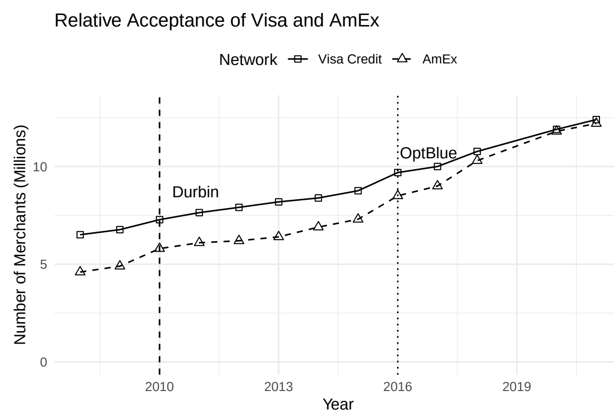
The decision to accept more or fewer credit cards is sensitive to relative merchant fees. Figure A.9a shows that over the past decade, the gap between AmEx's and Visa's credit card merchant fees have decreased by around 20 bps. This has been the result of

Figure A.9: Incentives for Merchant and Consumer Multi-homing

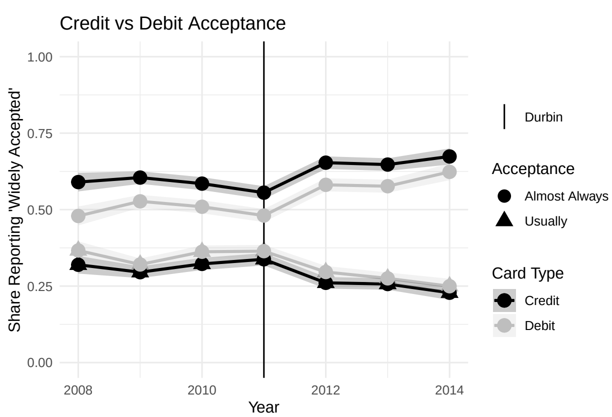
(a) Merchant Fees



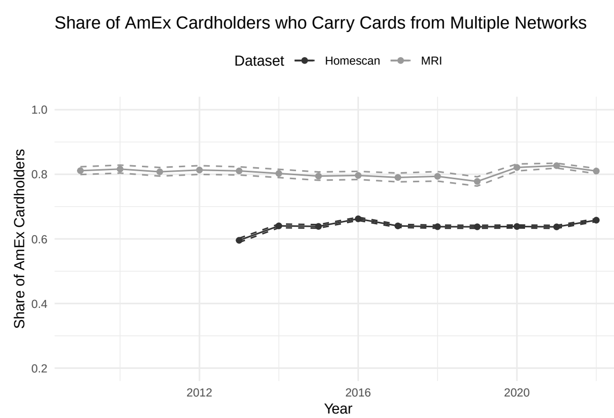
(b) Credit Card Acceptance



(c) Credit and Debit Acceptance



(d) AmEx Multihoming



the OptBlue program, which has reduced merchant fees for small businesses (Glasheen, 2020). Figure A.9b shows that as the fee gap has closed, the acceptance gap has also closed by around 14 pp.

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 adjust. Figure A.9a shows that the 2010 Durbin Amendment cut debit fees. However, Figure A.9c shows that consumers' ratings of credit and debit card acceptance did not change. In the 2014 Ohio v. AmEx case, the U.S. Department of Justice used exactly this Durbin experiment and the resulting lack of response in merchant acceptance to argue for a market definition that included credit cards but not debit cards.

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 5b).

While these fee changes do occur with potential changes on the other side of the market, the contrast between the strong relationship between different networks' credit card fees and relative acceptance and the weak relationship between credit vs debit acceptance costs and relative acceptance provides evidence that accepting debit cards are poor substitutes for accepting credit cards.

Credit card acceptance may not respond to debit card fees because the ability to borrow differentiates debit and credit cards at the point of sale. The ample testimony in the USA v. Visa and USA v. AmEx lawsuits supports this interpretation (Conrath, 2014). The increase in sales at the grocer in Section III.B highlights how credit card acceptance can incrementally increase sales even when all credit card consumers own debit cards. The fact that consumers respond to Discover's rewards at grocery stores primarily by substituting from other credit cards and not debit cards (Appendix B.1) further supports the fact that, even for consumers who carry both credit and debit cards, credit and debit do not provide the same payment services.

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.9b, AmEx acceptance used to lag that of Visa's, 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.9d 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 own 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 rewards 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 rewards-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

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.

the dependent variable mean, this regression says that a one percent increase in income is associated with a 0.19 percent increase in the switching propensity. The second model is a similar regression, but uses MRI data. The dependent variable is an indicator for 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)

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 that credit card use is crucially supported by the high levels of rewards.

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. This is 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).

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	0.31	0.42	0.27
Rewards	0.00	0.03	0.29

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.

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 29% 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 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 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 has only small effects on the amount of redistribution.

C.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 ot 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).

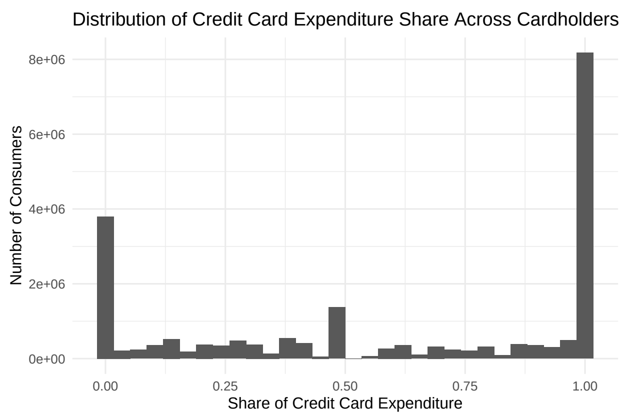
The MRI data on credit and debit card usage includes the amounts spent with both types of cards, further broken down by the bank and network that issued the card. Unfortunately, the data on cash usage does not provide information on expenditures. To characterize each consumer's payment preference between 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[30]. 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 allows me to equate the payment mix at a store with the mix of consumers preferring each payment method

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

(cash, debit, and credit) making purchases at each store. For such large merchants, all payment methods are accepted and 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. But given that consumers tend to concentrate their spending on their preferred payment method (see Figure A.10), this is not a significant limitation.

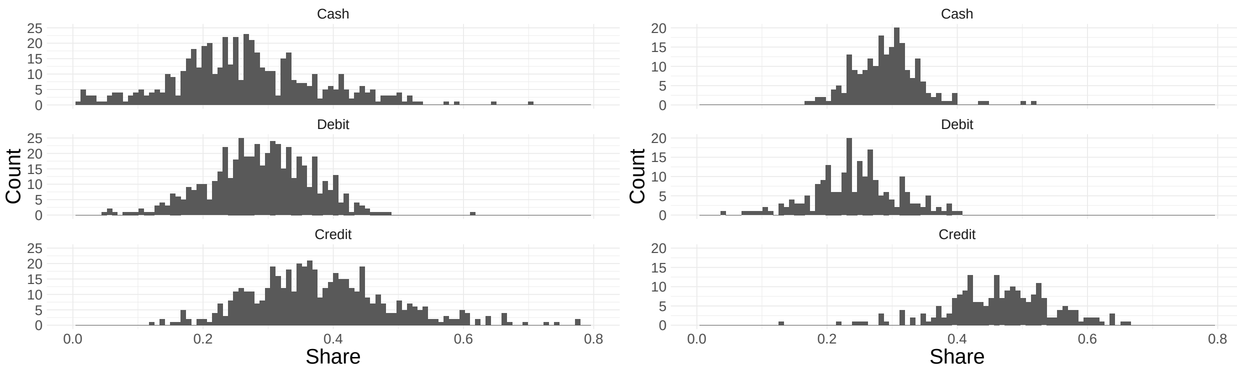
Figure A.10: Distribution of Credit Card Expenditure Share Across Consumers with Cards



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.11a and A.11b 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.

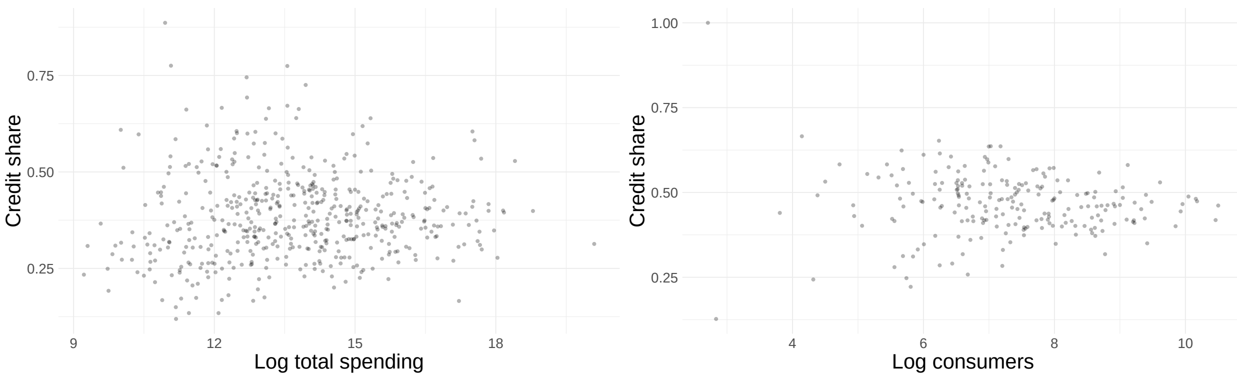
Larger stores also have less disperse payment mixes. Figure A.12a shows the relationship between a firm's log revenue in Homescan and the share of transactions on credit cards. In general, the dispersion is higher to the left of the plot among the smaller firms. This firm size relationship is important 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.12b shows an analogous result for the MRI dataset, but with log consumers instead of log revenue.

Figure A.11: Share of Spending on Different Payment Methods Across Merchants



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

Figure A.12: Credit card share and firm size



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

In each separate sample, I take the weighted covariances between these shares, as well as 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 covariance reflects 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 analogue, which reflects the previously mentioned fact that larger stores see less disperse payment mixes.

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

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	0.0026	0.0001	-0.0027
Debit		0.0044	-0.0044
Credit			0.0071

(d) MRI - Weighted

	Cash	Debit	Credit
Cash	0.0011	0.0002	-0.0013
Debit		0.0016	-0.0018
Credit			0.0032

effect is ultimately small.

C.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 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 just 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.

C.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 is reasonable, as stores where credit (debit) consumers shop most must have a large share of credit (debit) transactions and 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. This shows 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	0.252	0.452
Debit	0.258	0.449
Credit	0.247	0.464
Mean exp share	0.251	0.457

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	1.001	0.980
Debit	1.073	0.961
Credit	0.961	1.033

(d) MRI - Weighted

	Debit	Credit
Cash	1.003	0.990
Debit	1.025	0.984
Credit	0.984	1.015

D Model Details

D.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:

$$U^w = \max_{q^w} \left(\int_0^1 \left(1 + \gamma(\omega)\, \pi^w_{M^*(\omega)}\right)^{\frac{1}{\sigma}} q^w(\omega)^{\frac{\sigma-1}{\sigma}} \, \mathrm{d}\omega \right)^{\frac{\sigma}{\sigma-1}} \tag{26}$$

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

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:

$$q^w(\gamma, p, M, y) = (1 + \gamma \pi^w_M)\, p^{-\sigma} \times \frac{y \times (1 + f^w)}{(P^w)^{1-\sigma}} \tag{27}$$

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

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.[31]

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

[31] 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.

D.2 Microfounding Merchant Profits

Merchant profits can be built up from quantities purchased by consumers with different income levels and payment prefereces, 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. This is not the same as the probability $\pi_{M,j}^w$ that card j is used as the consumer also increases their consumption by γ percent when they use their card. Thus the per-unit margin not only depends on the merchant's price and acceptance decisions, but also on 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.

D.3 Deriving Merchant Optimal Pricing

The merchant's optimal pricing problem is:

$$\hat{p}(\gamma, M^*(\gamma), \tau) = \underset{p}{\operatorname{argmax}} \, \Pi(\gamma, p, M, \tau) \tag{28}$$

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 27) and the definition of the demand shares μ^w (Equation 8), we get that

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

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

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

as desired.

D.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

$$\overline{\Pi}(\gamma, M, \tau) \equiv C \times \left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma} \left\{-a_M + b_M\gamma + \frac{1}{\sigma}\right\} \tag{29}$$

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

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

$$\tau^{\max} = \max_j \tau_j \tag{30}$$

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 D.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

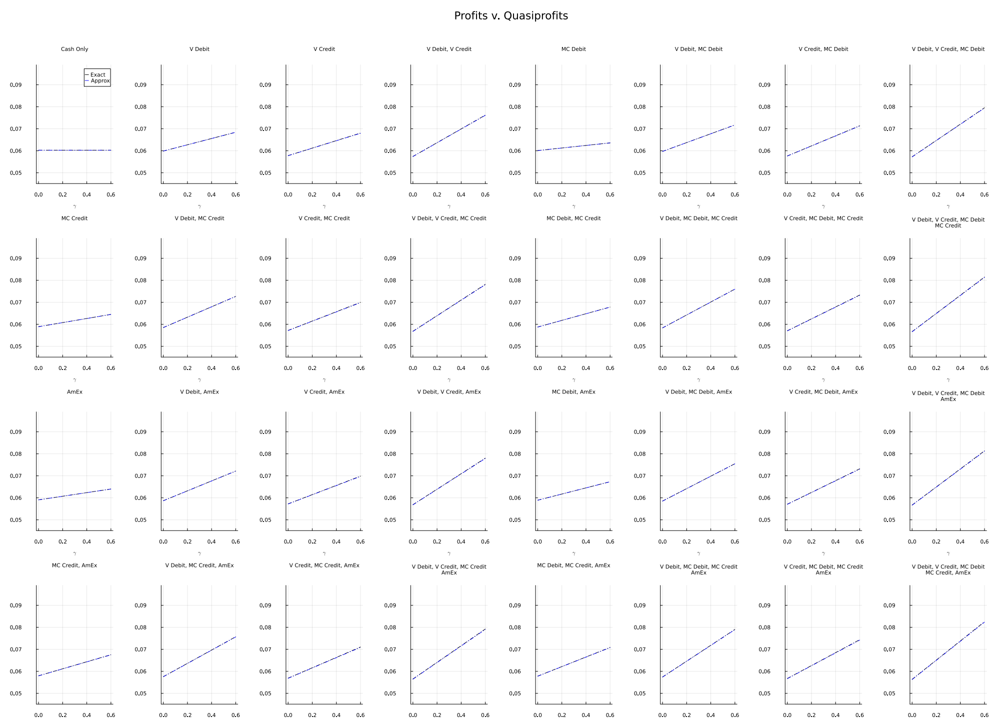
$$\begin{aligned}
\Pi(\gamma, p, M) &= C \times \left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma} \sum_{w\in\mathcal{W}} \mu^w \left(1+\gamma\pi_M^w\right) \times \left(1 - \frac{(1+\gamma)\,\tau_M^w}{1+\gamma\pi_M^w} - \frac{\sigma-1}{\sigma}\right) \\
&= C \times \left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma}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

□

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.

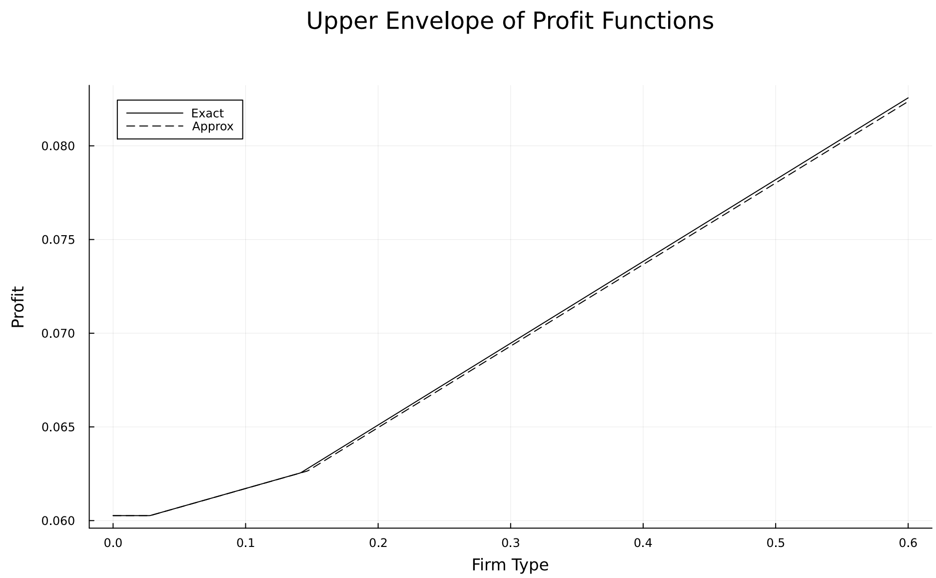
A natural question is whether the quasiprofit functions are a good approximation of true profits. Figure A.13 compares exact and approximate profits for all 32 potential payment bundles in the baseline equilibrium. The fit is very close for all values of the merchant type γ.

Figure A.13: 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.

Figure A.14: Comparison of the upper envelope of profits computed with the exact profit formula versus the quasi-profi approximation.



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

The linearity of quasiprofits also reveals how the extent to which consumers hold one card or two shapes merchants' willingness to substitute between accepting different cards, as in (Rochet and Tirole, 2003).

Consider a simplified economy in which consumers pay with cash and two cards, Visa (v) and American Express (a). Visa and American Express charge merchant fees of $0 < \tau_v < \tau_a$. Let the insulated shares be μ. Then the merchant adoption equilibrium will feature three regions:

1. Merchants of types $\gamma \in \left[0, \frac{\sigma\tau_v}{1-\sigma\tau_v}\right]$ accept only cash
2. Merchants of type $\gamma \in \left[\frac{\sigma\tau_v}{1-\sigma\tau_v}, \frac{\mu^{a,v}(\tau_a-\tau_v)+\mu^{a,0}\tau_a}{-\sigma\mu^{a,v}(\tau_a-\tau_v)+\mu^{a,0}(1-\sigma\tau_a)}\right]$ accept Visa only, where $\mu^{a,v}$ is the insulated share of consumers who primarily use American Express but who also have a Visa, and $\mu^{a,0}$ is the insulated share of consumers who only have an American Express and do not have a Visa.
3. Merchants of type $\gamma > \frac{\mu^{a,v}(\tau_a-\tau_v)+\mu^{a,0}\tau_a}{-\sigma\mu^{a,v}(\tau_a-\tau_v)+\mu^{a,0}(1-\sigma\tau_a)}$ accept both

When many American Express holders carry Visa, then $\mu^{a,v}$ is 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 $\mu^{a,v}$ is zero and the lowest type merchant who accepts American Express is $\frac{\sigma\tau_a}{1-\sigma\tau_a}$. In this case, the set of merchants that accepts American Express no longer depends on the fees that Visa charges. This would dramatically weaken Visa's incentives to compete for merchants.

D.5 Alternative Conduct Assumptions

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.

D.6 Non-Differentiability of Profits + Equilibrium Selection

Network profits are not differentiable in the merchant fee. This poses a challenge for equilibrium selection. The assumption of small trembles in the choice variables chooses an equilibrium in which networks stand to lose the same amount of 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, and therefore, profits are not differentiable in the neighborhood of the original symmetric fee. Rochet and Tirole (2003) do not encounter this issue in their two-network model, but past theoretical work has shown that problems arise with more networks (Teh et al., 2022).

The non-differentiability of profits means there are many potential equilibria that 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 as 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.

D.7 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 17). 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 19 and 21.

When implementing the demand function, I use 1000 draws of random coefficients for the unobserved heterogeneity, and then use 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. 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.

To handle the normal expectation, I use an N-dimensional Gauss-Hermite quadrature scheme with 2 points per dimension. This essentially enforces the requirement that each networks' 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.

E Estimation Details

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

E.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 on how incomes relate to payment preferences from the DCPC.

E.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 asks 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 analogues. 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 types.

In the model, I then compute diversion ratios from 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. By taking out one issuer, that 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 if a consumer would switch to becoming a primary cash consumer if credit cards did not exist. Let $S_{i,2}$ be an indicator if a consumer would switch to becoming a primary cash consumer if debit cards did not exist. And let $S_{i,3}$ be an indicator for if 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:

$$\hat{g}_1 = \begin{pmatrix} N_c^{-1} \sum_{i,r_i=\text{CC}} S_{i,1} \\ N_d^{-1} \sum_{i,r_i=\text{DC}} S_{i,2} \\ \frac{\sum_i S_{i,3} - \iota}{N-\iota} \end{pmatrix} \tag{31}$$

$$\iota = \sum_{i=1}^{N} S_{i,3} \times \left(1 - \left(\sum_{k\in\{\text{Visa,MC}\}} n_{b_i}^{k,t_i} \times \left(\frac{1}{|\mathcal{C}_i|} \sum_{j\in\mathcal{C}_i} n_j^{k,t_i}\right)\right)\right) \tag{32}$$

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:

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

E.1.2 Durbin Event Study: Overall Rewards Sensitivity

I compute the model analogue of the difference-in-difference estimate for debit cards in Figure 3. Starting from the baseline allocation, I calculate how consumers would switch their primary and secondary payment methods if debit cards paid 25 bps in additional rewards. For each payment method, I can compute the change in dollars spent on that payment method with equation 20.

Holding fixed merchant adoption, I then translate that change in primary and secondary payment methods into a change in total dollars spent d_j on each payment method given by Equation 20. The main parameter identified by this exercise is the baseline reward-sensitivity parameter α_0.

E.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. This 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

$$\text{Log Income of Primary Cash Consumers} = \frac{\mathbb{E}\left[\tilde{\mu}_y^{(0,0)} \times \log y\right]}{\tilde{\mu}^{(0,0)}} \tag{33}$$

$$\text{Log Income of Primary Debit Consumers} = \frac{\mathbb{E}\left[\sum_{w \in \mathcal{W}_D} \tilde{\mu}_y^w \times \log y\right]}{\mathbb{E}\left[\sum_{w \in \mathcal{W}_D} \tilde{\mu}_y^w\right]} \tag{34}$$

$$\text{Log Income of Primary Credit Consumers} = \frac{\mathbb{E}\left[\sum_{w \in \mathcal{W}_C} \tilde{\mu}_y^w \times \log y\right]}{\mathbb{E}\left[\sum_{w \in \mathcal{W}_C} \tilde{\mu}_y^w\right]} \tag{35}$$

To match how rewards 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.

E.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 a primary and secondary cards, the probability of having a primary credit card and a secondary card, the probabilities 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 card. 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

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

And in the data I can compute

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

E.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. This includes most of PCE, but then excludes 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 20. I then match the model-implied shares with the data shares. This is not quite the same as matching market shares in Homescan or the DCPC because the dollars overweight the spending by high-income individuals.

E.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 $(\sigma, \overline{\gamma}, \sigma_\gamma)$ 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 rewards rate that I derive from financial statements.

Second, I require that the five first order conditions with respect to the adoption utilities A_j are 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. Given the adoption utilities A_j and the observed merchant fees, I can solve the merchant adoption problem in Equation 10 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.

In the last step, I recover the distribution of merchant types and MC and AmEx's fees in order to match Visa Credit's merchant fee FOC and data from the DCPC on the share of transactions are conducted at card-accepting merchants.

E.6 Alternate Estimation with Acceptance Complementarities

F Price Coherence

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

F.1 A Brief History of Price Coherence in the US

While cash discounts have long been legal in the U.S., merchants' ability to apply card surcharges has only gradually increased over time.[32] 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's 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 US 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.[33]

[32]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).

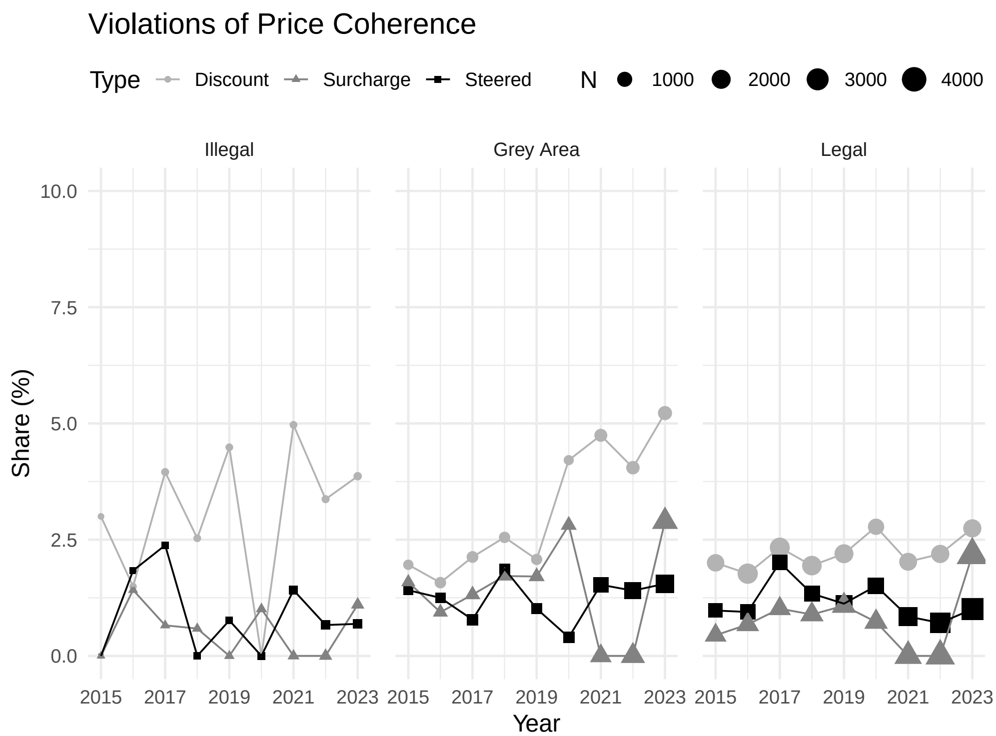
[33]In New York and Maine, retailers must disclose the dollars and cents value of the credit card price and the cash price in order to surcharge. This would entail posting twice the number of prices. In New York, this requirement is explicitly described as making sure consumers "should not have to do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

F.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. 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 payments volumes from Nilson (2020b). 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. "Discount" are cash (or check) transactions in which a discount was applied specifically because of using this payment instrument. "Surcharge" are credit card transactions in which a fee was 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 because it was not always legal. This 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.

F.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 US 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.

F.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 make a choice of 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 card versus cash, such that card consumers pay a price that is $1 + s(\omega)$ higher. Consumers solve

$$U = \max_{c,a} \left(\int_0^1 q(\omega)^{\frac{\sigma-1}{\sigma}} \, \mathrm{d}\omega \right)^{\frac{\sigma}{\sigma-1}} \tag{36}$$

$$\text{s.t. } q(\omega) = \left(1 + \gamma(\omega)\, v^w_{M(\omega)}\right)^{\frac{1}{\sigma-1}} c(\omega) + a(\omega) \tag{37}$$

$$y \geq \int_0^1 \left(c(\omega)(1 + s(\omega)) + a(\omega)\right) p(\omega) \, \mathrm{d}\omega \tag{38}$$

The linear aggregation corresponds to the idea that card goods are higher quality and perfect substitutes with 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 $I = \int_0^1 q(\omega)^{\frac{\sigma-1}{\sigma}} \, d\omega$ 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 $a = 0$. □

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 because 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).

F.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

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

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 method specific prices is:*

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

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 7 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

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

By plugging in the optimal price, we get

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

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 has no effect on 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 on the order of 20 *basis points* of profit.

F.3.3 Gains from Charging One Credit Card Versus Another

The above results focus on why surcharges on card 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, 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. This means that 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.

G Additional Tables

Table A.10: Summary statistics of Nilson Report panel

	N	Mean	P25	P50	P75
Assets	274	27400.39	3979.70	8276.57	24866.06
Credit	259	1547.87	396.90	611.00	1604.00
Debit	251	5475.88	1270.50	2495.00	5424.00
Signature Debit	250	3335.99	796.25	1232.50	2991.75
Sig Debit Ratio	236	0.65	0.58	0.67	0.77
Treated	274	0.42	0.00	0.00	1.00

Notes: Treated refers to whether the financial institution had more than $10 billion in assets in 2010. Assets are measured in millions. Credit, Debit, Signature Debit all refer to measures of card volumes in millions.

Table A.11: 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.12: 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.13: Event study estimates for the effect of the Durbin Amendment on signature credit, debit card, and total volume

	Interchange	Signature Debit	Credit	All Cards
Treat, t=-4	-0.050	-0.015	-0.193*	-0.117+
	(0.096)	(0.055)	(0.086)	(0.063)
Treat, t=-3	0.043	-0.036	-0.095	-0.071
	(0.096)	(0.044)	(0.074)	(0.044)
Treat, t=-2	-0.082	0.010	-0.067	-0.034
	(0.078)	(0.037)	(0.053)	(0.025)
Treat, t=0	-0.009	-0.102*	0.123**	-0.015
	(0.066)	(0.044)	(0.034)	(0.034)
Treat, t=1	-0.463***	-0.169**	0.109	-0.030
	(0.116)	(0.062)	(0.069)	(0.040)
Treat, t=2	-0.409**	-0.271***	0.194*	-0.073+
	(0.128)	(0.067)	(0.072)	(0.043)
Treat, t=3	-0.414**	-0.338***	0.279**	-0.104+
	(0.118)	(0.066)	(0.091)	(0.057)
N	261	250	259	236
Bank FE	X	X	X	X
Year FE	X	X	X	X

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

Table A.14: Event study estimates for the effect of card acceptance on sales to credit-card consumers

	Trips	Spending
Credit Share at Treated Retailer, t=-8	-0.034	-0.048
	(0.036)	(0.047)
Credit Share at Treated Retailer, t=-7	-0.034	-0.043
	(0.036)	(0.051)
Credit Share at Treated Retailer, t=-6	-0.036	-0.046
	(0.035)	(0.046)
Credit Share at Treated Retailer, t=-5	-0.027	-0.076*
	(0.026)	(0.035)
Credit Share at Treated Retailer, t=-4	-0.002	-0.020
	(0.024)	(0.033)
Credit Share at Treated Retailer, t=-3	-0.011	-0.038
	(0.023)	(0.031)
Credit Share at Treated Retailer, t=-2	-0.021	-0.016
	(0.021)	(0.029)
Credit Share at Treated Retailer, t=0	0.059**	0.054+
	(0.022)	(0.029)
Credit Share at Treated Retailer, t=1	0.093***	0.080*
	(0.025)	(0.033)
Credit Share at Treated Retailer, t=2	0.053*	0.092**
	(0.026)	(0.035)
Credit Share at Treated Retailer, t=3	0.072**	0.051
	(0.028)	(0.038)
Credit Share at Treated Retailer, t=4	0.091**	0.107*
	(0.032)	(0.043)
Credit Share at Treated Retailer, t=5	0.087**	0.107*
	(0.033)	(0.043)
Credit Share at Treated Retailer, t=6	0.125***	0.149***
	(0.033)	(0.044)
Credit Share at Treated Retailer, t=7	0.105**	0.166***
	(0.034)	(0.044)
Credit Share at Treated Retailer, t=8	0.137***	0.211***
	(0.039)	(0.052)
N	610960	610960
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.15: Correlation between being the card with the top number of trips and the card with the top share of spending.

Top Card by Trips		Top Card by Spend: 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.16: 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	0.96
Debit	0.82	0.14	0.96
MC	0.74	0.20	0.94

Table A.17: Estimated parameters without passthrough

Panel A: Consumer Parameters

Parameter	Est	SE
S.D. of Card R.C.	0.74	0.26
S.D. of Credit R.C	1.84	0.69
Correlation of R.C.	-0.69	0.06
S.D. of T1EV	0.10	0.03
$\chi_{\text{Card, Card}}$	0.07	0.64
$\chi_{\text{Card, Cred}}$	3.78	0.99
$\chi_{\text{Cred, Card}}$	3.25	0.90
$\chi_{\text{Cred, Cred}}$	-3.66	1.20
Visa Debit Ξ	-3.11	0.43
Visa Credit Ξ	-5.14	0.36
MC Debit Ξ	-3.26	0.48
MC Credit Ξ	-5.35	0.41
Amex Ξ	-5.42	0.42
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	0.35	0.36
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	1.47
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.

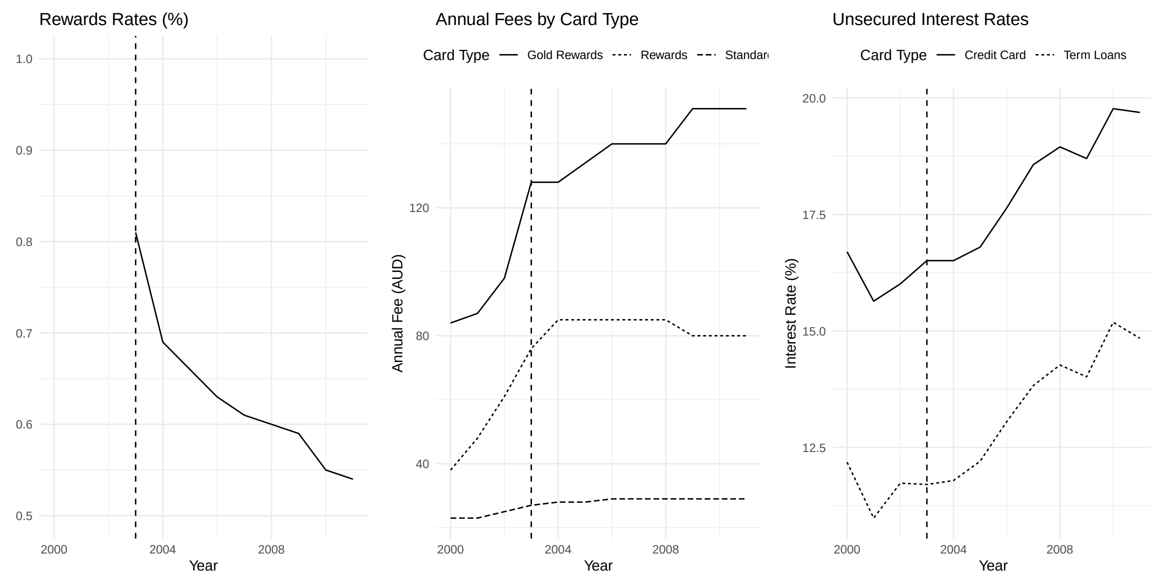
Table A.18: Summary of Counterfactual Effects Under No Merchant Pass-through

	Price Controls				Change Competition			
	Cap Fees		Uncap Debit		Monopoly		Credit Entry	
Δ Prices (bps)								
Credit Fees	−194	(0)	−4.5	(0.8)	18	(4)	−0.4	(0.3)
Credit Rewards	−234	(5)	−21	(4)	−90	(29)	−0.2	(2.0)
Debit Fees	−41	(0)	25	(0)	0.0	(0.0)	0.0	(0.0)
Debit Rewards	−36	(1)	26	(0)	−33	(7)	0.8	(0.1)
Δ Shares (pp.)								
Cash	45	(9)	−8	(2)	31	(1)	−1.7	(0.3)
Debit	−13	(8)	21	(5)	−9	(1)	0.9	(0.5)
Credit	−31	(2)	−13	(4)	−21	(1)	−9	(0)
Entrant							10	(0)
Δ Fees, Rewards ($Bn)								
Total Fees	−101	(5)	−10	(6)	−53	(4)	1.4	(1.6)
Total Rewards	−80	(5)	−11	(5)	−65	(8)	1.8	(2.0)
Δ Consumption (bps)								
Low Income	−62	(7)	7	(1)	−36	(9)	0.4	(0.4)
Median Income	−89	(2)	3.6	(2.0)	−48	(13)	0.4	(0.6)
High Income	−159	(5)	−4.3	(3.9)	−78	(20)	0.4	(1.2)
Δ Welfare ($Bn)								
Consumers	−58	(9)	4.7	(0.7)	−44	(11)	3.7	(1.9)
Merchants	89	(6)	2.4	(3.9)	40	(5)	−1.6	(1.0)
Networks	−8	(1)	3.9	(0.5)	22	(6)	−1.2	(0.4)
Total	24	(11)	11	(4)	18	(8)	0.9	(0.7)
No Logit Shocks								
Consumers							0.7	(1.0)
Total							−2.1	(0.5)

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 30 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.

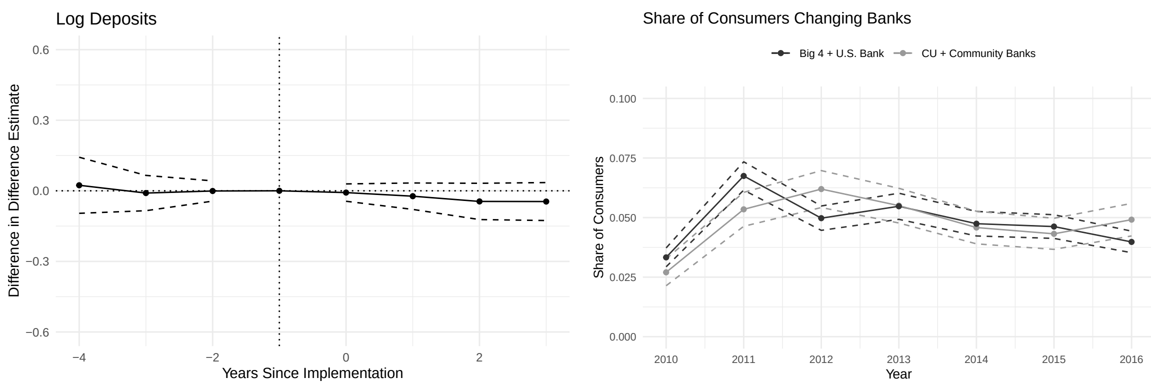
H Additional Figures

Figure A.15: Key changes in the Australian credit card market after interchange regulation



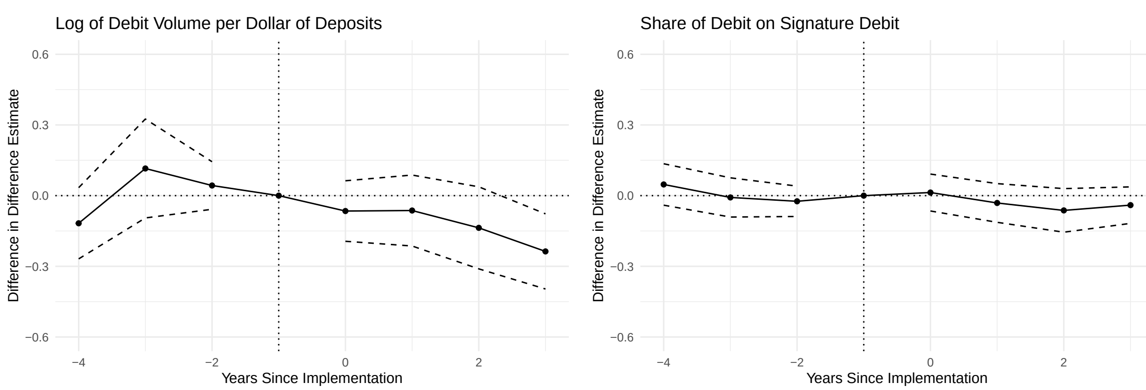
Notes: The vertical line marks the 2003, the start of interchange regulation in Australia. 'Gold' refers to the highest tier of rewards credit cards, whereas 'Rewards' refers to the basic tier of rewards credit cards. 'Basic' refers to credit cards without rewards. Data on rewards comes from Chan et 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.16: 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.

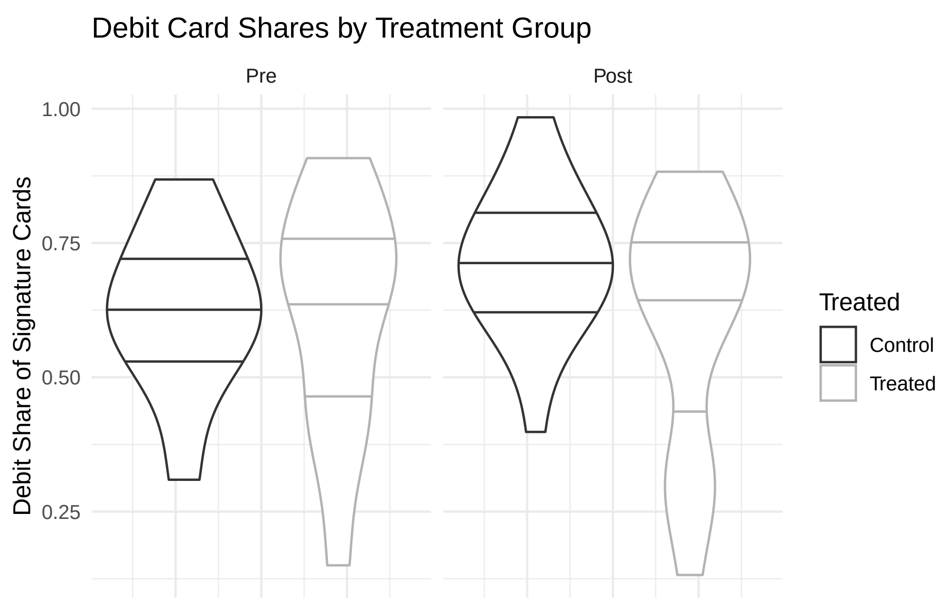
Figure A.17: The effect of the Durbin Amendment on overall debit volumes



[H]

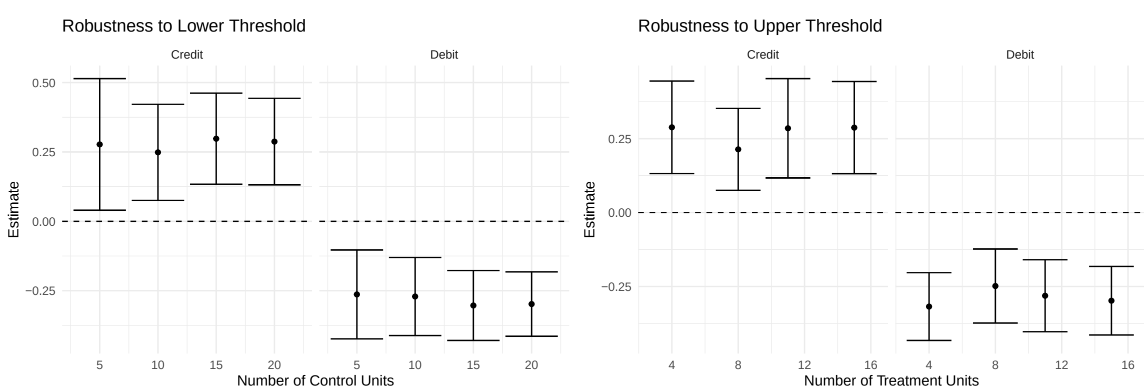
Notes: The vertical line marks 2010, the year before the policy began to be implemented.

Figure A.18: Comparing debit versus credit shares at treatment and control banks



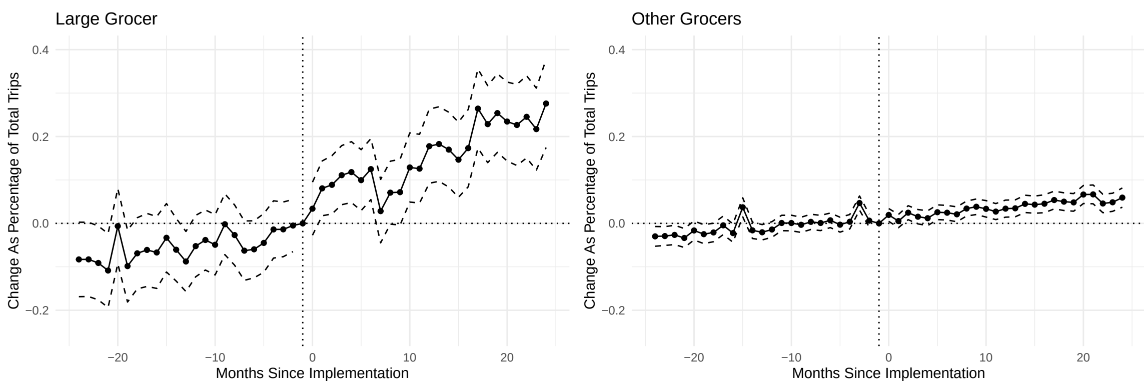
Notes: Each panel shows a violin plot illustrating the distribution of signature debit as a share of total card transactions by value for the control (<$10 billion in assets in 2010) and treatment banks (>$10 billion) in the pre and post periods. The dashed lines show the 25th, 50th, and 75th percentiles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

Figure A.19: Testing robustness of estimate to varying asset size cutoffs



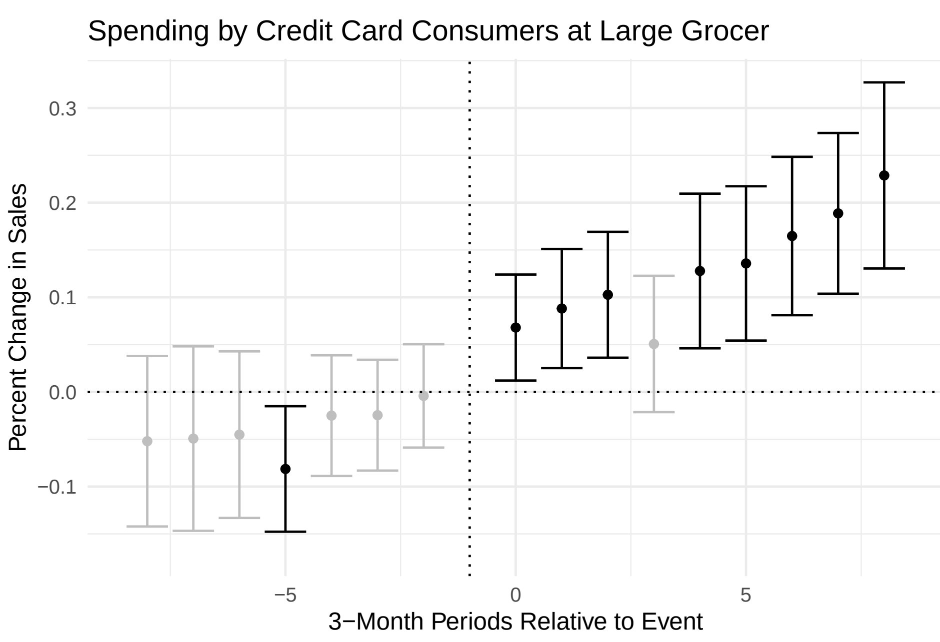
Notes: The panels show the results of how the difference-in-difference estimates of the effect of Durbin on debit and credit card volumes change as I increase the minimum asset requirement up towards $10 billion (for the control group) or as I decrease the maximum asset size down towards $10 billion (for the treatment group) until the treatment or control group is of the desired size. I find the estimates do not substantially change as the control and treatment groups change.

Figure A.20: Double differences for the large grocer (left) and all other grocers (right)



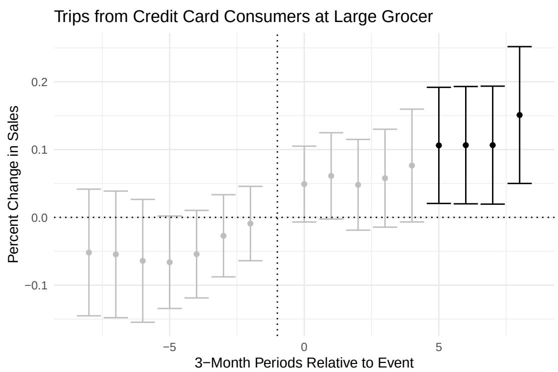
Notes: The left panel shows the dynamic estimates of the effect of card acceptance on the number of trips of credit card consumers versus non credit-card consumers at the large grocer that started accepting credit cards. The right panel shows the same dynamic estimate for all non-treated grocer. The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

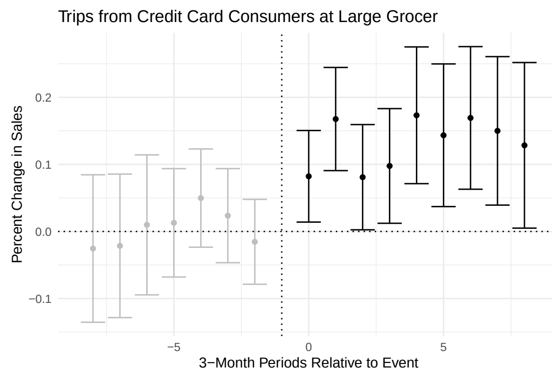
Figure A.21: Spending instead of trips for the large grocer



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.

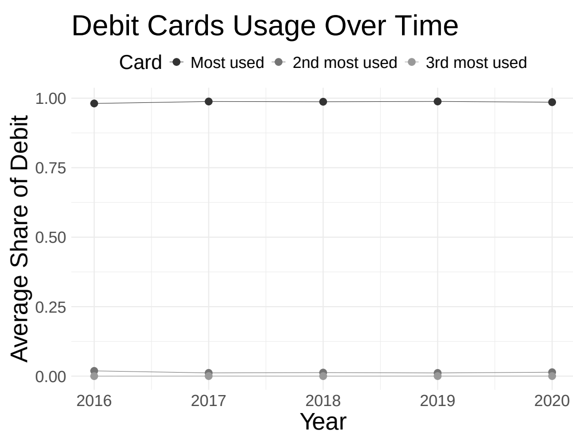
Figure A.22: Triple-difference specifications for the effect of card acceptance on total trips, split by income





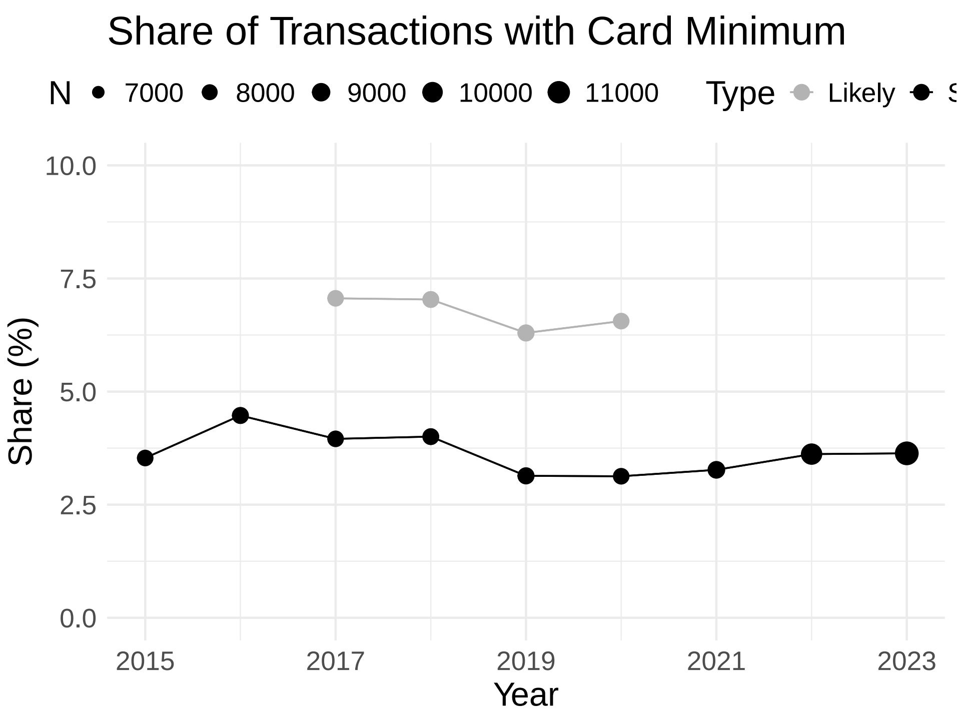
Notes: The left panel shows the dynamic estimates of the effect of card acceptance on the number of trips by credit card consumers for consumers with above median income. The right panel shows the same estimation on a sample of consumers with below median income.

Figure A.23: Share of debit card spending on primary debit card



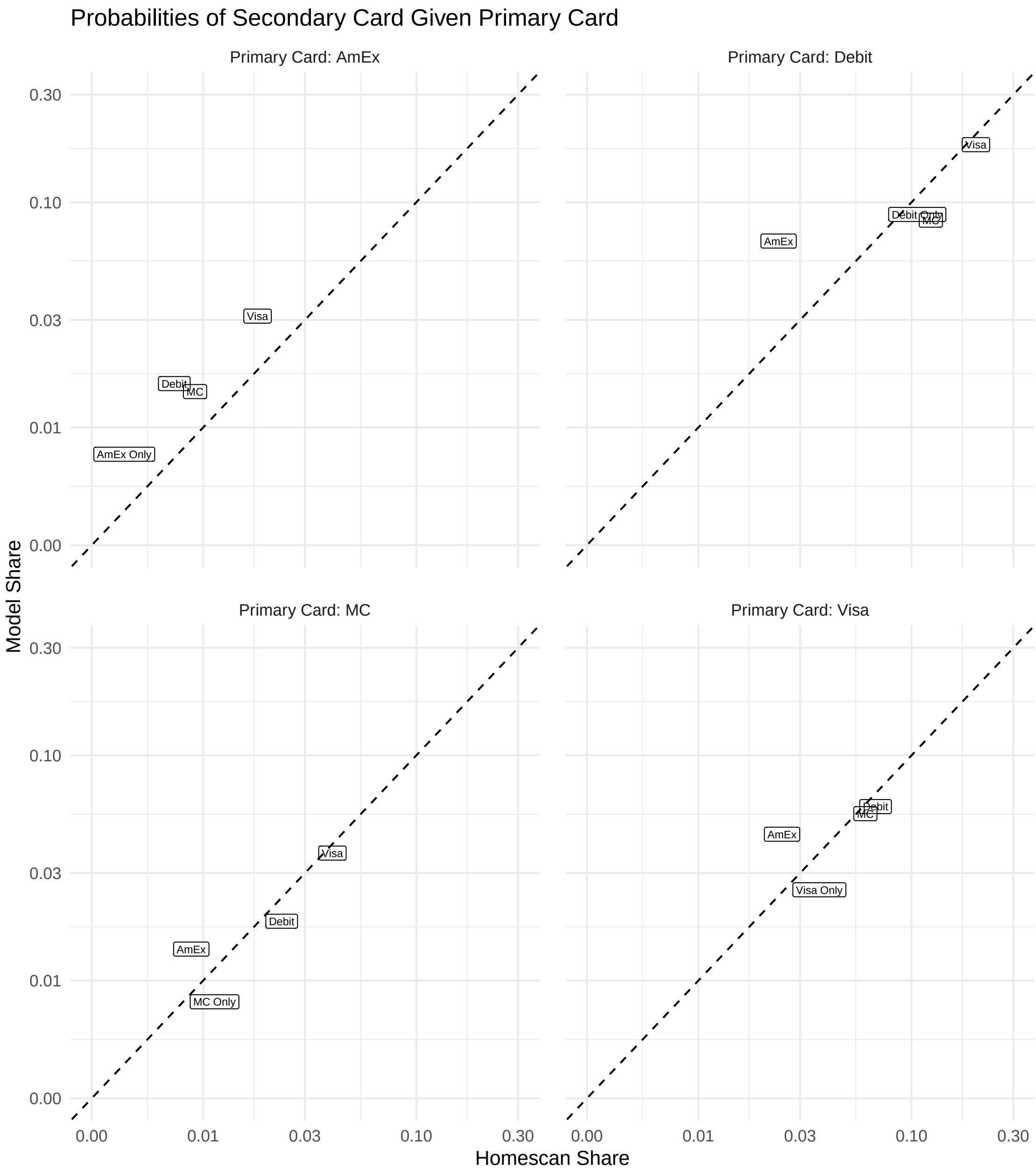
Notes: The graph shows data from the DCPC on the share of debit card spending that consumers allocate to their primary debit card. The primary debit card is defined at the consumer level as the card with the plurality of their debit card spending by counts.

Figure A.24: 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.25: 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 card 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.