

Payment Network Competition

Lulu Wang*

November 15, 2022

[Click for Most Recent Version](#)

Abstract

Three networks—Visa, Mastercard, and American Express—dominate U.S. consumer payments. Payment markets are two-sided: consumers are paid rewards for card usage, and merchants are charged fees to accept cards. I show that network competition increases merchant fees and consumer rewards and decreases consumer and total welfare. Data on bank payment volumes and consumer payment preferences suggest that consumers are sensitive to rewards, but merchants are insensitive to fees. I develop a structural two-sided model of network pricing, consumer adoption, merchant pricing, and merchant acceptance, and estimate it by matching the reduced-form facts. Using the estimated model, I simulate network entry. Given that consumers are more price sensitive than merchants, the entrant charges high fees and pays large rewards. Incumbent credit card networks respond by raising merchant fees and rewards, increasing credit card use. Merchants pass on merchant fees to retail prices, creating a regressive transfer from cash and debit card consumers to credit card consumers. Entry exacerbates excessive credit card use, reducing annual consumer and total welfare by \$7 billion and \$10 billion, respectively. Three counterfactuals on price regulation and mergers demonstrate that excessive credit card adoption shapes the welfare effects of payment policies.

*Wang: Stanford GSB, 655 Knight Way, Stanford, CA 94305. Email: luluyw@stanford.edu. Job market paper. I am extremely grateful to my advisors Amit Seru, Darrell Duffie, Ali Yurukoglu, and Claudia Robles-Garcia. I thank Lanier Benkard, Matteo Bennetton, Greg Buchak, Jacob Conway, José Ignacio Cuesta, Liran Einav, Matthew Gentzkow, Joseph Hall, Wesley Hartmann, Ben Hebert, Arvind Krishnamurthy, Hanno Lustig, Gregor Matvos, and Peter Reiss for helpful comments. I acknowledge support from the National Science Foundation Graduate Research Fellowship under Grant Number 1656518. Researcher(s)' own analyses calculated (or derived) based in part on data from Nielsen Consumer LLC and marketing databases provided through the NielsenIQ Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ data are those of the researcher and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

Section I Introduction

Merchants and regulators often blame high card acceptance fees on weak competition.¹ Indeed, Visa, Mastercard (MC), and American Express (AmEx) process 85% of the card payments in the United States, and merchants pay \$120 billion per year in merchant fees to accept credit and debit cards (Nilson, 2020b; Jensen, 2022). This argument suggests that more competition, either from fintechs such as PayPal or from public options such as central bank digital currencies, should reduce merchant fees.

Theoretical work on two-sided markets is less forceful and suggests that more competition has ambiguous effects on prices and welfare. Whereas merchants pay high fees to accept cards, consumers receive around \$50 billion per year in rewards to use cards.² When consumers are price sensitive but merchants are not, competing networks increase merchant fees to fund larger consumer rewards (Rochet and Tirole, 2003; Armstrong, 2006). Doing so substantially increases consumer adoption while only slightly reducing merchant acceptance. Higher merchant fees inflate retail prices, redistributing consumption among consumers (Felt et al., 2020). Consumer and total welfare can fall as payment choice is distorted toward payment methods with high rewards (Edelman and Wright, 2015). Despite the large theoretical literature on payment networks, there is limited empirical work on this topic. This paper fills this gap.

I quantify the effects of payment network competition on merchant fees, consumer rewards, and welfare. The core innovation is to map estimated consumer and merchant preferences into equilibrium prices with a structural model of competition in two-sided markets. I first provide reduced-form evidence that consumers are more price sensitive than merchants. Therefore, competing networks face strong incentives to raise merchant fees to fund more consumer rewards. To translate the reduced-form evidence into predictions for how competition affects welfare, I develop and estimate a structural model of network pricing, consumer adoption, merchant pricing, and merchant acceptance. With the estimated model, I simulate the entry of a new payment network that resembles credit cards and emerging fintech payment apps.

I find that entry creates regressive transfers and exacerbates excessive credit card use. Because consumers are more price sensitive than merchants, the entrant charges high fees to fund large rewards. Incumbent credit card networks respond to entry by raising merchant fees and rewards, increasing consumer credit card use. Because merchants charge consumers the same price no matter how they pay, merchants pass on the fees to retail prices for all consumers. Cash and debit card consumers, who tend to have lower incomes, are hurt relative to credit card consumers.

¹A U.S. retailers trade association recently wrote that “the absence of competition in the payments ecosystem allows Visa and Mastercard to get away with highway robbery when it comes to swipe fees” (Jensen, 2022). In 2020, the U.S. Department of Justice challenged Visa’s acquisition of a nascent payment network, Plaid, on the grounds that competition “would drive down prices for online debit transactions, chipping away at Visa’s monopoly and resulting in substantial savings to merchants and consumers” (Read et al., 2020). Many discussions of central bank digital currencies mention that one of the benefits of introducing one is to increase payment competition and drive down the cost of card acceptance (Shin, 2021; Usher et al., 2021; Federal Reserve, 2022).

²This is based on my calculation with merchant discount fee data from Nilson (2020b) and a 1.3% average rewards rate (Agarwal et al., 2018). I discuss how regulatory shocks to interchange fees highlight the importance of merchant fees in funding rewards in Section II.

Consumer and total welfare fall by \$7 billion and \$10 billion, respectively.

The central friction behind my price and welfare results is price coherence: merchants typically charge consumers the same retail price no matter how they pay (Stavins, 2018). Price coherence has three important effects. First, it enables networks to compete by raising merchant fees to fund rewards. In doing so, the network's consumers benefit from the full increase in rewards but only bear part of the cost of higher retail prices. Second, price coherence causes credit card rewards to redistribute consumption. Rewards increase the use of credit cards, and merchants pass on the merchant fees to higher prices for all consumers. After retail prices adjust, cash and debit card consumers are hurt by higher retail prices, whereas credit card users benefit from the higher rewards (Felt et al., 2020). Third, price coherence generates excess credit card adoption, so competition can lower consumer and total welfare by pushing credit card use further above the efficient level. Under price coherence, consumers do not internalize the effect of their payment choice on retail prices. Thus, even if consumers' payment preferences are such that they collectively prefer lower credit card use and lower retail prices, individual consumers are incentivized to deviate and use credit cards to earn rewards (Edelman and Wright, 2015). Higher credit card use inflates retail prices, dissipating the gains from rewards. In equilibrium, credit card use and retail prices are too high.

To motivate the importance of competition over rewards, I document four reduced-form facts about consumer and merchant demand for payments. The overarching theme of these facts is that networks have strong incentives to compete for consumers but weak incentives to compete for merchants. The first two facts suggest that consumers are price sensitive, particularly when choosing between different credit cards. First, I show that small reductions in debit rewards cause large declines in debit volumes. Variation in debit rewards arises due to the Durbin Amendment, which capped debit card interchange fees at large banks but not small ones starting in 2011. Second, data on consumers' card portfolios suggest that consumers are more willing to substitute between credit cards of different networks than between credit and debit cards. The next two facts show that merchants are price insensitive. One, merchants' benefits of higher sales from card acceptance dwarf the costs of merchant fees. Two, only some consumers carry credit cards from multiple networks. Merchants thus risk large declines in sales when they do not accept consumers' desired payment methods. Put together, these facts suggest that consumers are more price sensitive than merchants. Under these conditions, modeling rewards competition is crucial to understanding how payment networks compete.

Given the importance of rewards competition, I develop a two-sided model in which payment networks compete in both 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, as well as where to shop.³ They prefer cards that pay high rewards and are widely

³Even though consumers in the model have little incentive to carry cards from multiple networks, many consumers in the data carry credit cards from multiple networks. In Appendix B, I derive a dynamic micro-foundation featuring consumers who periodically update their primary payment method to explain why consumers' card holdings are informative about consumer preferences.

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 set retail prices. In choosing what to accept, merchants trade off the benefits from higher sales against the cost of merchant fees. Merchants pass on merchant fees to retail prices for all consumers. This pass-through generates distributional effects. Multiproduct networks maximize profits by adjusting consumer rewards and merchant fees, accounting for the effects on subsequent adoption decisions. Consumers vary in their preferences over payment instruments, and merchants vary in their benefits from card acceptance. Consumers' preferences over payment methods ultimately drive the consumer and total welfare results.

Two theoretical tools dramatically simplify the model solution. First, I show that merchant profits from accepting any subset of cards is approximately linear in the merchant's type. Therefore, solving for optimal merchant adoption strategies reduces to solving for the upper envelope of a collection of linear functions. Second, I select a unique adoption equilibrium through the insulated-equilibrium concept in White and Weyl (2016). This concept provides consumers with dominant strategies that do not depend on merchant actions, pinning down a unique consumer and merchant adoption subgame.

I estimate the model by matching the reduced-form facts and aggregate data on prices and market shares. First, I use the variation in rewards induced by the Durbin Amendment and data on card holdings to estimate consumer demand for payments as a function of rewards. Second, I invert the consumer demand system to recover networks' costs. Large rewards indicate that networks earn large profits from merchants, and thus networks' costs of processing transactions are low. Third, by comparing marginal costs and equilibrium merchant fees, I recover the elasticity of merchants' demand for payments in the observed equilibrium. Because merchants are charged large markups, merchant demand must be inelastic. Fourth, I recover merchants' margins and the distribution of merchants' benefits from card acceptance by matching the equilibrium merchant elasticity and the facts from the consumer payment surveys. I thereby estimate consumer and merchant demand for payments primarily with exogenous variation in rewards and the assumption that networks maximize their own profits.

My estimates indicate that consumers are price sensitive, while merchants are not. A one-basis-point (1-bp) increase in Visa credit rewards increases Visa credit's market share among consumers by 2.8%. In contrast, a 1-bp increase in merchant fees for Visa credit cards causes only a 0.16% decline in the share of merchants that accept Visa credit. This difference in price sensitivities drives my result that competing networks raise merchant fees to fund more consumer rewards.

I also estimate that the average consumer would prefer to use debit cards if credit cards did not pay rewards. The average consumer is indifferent between a Visa debit card that pays no rewards and a Visa credit card that pays 1.1% in rewards. My model infers this fact from revealed preference: many consumers use debit cards despite not earning rewards. This preference drives my welfare result that increases in credit card use relative to debit card use reduce welfare.

I validate the estimated model with two out-of-sample tests. First, I match out-of-sample predictions for how credit card volumes change after a shock to debit rewards. This validates the substitution patterns I recover from the cross section of consumers' card holdings with exogenous price variation. Second, the estimated network marginal cost parameters are consistent with the accounting data. Overall, these validation exercises suggest I accurately estimate how consumer payments demand changes with rewards, which is an essential part of predicting how networks adjust rewards.

In my main counterfactual, I simulate network entry. I assess the impact of a new payment app that shares characteristics of credit cards and of emerging fintech payment apps, such as PayPal or Klarna. I assume that the new app has the same characteristics and marginal costs as American Express. I also assume that app consumers shop less at merchants that do not accept the app, even if the merchants accept credit cards.⁴ Because consumers are price sensitive, but merchants cannot substitute app acceptance with credit card acceptance, the entrant charges high merchant fees to fund large rewards. Its merchant fees and consumer rewards are 39 basis points and 28 basis points higher than American Express' baseline fees and rewards, respectively. In response, incumbent credit card networks raise merchant fees by 8 basis points to fund rewards that are 15 basis points larger.

Entry creates regressive transfers by inflating retail prices. This result relies on the model prediction that merchants pass on fees to prices. Higher rewards both from incumbent credit card networks and the entrant increase use of payment methods that charge high merchant fees. Higher merchant fees are passed on to retail prices that are 16 basis points higher for all consumers. Among the consumers who do not switch, cash and debit users' welfare fall by 16 and 9 basis points, respectively. In contrast, credit card consumers' welfare falls by only 4 basis points, as higher rewards cushion the rise in prices.

Entry exacerbates excessive credit card use, reducing annual consumer and total welfare by \$7 billion and \$10 billion, respectively. This result relies on the assumption that revealed preference applies to payment choice and that the entrant has similar characteristics as credit cards. This assumption on the entrant's characteristics is crucial, as it means when the entrant expands, it is as if more consumers are using credit cards. Revealed preference implies that each consumer who switches to credit cards to earn higher rewards lowers total welfare. Empirically, many consumers who could use a credit card to earn rewards use a debit card instead.⁵ By revealed preference, these consumers find using credit cards costly, which I call credit aversion. When higher credit card rewards induce these consumers to switch to credit cards, these consumers incur the cost of credit aversion. While credit aversion is a social cost, rewards are merely transfers paid for with higher retail prices. The marginal increase in credit card use after entry thus lowers both

⁴The matches evidence from Berg et al. (2022) that PayPal users will shop less at a store if it does not accept PayPal, even if the store accepts debit and credit cards.

⁵Table 1 shows that most cash and debit consumers have access to credit cards. I discuss in Section VI.C why the presence of constrained consumers does not affect my estimated welfare results. I show in Appendix D that credit aversion likely reflects a combination of fear of overspending, concern about credit cards' complexity, and a general aversion to debt.

consumer and total surplus.

To illustrate that excessive credit card adoption drives the negative welfare effects of entry, I show that three other regulatory and market structure changes that all discourage credit card use also raise consumer and total welfare. The total welfare effects across these counterfactuals are all quantitatively well explained by a revealed preference estimate of the costs of excessive credit card adoption, demonstrating that the main value of the model is to give accurate predictions of how market shares change with prices.

In my first two counterfactuals, I show that either uncapping debit interchange or capping credit interchange increases consumer and total welfare by reducing credit card use. The model highlights how the consumer and total welfare effects of both policies are closely related to how the policies affect consumer payment choice. Both policy changes induce some credit-averse consumers to switch to cash or debit, raising welfare. I model interchange fee regulations as caps on merchant fees. When I let debit cards charge 1% merchant fees instead of the current 0.72%, debit rewards rise by 21 basis points and consumer and total welfare rise by \$5 and \$6 billion, respectively. When I cap Visa and Mastercard credit card merchant fees at 1%, credit card rewards fall by 71 basis points and consumer and total welfare rise by \$38 and \$28 billion, respectively. These two counterfactuals show that the current U.S. regulatory regime that only regulates interchange fees on debit cards but not credit cards is worse than either pure *laissez-faire* or fully regulating interchange.

In a third counterfactual, I show that merging AmEx and Mastercard without cost efficiencies raises consumer and total welfare by \$1 and \$6 billion, respectively, by lowering credit card use. The model's ability to predict changes in network margins is useful for separating out consumer versus network gains. In typical one-sided markets, mergers without cost efficiencies always reduce consumer and total welfare (Nocke and Whinston, 2022). However, this does not apply in payments. The merger reduces credit card rewards by 9 basis points, reducing credit card adoption and increasing welfare.

More broadly, my paper suggests platform competition under price coherence can be harmful. For example, advertising platforms like Facebook or Google connect merchants with consumers. These platforms charge merchants high advertising prices while investing in apps that consumers value. As in payments, competition can lead platforms to invest more in consumer apps and to fund these investments with even higher advertising prices. In equilibrium, retail prices rise and dissipate consumer gains from competition. Consumer welfare can fall due to excessive app adoption. I show how variation on one side of the market can help identify demand on both sides, enabling an empirical study of platform competition in other contexts.

I.A Related Literature

The closest related work is Huynh, Nicholls and Shcherbakov (2022), who also estimate a structural model of consumer and merchant card adoption. I build on their work by allowing merchants to pass on merchant fees to retail prices. Credit card rewards inflate retail prices and can hurt consumers in my model, whereas credit card rewards always benefit consumers in

their model. I also endogenize consumer rewards and merchant fees in an equilibrium model of network competition, whereas previous work has typically assumed they are exogenous.⁶

My paper contributes to the finance literature on payments by providing an equilibrium model of network competition. Many papers have documented forces that influence consumer payment choice, such as adoption externalities (Gowrisankaran and Stavins, 2004; Rysman, 2007; Higgins, 2020; Crouzet et al., 2020), unobserved preference heterogeneity (Koulayev et al., 2016; Huynh et al., 2020), and rewards (Agarwal et al., 2010; Arango et al., 2015; Ru and Schoar, 2020; Agarwal et al., 2022). My approach to estimating consumer demand is inspired by Mukharlyamov and Sarin (2022), who study the effect of the Durbin Amendment on bank fees. In the context of the literature, I show that incorporating the forces influencing adoption into an equilibrium model of how networks compete can help quantify the harms of network competition.

My paper also contributes to the literature on two-sided markets by estimating a quantitative model of network competition. Edelman and Wright (2015) argue that competition inflates merchant fees and exacerbates excess adoption of credit cards. I build upon their work by incorporating merchant heterogeneity (Rochet and Tirole, 2003; Guthrie and Wright, 2007) and consumer multihoming (Armstrong, 2006; Anderson et al., 2018; Liu et al., 2021; Bakos and Halaburda, 2020), which play important roles in shaping competition in two-sided markets. By introducing a quantitative model, I demonstrate that the stark theoretical results from Edelman and Wright (2015) on the harms of competition do not hinge on their assumptions of homogenous merchants and single-homing consumers.

My paper also contributes 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 (Buchak et al., 2020; Benetton, 2021; Robles-Garcia, 2022), credit cards (Nelson, 2020), and insurance (Cohen and Einav, 2007; Kojien and Yogo, 2015). My contribution is to take a structural approach to a two-sided market of payments.

More broadly, my paper echoes arguments from the banking and intermediation literature about the dark side of competition in the presence of externalities. Competing high-frequency traders overinvest in speed (Budish et al., 2015). Competing over-the-counter intermediaries overinvest in contact rates and bargaining ability (Farboodi et al., 2019; Farboodi and Jarosch, 2022). In the model, payment networks exert externalities on each other by inflating retail prices with high merchant fees.

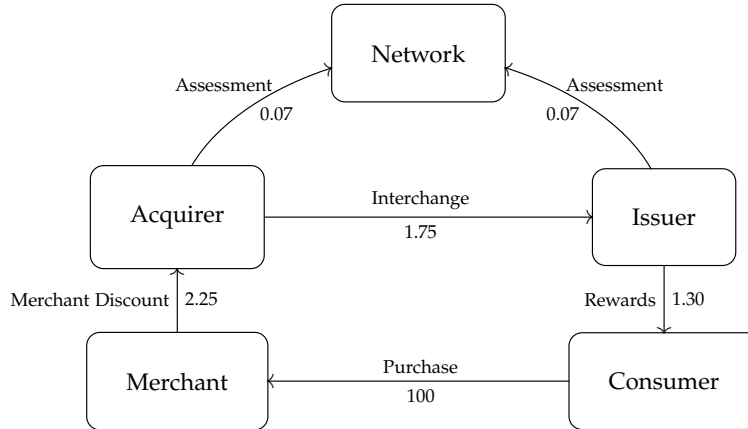
Section II Institutional Details and Data

II.A Network Pricing: Merchant Fees and Consumer Rewards

Networks influence the fees that merchants pay to accept cards, as well as the rewards consumers receive from using cards. Proprietary networks like AmEx set merchant and consumer

⁶Li et al. (2020) is an important exception, but they assume that merchants accept cards to reduce costs instead of increasing sales. Card users therefore cross-subsidize cash users in their model.

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 (2020b) and the average assessment comes from example rate sheets from acquirers. The interchange is derived from Visa’s interchange schedule for a Visa Signature card at a large retailer. The rewards are from Agarwal et al. (2018), with a fraud adjustment from Nilson (2020a).

prices 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. 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 might pay 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, who works with a bank to connect the merchant to the Visa network. The acquirer will use some of that fee to cover its costs, but then must also send \$1.75 to the issuing bank, such as Chase, in the form of interchange. The issuer and the acquirer collectively then pay around \$0.14 in assessment fees to Visa. While some of the \$1.75 of interchange fees goes toward covering the issuer’s costs, a large part of it is also rebated back to the consumer in the form of rewards. In this example, the rebate is \$1.30.

Visa and MC influence merchant fees and consumer rewards primarily by adjusting the *interchange fee*. Regulatory caps on interchange highlight how they affect merchant fees and rewards. When the EU and Australia mandated interchange fee reductions, merchant fees declined roughly one-for-one (Gans, 2007; Valverde et al., 2016; European Commission, 2020). After the EU capped credit card interchange in 2015, UK banks reduced credit card rewards (Gunn, 2016). After Australia capped interchange fees on Visa and MC credit cards in 2003, rewards fell.⁷

⁷The history of regulatory arbitrage around interchange regulations in Australia also highlights the importance of interchange in funding rewards. Because the original interchange regulations did not limit the merchant fees charged by American Express, banks started issuing American Express cards and continued to offer high rewards on those cards (Chan et al., 2012). When Australia closed this regulatory loophole in 2017, the same large banks substantially devalued their rewards programs and stopped issuing American Express cards (Emmertson, 2017; Reserve Bank of Australia, 2021).

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

	Cash	Debit, Low Credit Share	Debit, High Credit Share	Credit
Share	0.25	0.20	0.21	0.34
Owns credit card	0.68	0.61	1.00	1.00
Owns rewards credit card	0.45	0.32	0.76	0.85
Owns bank account	0.87	1.00	1.00	0.99
Balance/limit	0.22	0.32	0.26	0.10
Household income (\$k)	61.24	67.48	86.05	112.88
Debit share	0.29	0.73	0.55	0.14
Credit share	0.17	0.01	0.26	0.66

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. The share variable reports the share of the sample in each column. Credit share and debit share report the share of transactions by the consumers on either credit cards or debit cards. All other variables report averages within the group of consumers of a given payment choice.

II.B Data

I combine bank-level and aggregate data from a payments trade journal, the Nilson Report, with consumer-level data from the Nielsen Homescan panel and the Federal Reserve’s Diaries and Surveys of Consumer Payment Choice. These data provide key moments for estimating consumer and merchant demand for payments.

Issuer Payment Volumes: I construct an imbalanced 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. The Nilson Report publishes the dollar payment volumes of the top credit and debit card issuers every year. These issuers include both banks and large credit unions. My main difference-in-difference analysis focuses on a subset of 39 issuers, 19 of them above \$10 billion in assets and 20 below. Appendix Table F.1 reports the main summary statistics for this sample.

Consumer Payment Surveys: 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. I use the data from the 2015–2020 waves of both surveys for my main sample, although to study credit versus debit acceptance I also use data from the 2008–2014 waves of the SCPC. These data are useful in establishing basic facts about how consumers use different payment methods, as well as estimating merchants’ benefits from payment acceptance. Table 1 shows summary statistics on consumers’ payment preferences. Debit is the most popular payment instrument, followed by credit and then cash. Most consumers in the sample are banked and have access to credit cards.

Homescan: The Nielsen Homescan panel tracks the method of payment of around 90,000 households at large consumer packaged goods stores. I use this to build measures of primary and secondary cards at the consumer level. Appendix Table F.3 reports the main sum-

mary statistics at the household-year level. I focus on households without any missing payment data. The main shortcoming of the Homescan panel is that it does not cover certain spending categories, such as travel or restaurants, that tend to have a high prevalence of credit card use. Appendix Table F.4 shows that Homescan overrepresents cash and debit transactions while underrepresenting American Express.

Aggregate Prices and Shares: I use aggregate shares and prices derived from the Nilson Report (Nilson, 2020b,c,d), as well as the portfolio-level data on rewards from Agarwal et al. (2018). I document these data in Appendix Tables F.5 and F.6. These are used to estimate both consumer preferences and the network supply-side parameters.

Section III Reduced-Form Facts

The reduced-form facts show that consumers are sensitive to rewards, but merchants are insensitive to fees. These facts suggest that consumer rewards is an important dimension over which payment networks compete.

III.A Consumer Substitution Between Credit and Debit

The Durbin Amendment reduced debit interchange rates, led banks to cut debit rewards, and led to a large reallocation of spending from debit to credit. Consumer choice between debit and credit is thus sensitive to rewards.

The Durbin Amendment was part of the 2010 Dodd-Frank Act and reduced debit interchange fees at large banks and credit unions with more than \$10 billion in assets by around half.⁸ Credit interchange was unaffected. By reducing banks' income from debit card spending, this law led large banks to end debit rewards (Hayashi, 2012; Schneider and Borra, 2015). In contrast, small banks largely kept their rewards programs intact (Orem, 2016).

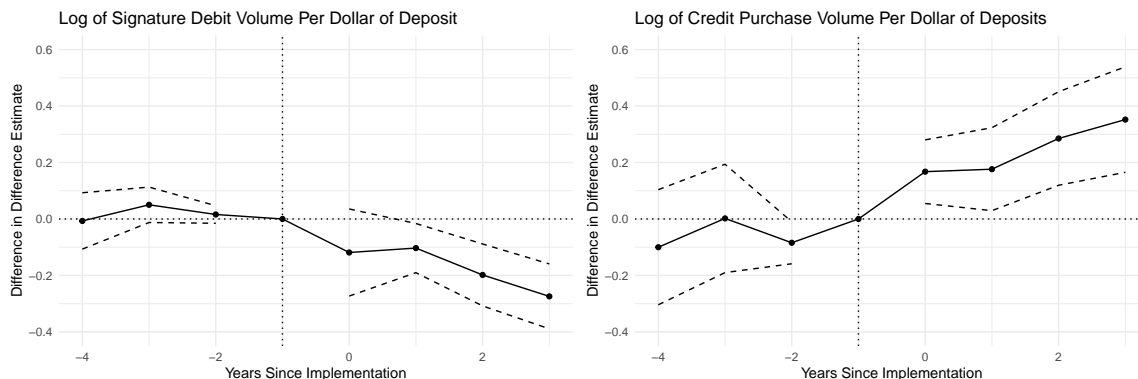
To study the effect of the Durbin Amendment on payment volumes, I employ a difference-in-differences approach similar to Mukharlyamov and Sarin (2022) that compares payment volumes at large banks with between \$10 and \$200 billion in assets versus small banks with between \$2.5 and \$10 billion in assets, around the time the Durbin Amendment was implemented. I estimate:

$$y_{it} = \sum_{k=-3}^3 \beta_k I\{t = k\} \times \text{Treated}_i + \delta_i + \delta_t + \epsilon_{it} \quad (1)$$

where y_{it} is the logarithm of signature debit or credit card payment volumes per dollar of deposits at bank i . Treated_i refers to whether bank i had more than \$10 billion in assets in 2010, and δ_i and δ_t represent bank and year fixed effects, respectively. By comparing large banks to small banks, I can difference out the effects of the Durbin routing requirements, the CARD act, and potential

⁸While the regulation covered both banks and credit unions, for the rest of the discussion I will refer to these financial institutions as simply "banks." The new cap was \$0.22 plus 5 bps of transaction value (Mukharlyamov and Sarin, 2022). Large banks previously earned around 1.3% (Huang, 2010). At an average debit transaction of \$40, this is a decline of 54%.

Figure 2: The effect of the Durbin Amendment on debit card and credit card volume.



Notes: Data are from the Nilson Report. The vertical line marks the year before the policy announcement. The policy started in Q3 2011 and went into full effect in year 2012, which is at $t = 1$. Standard errors are clustered at the issuer level.

changes in merchant acceptance on debit and credit card use.⁹ I define $t = 0$ as 2011. I use 2010 as my base year.

The regressions suggest that consumers are sensitive to rewards. Hayashi (2012) estimates that the average debit rewards program paid consumers around 25 bps of transaction value, yet even that small change led to a 27% decline in signature debit volumes and 35% increase in credit card volumes. Figure 2 shows the estimation results. Volume largely shifted between cards, as I estimate overall card spending fell by a small but statistically insignificant 5%. Consumers may be sensitive to rewards because they are salient in advertising (Ru and Schoar, 2020). My estimates are consistent with Mukharlyamov and Sarin (2022), who find that geographic areas that were more affected by the Durbin interchange caps saw larger increases in credit card volumes.¹⁰

III.B Consumer Substitution Between Networks

Data on consumers' primary and secondary cards show that credit cards from different networks are good substitutes for each other. This suggests that consumers' choices between cards of similar payment characteristics (e.g., debit or credit) but from different networks (e.g., Visa or Mastercard) should be particularly sensitive to rewards.

⁹While there have been a few empirical papers on the effects of interchange fee regulation (Chang et al., 2005; Valverde et al., 2016), these papers cannot identify consumer preferences because of potential merchant responses. In models of interchange, the level of the interchange fee should affect both consumer utilization and merchant adoption (Rochet and Tirole, 2002).

¹⁰In the Appendix, I include additional results and robustness checks. Appendix Table F.7 reports the exact coefficients and standard errors. Figure G.1 shows that the two groups of banks did respond to the \$10-billion cap by changing the growth trajectories. Besides signature debit, many banks offered PIN debit, which was not affected by Durbin since the interchange rates were already low (Hayashi, 2012). Figure G.2 shows that the overall debit cards, which included PIN debit cards that were not affected by the regulation, declined less. The differential pattern across debit cards suggests the effect I am identifying is about relative prices for credit and debit, and not just other shocks to big and small banks during this time period.

Table 2: Conditional probabilities of each secondary card given the consumer’s primary card.

Primary Card	Secondary Card				
	Cash	Debit	Visa	MC	AmEx
Debit	0.22		0.45	0.26	0.07
Visa	0.16	0.38		0.29	0.17
MC	0.13	0.29	0.45		0.13
AmEx	0.09	0.20	0.49	0.22	
Primary Card Share	0.26	0.44	0.18	0.08	0.04

Notes: Data are from Homescan. The bottom row shows the share of each column payment method among primary payment methods. If a consumer only uses one type of card, the secondary “card” is defined as cash.

I use the Homescan shopping data to construct primary and secondary cards.¹¹ I split consumers by cash and card users.¹² I define card users’ primary payment card as the card network used for the highest share of trips.¹³ I define the secondary card as the card network used the second most often. If the consumer only uses one card, I define the secondary “card” to be cash.

I identify substitution patterns by interpreting primary and secondary card holdings as hypothetical first and second choices over all primary payment methods. Primary AmEx users often carry a secondary Visa credit card. I infer from this fact that primary AmEx users are therefore likely to use Visa credit cards in an alternative world without AmEx. This interpretation depends on the absence of complementarity and substitution effects at the network level. I discuss a dynamic micro-foundation for this assumption in Section IV.G.4. I then apply techniques from Berry et al. (2004) for studying second-choice data to identify how willing consumers are to substitute between credit cards from different networks.

The primary and secondary card data indicate that the closest substitute for a credit card is a credit card from a different network, not a debit card. Table 2 shows both the aggregate shares of each primary payment method and the conditional probability of each payment option occurring as the second choice. In the Homescan panel, debit cards are the most popular primary payment method, followed by cash, Visa credit cards, MC credit cards, and lastly AmEx. However, the second choice of a primary credit card consumer is more likely to be a credit card from a different network than a debit card. For example, only 0.38% of primary Visa credit consumers use a debit card as a secondary card, whereas 0.46% use an MC or AmEx credit card. Thus, credit cards from different networks are better substitutes for each other than credit and debit cards.

¹¹Appendix Table F.10 shows that two card networks cover around 95% of card spending for the typical Homescan consumer who carries cards from at least two networks. The primary network typically covers around 80% of the card spending, while the remainder is on a second network.

¹²I match the share of consumers who prefer cash in the DCPC as in Homescan.

¹³In Appendix Table F.9, I show that the total number of trips is highly correlated with the card with the highest share of spending.

III.C Merchant Benefits from Card Acceptance

The average merchant’s sales increase around 30% from card acceptance. The large sales benefit relative to the level of fees also suggests that merchant demand should be price insensitive.

I exploit variation in consumer payment preferences to identify how much merchants’ sales increase from card acceptance. Although this approach is less well identified than random shocks to merchant adoption, it lets me compute the average—rather than marginal—benefit of card acceptance for merchants in the United States.¹⁴ I assume that variation in payment preferences among consumers is orthogonal to consumers’ baseline preferences over merchants, conditional on observables. If card acceptance increases sales, then card consumers should spend more at merchants who accept cards when compared to cash consumers.

I use a logistic regression to measure the effect of card acceptance. Index consumers by i and transactions by t . Let y_{it} be the indicator for whether the transaction t occurred at a store that accepts cards. Let X_i be the indicator of whether the consumer prefers cards. Let δ_{it} be a vector of fixed effects such as the consumer’s characteristics (e.g., income, education, credit score, and age) and transaction characteristics (e.g., ticket size, merchant type). I estimate the logistic regression:

$$\log \frac{P(y_{it} = 1)}{1 - P(y_{it} = 1)} = \phi X_i + \delta_{it} + \epsilon_{it}. \quad (2)$$

Because most merchants accept cards, the coefficient ϕ can be interpreted as the average increase in sales experienced by the merchants who accept cards. This increase in sales nets the positive effect from increased convenience against the negative effect of higher fees that may be passed through to higher prices.

My preferred model includes both the transaction and consumer controls and suggests that the average consumer who prefers cards is around 30% more likely to shop at a store that accepts cards than a consumer who prefers cash. Table 3 shows the results with different options for fixed effects. The relative stability of the results, even as I adjust the consumer and transaction fixed effects, suggests there is little unobserved variation driving the result.¹⁵

III.D Merchant Substitution Between Networks

Merchants do not view credit card and debit card acceptance as substitutes. Consumer holding data suggest that different credit card networks are imperfect substitutes for each other.

I use a large change in the cost of debit versus credit acceptance to show that merchants do not treat debit card and credit card acceptance as substitutes. Intuitively, two goods are good substitutes if changes in their relative prices induce large changes in relative quantities.

¹⁴Given the ubiquity of credit cards in the United States, the marginal merchant deciding whether or not to accept cards has very different benefits from card acceptance than the average. Studies that use merchant shocks in other countries find that accepting consumers’ preferred payment methods can raise sales from those consumers by 10%–40% (Higgins, 2020; Berg et al., 2022).

¹⁵Appendix Table F.8 shows that this effect does not vary much across debit versus credit card users, those who hold one or multiple cards, or high- or low-income respondents. This motivates why I do not model heterogeneity in the effect of card acceptance on sales for these different groups.

Table 3: Logistic regressions predicting the probability that a given transaction occurs at a merchant who accepts credit cards as a function of consumer preferences.

	No Controls	Transaction Controls	Consumer Controls	Both
Prefer Card	0.35*** (0.07)	0.34*** (0.08)	0.36*** (0.08)	0.30*** (0.09)
N	29661	29661	29661	29661
State, year FE	X	X	X	X
Transaction controls		X		X
Consumer controls			X	X

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

Notes: Data are from the DCPC. Standard errors are clustered at the consumer level. Transaction characteristics fixed effect refers to fixed effects for the ticket size and merchant type (e.g., restaurant or retail). Consumer characteristics fixed effect refers to fixed effects for the consumer’s income, education, credit score, and age.

However, Figure 3 shows that after the Durbin Amendment cut debit card merchant fees, there was no significant decline in the number of merchants that accepted credit cards. This is unlikely to be the result of bundling between credit and debit cards, and likely reflects the fact that the consumers who use both debit cards and credit cards use them for different purposes.¹⁶

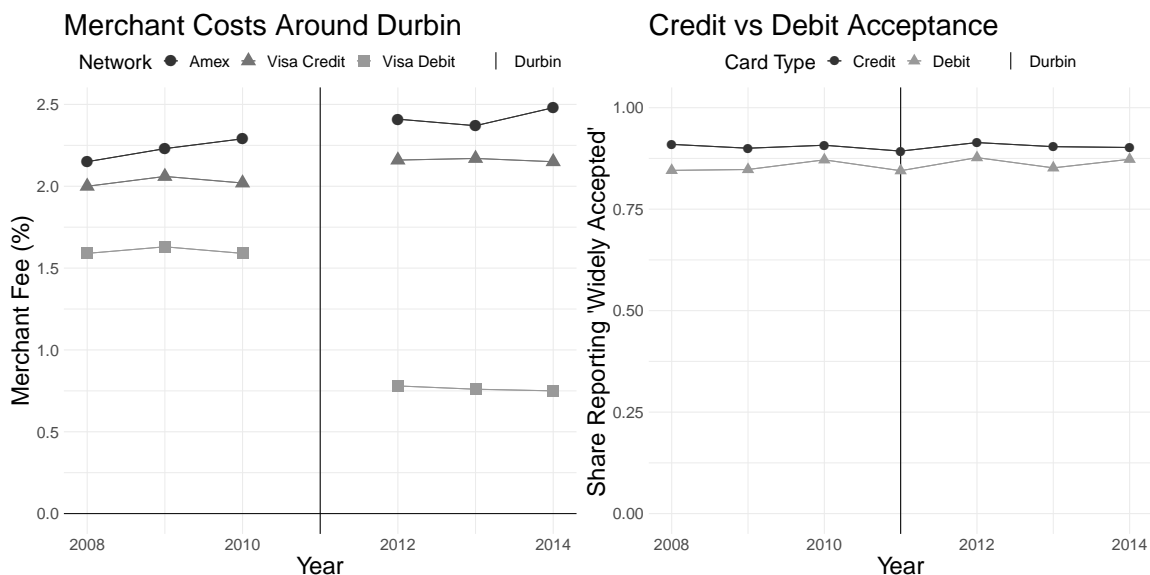
Accepting one network’s credit cards is an imperfect substitute for accepting a different network’s credit cards. Appendix Table F.11 shows data from the DCPC and Homescan indicate around 40% of consumers carry a card from only one of the three major networks (Visa, MC, and AmEx). This is somewhat lower than past results using the Visa Payments Panel data (Rysman, 2007). The data suggest that rejecting a credit card network may lose sales from a sizeable fraction of that network’s cardholders.

III.E Summarizing the Reduced-Form Facts

The large change in debit volumes in response to the Durbin Amendment and primary credit card consumers’ willingness to substitute between credit card networks suggest that consumers are quick to switch to networks with high rewards (Facts 1 and 2). Merchants’ large sales benefits from card acceptance and the presence of consumers with cards from only one network suggest that merchants who try to reject cards from high-fee networks risk large declines in sales (Facts 3 and 4). These facts suggest that consumers are more price sensitive than merchants. Under these conditions, network competition can result in higher merchant fees and higher consumer rewards (Rochet and Tirole, 2003; Armstrong, 2006). I now quantify these forces in a model.

¹⁶A 2003 settlement ended Visa’s and MC’s “honor all cards” rules tying debit and credit (Constantine, 2012). A consumer may use a debit card when she has money in her checking account, but then switch to a credit card when she does not. Therefore, when the consumer wants to use the credit card, using a debit card is not an acceptable substitute. Table 1 shows that when compared to consumers who pay only with credit cards, debit card consumers carry larger balances.

Figure 3: Card fees and acceptance around Durbin.



Notes: Merchant costs come from the Nilson Report. Consumer ratings of credit and debit acceptance come from the SCPC, and count the proportion of consumers in each year who rate credit and debit cards as either “usually accepted” or “almost always accepted.”

Section IV Model

The importance of rewards competition motivates a two-sided model of payment network competition. The model maps reduced-form facts into estimates of consumer and merchant preferences. Once I estimate the parameters, solving the game under different conditions will enable me to predict network behavior under different market structures and calculate the welfare effects of changes in competition and regulation.

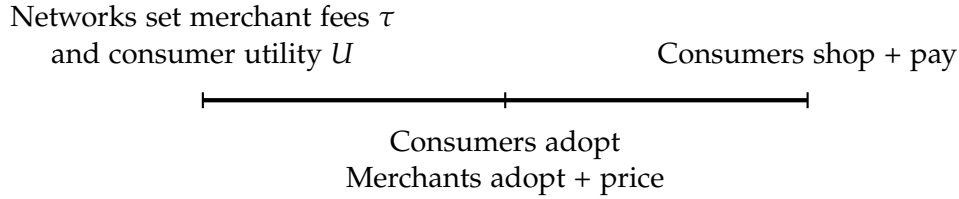
IV.A The Need for a Model

The model lets me empirically study three insights from the theoretical and empirical literature on payments and two-sided markets.

First, the model lets me estimate consumer and merchant price sensitivities in order to test the theories of Rochet and Tirole (2003); Armstrong (2006). In traditional one-sided markets, firms cut prices in response to entry. This would be valid if payment networks only charged fees to merchants. In reality, payment networks are two-sided. They not only charge merchant fees, but they also pay consumer rewards. Rochet and Tirole (2003); Armstrong (2006) show that if consumers are sufficiently price sensitive and merchants are price insensitive, competing networks may charge higher merchant fees to fund larger rewards. My model shows how to map the reduced-form facts to consumer and merchant price sensitivities, and lets me evaluate how merchant and consumer prices change with competition.

Second, the model shows that the regressive effects of credit card rewards are amplified

Figure 4: Timeline of the model.



when consumer payment choice responds to rewards. Felt, Hayashi, Stavins and Welte (2020) conduct an accounting exercise and argue that high merchant fees and large credit card rewards create regressive transfers, holding fixed consumer adoption. My model shows that changes in consumer payment choice are crucial to understanding transfers. Higher credit card rewards, even if merchant fees are held fixed, can inflate retail prices and create regressive transfers by increasing the use of payment methods with high merchant fees. Cash and debit users ultimately pay higher retail prices, and credit card consumers benefit from higher rewards. By modeling how consumers change their payment methods, my model captures this additional channel.

Third, the model's estimates of consumer preferences let me test the provocative claim in Edelman and Wright (2015) that payment network competition lowers consumer welfare by distorting payment choice toward high-rewards payment methods. Their story depends on an assumption that the marginal consumer dislikes the non-price characteristics of high-rewards payment methods. By relating consumer preferences to market shares, my model allows me to test that assumption in the data. My model also allows me to compute measures of welfare to evaluate the original claim that competition can lower consumer welfare.

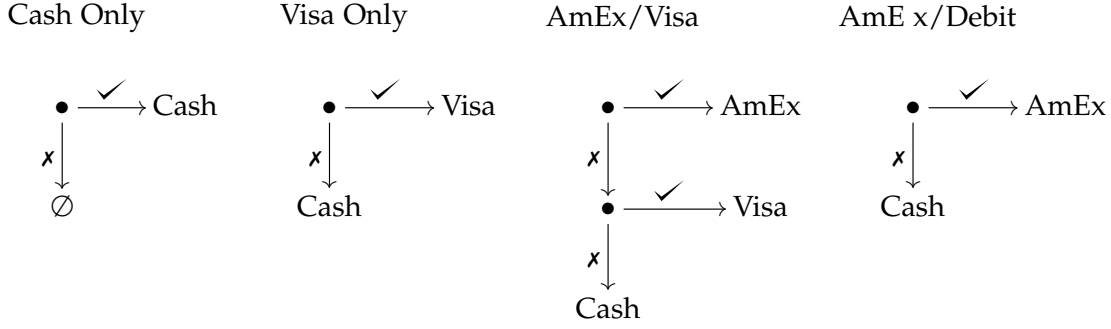
IV.B Structure of the Game

I model competition between card networks as a static game with three stages and three kinds of players: networks, consumers, and merchants. Figure 4 shows the three stages. I solve for a subgame perfect equilibrium of this game.

In the first stage, profit-maximizing networks set per-transaction fees for merchants and promised utility levels for consumers. In the second stage, a unit continuum of consumers and merchants make adoption and pricing decisions. Consumers choose up to two cards to put in their wallets. Merchants set retail prices and choose which cards to accept. In the third stage, consumers decide how much to consume from each merchant and pay with the cards in their wallets. Consumers vary in their preferences over payment methods. Merchants vary in how much their sales increase from card acceptance.

The model makes several simplifying assumptions. First, it abstracts from acquirers and issuers and treats the payment network as directly setting fees and rewards. Second, it assumes merchants can only charge one price to all consumers. Third, it ignores the credit function of credit cards. Fourth, it assumes that consumers are free to choose between cash, debit cards, and credit cards. The model also predicts that merchants pass through merchant fees to prices, and

Figure 5: Illustration of how consumers choose payment methods at the point of sale.



Notes: The AmEx/Debit consumer does not spend on her debit card because it is not the same type as her primary card. All merchants accept cash in equilibrium, and so the cash-only consumer can always pay with cash. In this diagram, Visa refers to Visa credit cards.

that primary and secondary cards accurately reflect consumers' hypothetical first and second choices over payment instruments. I defer the discussion of choice sets to Section VI.C, but discuss the other assumptions and predictions in Section IV.G.

IV.C Stage 3: Consumer Shopping and Payment

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

At the point of sale, consumer payment behavior is mechanical and reflects the order of the cards in their wallet. Consumers first try to use their primary card. If that is not possible, they will use their secondary card if it shares the same card type as their primary card. Otherwise, they pay with cash. I require consumers to only use the secondary card if it shares the same type to match the reduced-form fact that lower debit card merchant fees do not reduce merchants' acceptance of credit cards (Section III.D). Although high-reward cards are more likely to be chosen as the primary card in an earlier stage of the game, rewards have no effect on the intensive margin.

Define the set of all inside payment methods (i.e., cards) as $\mathcal{J}_1 = \{1, \dots, J\}$, and the set of all payment methods as $\mathcal{J} = \{0\} \cup \mathcal{J}_1$, where 0 refers to cash. Each payment method has a type $\chi^j \in \{0, D, C, A\}$ for cash, debit, credit, or a new app.

Each consumer has a wallet w with zero, one, or two cards that have already been chosen in the second stage of the game. Let $\mathcal{W} = \{(j, k) : j, k \in \mathcal{J}, j \neq k\}$ denote the set of all possible wallets. For a wallet $w = (w_1, w_2)$, the term w_1 is the primary payment method and w_2 is the secondary payment method. I define an indicator $I_{j,M}^w$ for whether a consumer with wallet w pays with j , provided the merchant accepts the cards $M \subset \mathcal{J}_1$. This indicator encodes the payment logic from the start of this subsection, and mathematically it is:

$$I_{j,M}^w = \{w_1 = j, j \in M\} \vee \{w_1 \neq j, w_2 = j, \chi^{w_1} = \chi^{w_2}, j \in M\} \quad (3)$$

I simultaneously model cash consumers, consumers who use only one card (single-homers),

and consumers who use multiple cards (multihomers). Figure 5 shows how different types of consumers pay. A cash-only consumer's primary payment method is cash, $w_1 = 0$. A single-homing Visa consumer has $w_1 = \text{Visa}$ but $w_2 = \text{Cash}$. A multihoming consumer who carries an AmEx as their primary card and a Visa as a backup has $w_1 = \text{AmEx}$, $w_2 = \text{Visa}$. The AmEx/Debit consumer either pays with AmEx or cash, skipping over the debit card. This occurs because AmEx and debit cards are different types of payments.

Consumer payment choices only reflect the order of cards in their wallet and not the identity of the merchant. When the AmEx-Costco exclusivity agreement ended, it was revealed that 70% of the spending on the Costco AmEx card was not at Costco (Sidel, 2015). Table F.10 shows that when consumers spend on more than one network, around 80% of consumers' card spending is on their primary network. This supports my assumption that consumers generally use their primary card when given the option.

IV.C.2 Consumption Decisions Over Merchants

Consumers value both card acceptance and low prices. Holding prices fixed, if a merchant accepts the consumer's card, then the consumer buys γ percent more. The value of $\gamma \sim G$ varies across merchants. A low γ firm may be a small business with a loyal customers, for whom the method of payment is not important. A high γ firm may be an e-commerce firm, who benefits from significantly higher sales if the online checkout process is convenient (Berg et al., 2022).

I use a constant-elasticity of substitution (CES) demand curve to capture both preferences. Suppose that all other merchants charge prices $p^*(\gamma)$ and accept payment methods $M^*(\gamma) \subset \mathcal{J}_1$, where their actions depend on their types. 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 $w = (w_1, w_2)$ and income y^w buys q^w , where:

$$q^w(\gamma, p, M, y^w, P^w) = (1 + \gamma v_M^w) p^{-\sigma} \frac{y^w}{(P^w)^{1-\sigma}}$$

$$(P^w)^{1-\sigma} = \int \left(1 + \gamma v_{M^*(\gamma)}^w\right) p^*(\gamma)^{1-\sigma} dG(\gamma) \quad (4)$$

$$v_M^w = I_{w_1, M}^w + I_{w_2, M}^w$$

The variable v_M^w equals one provided that the consumer pays with either her primary or secondary card, and is zero if she pays with cash. The price index P^w summarizes the effect of other merchants' actions on the consumer's choice. In Appendix A.1, I micro-found this demand function as the solution of a consumer problem with CES utility in which payment acceptance affects perceived quality.

In equilibrium, consumers will consume according to a consumption schedule $q^{w*}(\gamma)$ for each merchant type γ that is optimal given all merchants' equilibrium pricing p^* and adoption M^* decisions:

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

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

IV.D.1 Merchant Pricing

Merchants are single-product firms that maximize profits by setting prices and choosing the subset of payments to accept. Conditional on the payment acceptance decision M , optimal prices pass on the average transaction fee to the consumer.

Collapse the wallet-specific price indices from the consumer problem to $P = (P^w)_{w \in \mathcal{W}}$. Let the merchant fee for payment method j equal τ_j of sales. The cost of cash is $\tau_0 \geq 0$ to capture the possibility of cost savings from card use. Let the share of consumers with wallet w be $\tilde{\mu}^w$ and collapse the vector of shares as $\tilde{\mu}$. These shares should be thought of as the share of dollars in the economy in a wallet of type w . Normalize the firm's marginal costs to 1. In Appendix A.2, I show that if the merchant accepts $M \subset \mathcal{J}_1$, the optimal price is:

$$\begin{aligned}\hat{p}(\gamma, M, P, \tau, \tilde{\mu}) &= \frac{\sigma}{\sigma - 1} \times \frac{1}{1 - \hat{\tau}} \\ \hat{\tau}(\gamma, M, P, \tau, \tilde{\mu}) &= \frac{\sum_{w \in \mathcal{W}} q^w \tilde{\mu}^w \tau_M^w}{\sum_{w \in \mathcal{W}} q^w \tilde{\mu}^w}\end{aligned}$$

The realized transaction fee $\hat{\tau}$ captures the weighted average transaction fee the merchant pays, where different payment methods are weighted by their sales. The fee $\tau_M^w = \sum_{j \in \mathcal{J}} I_{j,M}^w \tau_j$ depends on both the consumers' wallets and what the merchant accepts.

In equilibrium, merchants set optimal prices given the optimal pricing and adoption strategies of other merchants:

$$\hat{p}(\gamma, M^*(\gamma), P, \tau, \tilde{\mu}) = p^*(\gamma) \quad (6)$$

IV.D.2 Merchant Acceptance

Merchants choose the optimal subset of payments to accept. Solving for merchants' optimal adoption strategies reduces to solving for the upper envelope of a collection of linear functions. Let $\hat{\Pi}(\gamma, M, P, \tau, \tilde{\mu})$ be the profit function from accepting a particular subset of payments $M \subset \mathcal{J}_1$, accounting for the optimal price. In Appendix I, I prove that $\hat{\Pi}$ is approximately linear in γ when the other parameters are held fixed. Merchants adopt subsets M that maximize this linear approximation $\bar{\Pi}$, which I will call quasiprofits. Each merchant of type γ solves:

$$\hat{M}(\gamma, P, \tau, \tilde{\mu}) = \operatorname{argmax}_{M \subset \mathcal{J}_1} \bar{\Pi}(\gamma, M, P, \tau, \tilde{\mu}) \quad (7)$$

Merchants can accept any subset of cards. This disciplines networks' incentives to raise merchant fees. In the United States, almost all merchants who accept Visa credit cards also accept MC credit cards. This makes sense given the two networks charge similar fees. But in an alternative world in which Visa charged higher fees, merchants would be able to drop Visa while still accepting MC. Otherwise, Visa would face strong incentives to raise merchant fees, since doing so would not have a large effect on merchant acceptance.

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

$$\hat{M}(\gamma, P, \tau, \hat{\mu}) = M^*(\gamma) \quad (8)$$

IV.D.3 Consumer Adoption

Consumers choose the two payment instruments that offer the highest payment utility to put in their wallet.

Primary Cards: Each consumer's primary card is the one with the highest payment utility from adoption. I define the log payment utility V_i^j from a payment method $j \in \mathcal{J}$:

$$\log V_i^j = \underbrace{\log U^j}_{\text{CES}} + \underbrace{\Xi^j}_{\text{Unobs Char}} + \frac{1}{\alpha} \left(\underbrace{\eta_i^j}_{\text{T1EV}} + \underbrace{\beta_i X^j}_{\text{R.C.}} \right) \quad (9)$$

$$\beta_i \sim N(0, \Sigma)$$

The CES utility, U^j , represents the maximized utility attained from solving the consumption problem over merchants for a consumer who only uses card j . It allows me to measure the level of consumer welfare in terms of consumption instead of measuring surplus relative to a fixed outside option. If the network pays consumers who single-home on card j a reward f^j , then standard results on CES give that the consumer's optimized utility is:

$$\log U^j \approx f^j - \log P^j \quad (10)$$

where P^j is the CES price index associated with a customer who only carries j , defined in Equation 4. The utility from the CES system increases for a payment method that earns a large reward, decreases if the overall level of retail prices is high (which increases P^j), and increases for a payment method that is widely accepted (which decreases P^j). It also captures the intuition that a 1% increase in retail prices cancels out a 1% increase in rewards.

The other parameters are more standard. The variables Ξ^j represent unobserved characteristics that rationalize market shares. I normalize the unobserved characteristic of cash as $\Xi^0 = 0$. The parameter α is a measure of consumers' price sensitivity. If α is large, a small increase in rewards f^j leads to a large increase in j 's market share. The shocks η_i^j represent unobserved reasons different consumers might choose one payment method over another. The characteristics X^j are indicators for whether a payment method is a card or cash and whether it has a credit function. The random coefficients are distributed $\beta_i \sim N(0, \Sigma)$ for some covariance matrix Σ . This unobserved heterogeneity allows consumers to vary in their preferences over payment characteristics.

Secondary Payment Cards: The payment method with the second highest utility becomes the

secondary payment method in the wallet. Consumers' primary and secondary cards therefore reveal their first and second choices. I define *insulated* market shares for the wallet $w = (w_1, w_2)$ as:

$$\mu^w = P \left(\left(V_i^{w_1} = \max_{j \in \mathcal{J}} V_i^j \right) \cap \left(V_i^{w_2} = \max_{j \in \mathcal{J} \setminus \{l\}} V_i^j \right) \right) \quad (11)$$

Insulated versus Consumer Market Shares: Consumer market shares $\tilde{\mu}$ are reverse-engineered so that each merchant's decision on which cards to accept depends only on the insulated shares μ , and not on the underlying price index P^w or the rewards f^w . Actual market shares $\tilde{\mu}$ among consumers for different wallets are thus derived from the insulated shares as:

$$\begin{aligned} \tilde{\mu}^w &= \frac{1}{C} \frac{\mu^w (P^w)^{1-\sigma}}{1 + f^w} \\ C &\equiv \sum_{w \in \mathcal{W}} \frac{\mu^w (P^w)^{1-\sigma}}{1 + f^w} \end{aligned} \quad (12)$$

where f^w is the total rewards paid to a consumer with wallet w .¹⁷ The constant C has been defined in a way to make the market shares add up to 1.

Whereas the consumer market share $\tilde{\mu}^w$ is the share of consumers who carry a wallet, the insulated market share μ^w captures the share of a cash-only merchant's demand coming from consumers with a given wallet. The two shares differ because consumers shop over merchants. For a fixed number of Visa customers $\tilde{\mu}$, as more merchants accept Visa, Visa customers make up a smaller share of the customers at any one merchant. The reverse engineering shuts this channel down, so that knowledge of μ is sufficient for merchants to know the composition of their customer base.¹⁸

IV.E Stage 1: Network Competition

IV.E.1 Profits

Network profits equal transaction fees charged to merchants, less costs and the rewards paid to consumers. A useful quantity for computing profits is the total dollar amount \tilde{d}_j^w that consumers with wallet w spend on card j . This is:

$$\tilde{d}_j^w = \tilde{\mu}^w \int I_{M^*(\gamma),j}^w q^{w*}(\gamma) p^*(\gamma) dG(\gamma)$$

¹⁷The rewards f^w for consumers who only hold one card will be set by the networks, and the rewards for the consumers who multihome will be based off the single-homing rewards under the assumption that the reward from a card is proportional to the amount of spending done on that card. I discuss the calculation of these rewards in Appendix A.3.

¹⁸If one alternatively defined the market shares $\tilde{\mu}$ in terms of the joint distributions of the payment methods delivering the top two highest V_i^j , that would create a strategic substitutability by which merchants are less likely to adopt payment methods if other merchants have already adopted. A pure strategy equilibrium for consumer and merchant adoption may no longer exist in the alternative setting. In practice, the two approaches deliver almost identical estimates for preferences because the price sensitivity coefficient α is large.

where the indicator $I_{M,j}^w$, defined in Equation 3, detects if payment method j is used when the merchant accepts M and the consumer has a wallet w .

Total profits from the merchant side of the market for card j are:

$$T_j = (\tau_j - c_j) \sum_{w \in \mathcal{W}} \tilde{d}_j^w$$

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

$$S_j = \sum_{w \in \mathcal{W}} \tilde{\mu} f_j^w$$

where f_j^w is the amount of rewards that need to be paid to a consumer with wallet w for her use of j . Note that rewards may be paid both to consumers who use j as a primary card and those who use j as a secondary card.

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

$$\Psi_n = \sum_{j \in \mathcal{O}_n} (T_j - S_j) \tag{13}$$

I discuss how to calculate these terms in Appendix A.3.

IV.E.2 Conduct and Equilibrium Determinacy

Networks maximize profits by adjusting promised CES utility levels for consumers U^j and transaction fees for merchants τ_j , holding fixed the utility levels and transaction fees from other networks. This conduct assumption is in line with the insulated equilibrium framework of Weyl (2010); White and Weyl (2016) and guarantees that for every vector of network choice variables, the merchant and consumer subgame is unique.

One challenge in modeling network competition is dealing with a potential multiplicity of equilibria because consumer adoption depends on expectations of merchant actions (Caillaud and Jullien, 2003; Chan, 2021). To resolve this problem, I assume that networks promise to compensate consumers with high rewards if merchants do not adopt. Consumers then have dominant strategies, which pin down merchant actions. Weyl (2010) argues that this is a reduced-form way of capturing penetration pricing by which networks subsidize consumer adoption when merchant acceptance is low. To implement this idea, I have networks compete in CES utility U^j and merchant fees τ instead of in rewards f and fees τ . With this conduct assumption, I can solve for the unique merchant and consumer subgame and network profits given U and τ .¹⁹ Appendix A.4 explains how to calculate profits under this conduct assumption.

I employ a refinement to deal with the non-differentiability of network profits with respect to the merchant fees.²⁰ I assume that when each network chooses utility levels and transaction fees,

¹⁹There is a separate question of whether networks will choose the same fees and utility in every equilibrium, which I do not consider here.

²⁰Starting from the symmetric equilibrium, a network that raises its merchant fee is now competing with the option

it maximizes expected profits while assuming small trembles in the choice variables. Appendix H explains why this makes the profit function differentiable and how to efficiently calculate the derivative of the expectation.

Thus, for each network $n = 1, \dots, N$, networks set promised utility levels U^{j*} and transaction fees τ_j^* for the cards that they own \mathcal{O}_n such that:

$$\left(U^{j*}, \tau_j^* \right)_{j \in \mathcal{O}_n} = \operatorname{argmax}_{(U^j, \tau_j)_{j \in \mathcal{O}_n}} \mathbb{E} \left[\Psi_n \left(\tilde{U}^j, \tilde{\tau}_j, \tilde{U}^{-j}, \tilde{\tau}_{-j} \right) \right] \quad (14)$$

$$\tilde{U}^j \sim N \left(U^j, \sigma^2 \right), \tilde{\tau}_j \sim N \left(\tau_j, \sigma^2 \right) \text{ iid}$$

where σ^2 is a small variance that I set to 10^{-10} , and U^{-j}, τ_{-j} capture all the CES utilities and fees set by the other networks. I model cash as a network that sets fees to the cost of cash $\tau_j = c_0$ and sets a utility level U^0 equal to $1/P^0$ so as to not pay any rewards.

IV.F Equilibrium

A full equilibrium is characterized by fees τ^* , CES utility levels U^* , insulated shares μ , a merchant pricing schedule $p^*(\gamma)$, a merchant adoption schedule $M^*(\gamma)$, and wallet-specific consumer demand schedules $q^{w*}(\gamma)$ that satisfy five conditions:

1. The demand schedule $q^{w*}(\gamma)$ is optimal given the network's choice of reward, and merchants' acceptance and pricing policies (Eq. 5).
2. For each merchant of type γ , she maximizes quasiprofits by accepting $M^*(\gamma)$ and sets the price $p^*(\gamma)$ (Eq. 6 and 8), holding fixed the adoption and pricing decisions of all other merchants, consumers' choices of wallets, and networks' choices.
3. The insulated shares μ reflect consumers' optimal wallet choices, holding fixed the networks' promised utility levels (Eq. 11).
4. Non-cash networks maximize profits at the fees τ^* and promised utility levels U^* , holding fixed the promised utility levels and fees of other networks (Eq. 14).
5. Cash pays no reward and charges a fee τ_0 equal to the cost of cash c_0 .

IV.G Discussion of Key Assumptions

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

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 symmetric, two-network model, but subsequent work has shown that transaction volumes are generally non-differentiable in transaction fees when consumers carry multiple cards (Liu et al., 2021).

IV.G.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 can be justified under the assumption that Visa, the issuers, and acquirers can cooperate to maximize joint profits. Joint profit maximization holds whenever parties bargain under complete information with a complete contract space. Visa pays substantial side payments to both issuers and acquirers, separate from the fees in Figure 1.²¹ 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 imperfectly competitive issuers or a monopoly issuer.

IV.G.2 Price Coherence

I assume price coherence: merchants in the model charge the same price to consumers who use different payment methods. Historically, price coherence was the result of no-surcharge rules and laws imposed at different times by the U.S. federal government, the payment networks, and U.S. state governments (Blakeley and Fagan, 2015). Despite the gradual repeal of these laws, merchants are reluctant to pass on merchant fees to consumers (Stavins, 2018). In the DCPC, I find that only 0.9% of card transactions incur a surcharge and 2.5% of cash transactions earn a discount.

Merchants may choose to charge one price because the benefits of surcharging are small. If consumers do not change their payment method in response to a surcharge, then the loss from charging one price relative to surcharging is second order in the size of the merchant fees.²² The typical merchant in my estimated model gives up 0.0016% of their profits from charging one price relative to charging payment-specific prices. Potential first-order costs to surcharging such as menu costs or reputational costs could then overwhelm the benefits of surcharging.²³ If all merchants surcharge, that changes networks' incentives to raise merchant fees, which has large equilibrium effects. But if any one merchant surcharges, that only changes their own profits without affecting networks' incentives.

IV.G.3 Credit Cards as a Borrowing Instrument

I do not model the borrowing features of credit cards. To the extent consumers value paying on credit, this will increase the unobserved product characteristics of credit cards. If profits from interest charges fund rewards, the profits would show up as lower marginal cost estimates for

²¹In their 2019 10K, Visa reported \$6.2 billion in client incentives to issuers and acquirers on a total of \$29.2 billion in gross revenue.

²²In Appendix I.6, I show that in the model, no consumer would switch.

²³Caddy 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 that surcharges are only paid on 4% of card transactions.

credit card payments (Ru and Schoar, 2020; Agarwal et al., 2022). My model only relies on the importance of merchant fees in funding rewards, which is confirmed by the response of consumer rewards to interchange fee regulations discussed in Section II.

IV.G.4 Primary and Secondary Cards Reflect First and Second Choices

The model predicts that primary and secondary cards reveal first and second choices, even though consumers do not have a reason to hold multiple cards in a symmetric equilibrium. In Appendix B, I derive a dynamic micro-foundation for consumers' primary and secondary card holdings. Suppose consumers periodically update their primary card, and the payment utilities V_i^j are the utilities from choosing card j to be a new primary card. Then the stationary distribution of consumers' primary and secondary cards (as a Markov chain) exactly matches first and second choices. This interpretation is compatible with complementarities between rewards categories, provided that differences in quality across networks are similar for different rewards categories. Thus, consumers may carry cards from multiple networks not out of any conscious intent, but rather as a natural result of periodically choosing a new primary card.

If consumers' choices of primary and secondary cards reflect a portfolio problem, one might also expect that some consumers may choose two cards that are maximally differentiated, such as credit and debit. In this case, interpreting primary and secondary cards as first and second choices understates how willing consumers are to substitute between credit cards from different networks. But given that my estimated welfare effects increase in consumers' price sensitivities, my approach is conservative.

Section V Estimation

By estimating the model, I translate the reduced-form facts into quantitative statements about how competition affects 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 assume the aggregate shares and prices are an equilibrium of the model with three multiproduct payment networks—Visa, MC, and AmEx. Both Visa and MC each own two cards (debit and credit), while AmEx only owns a credit card network.

V.A Estimation Procedure

Although many steps occur jointly, estimation is most easily understood as a four-step process. I start by estimating consumer demand with variation in rewards and second-choice data. Second, I recover networks' marginal costs by inverting the networks' first-order conditions with respect to consumer rewards. Large rewards indicate that networks earn large profits from merchants, and thus networks' costs of processing transactions are low. Third, I infer that merchant demand must be inelastic from the fact that observed merchant fees far exceed marginal costs. Fourth, the elasticity, combined with moments from payment surveys, identifies the CES substitution parameter and the distribution of merchants' benefits from card acceptance.

V.A.1 Consumer Substitution Patterns

I first estimate how consumers substitute between payment methods of different characteristics and how consumers respond to changes in rewards. The distribution of random coefficients summarized in Σ governs substitution patterns, while the parameter α governs price sensitivity. These parameters are identified by the reduced-form facts on consumers' primary and secondary cards (Section III.B) and the effects of the Durbin Amendment on debit volumes (Section III.A).

I estimate substitution patterns without solving the full model. I leave the full details to Appendix C. I first derive a simplified representation of consumer preferences over cards that is valid when merchant adoption is held fixed. Second, I use this model to derive a mapping from the price sensitivity α and random coefficient distribution Σ to the predicted moments. Third, I estimate α, Σ jointly by matching the empirical moments, weighted by an optimal weight matrix.

I allow consumers in different data samples to have different mean valuations over payment options and different choice sets, but assume that the distribution of random coefficients Σ , the price sensitivity α , and the characteristics X^j of payment methods are the same across samples. This assumption is natural because I hold these variables constant across counterfactual simulations in which I introduce new products.

The simplified representation generates the insulated shares μ of each payment option a discrete choice model where the utility for payment method j is:

$$\begin{aligned} u_j &= \delta_j + \alpha f^j + \beta_i X^j + \eta_i^j \\ \beta_i &\sim N(0, \Sigma), \eta_i^j \sim \text{T1EV} \end{aligned} \tag{15}$$

where the new intercept δ_j absorbs the unobserved characteristics Ξ^j and the CES price indices $\log P^j$. The price sensitivity α and distribution of random coefficients Σ are the same as in the full model. This simplified model generates the same first- and second-choice probabilities as the full model.

I recover the distribution of random coefficients Σ by minimizing the distance between theoretical and empirical probabilities of each primary and secondary card combination. Intuitively, if the random coefficient on the credit characteristic is volatile, then primary credit card users' second choices are likely to also be credit cards. Since there is no price variation in HomeScan, I normalize $f^j = 0$ in Equation 15. I use second choice formulas from Berry et al. (2004) and the simplified representation to predict the probability of each primary and secondary card combination as a function of δ and Σ .

I estimate the price sensitivity coefficient α by matching the effects of the Durbin Amendment on debit card volumes. A large α matches the large effect of the Durbin Amendment on debit card volumes. From the Nilson panel, I estimate two micro-moments: the effect of the Durbin Amendment on signature debit volumes (Figure 2) and the share of signature debit card volumes of total signature debit and credit volumes (Table F.1). I impose a third aggregate moment that 20% of overall transactions by value are done by cash (Table F.5). Next, I simu-

late these moments with the representation in Equation 15 and minimize the difference between theoretical and empirical moments.

V.A.2 Merchant Benefits, Network Costs, and Unobserved Characteristics

I estimate the remaining parameters by matching the estimated effect of card acceptance on sales, the share of card consumers' spending at card merchants (both from Section III.C), and aggregate shares, and by inverting the networks' first-order conditions at the observed prices and shares.

I parameterize the distribution of merchant benefits G as a Gamma distribution with a mean $\bar{\gamma}$ and a standard deviation of σ_γ and adjust the mean and standard deviations to match the facts from the payment surveys. When the mean $\bar{\gamma}$ is large, merchants benefit more from accepting cards. As the standard deviation σ_γ increases, the share of merchants who do not benefit from card acceptance also increases, reducing consumers' expenditures at stores that accept cards. Thus, I can identify the distribution G from these empirical moments from the payment surveys. I set the cost of cash $c_0 = \tau_0 = 30$ bps to match past studies (European Commission, 2015; Felt et al., 2020). I leave the remaining details of this step to Appendix C.2.

V.B Estimated Parameters

I estimate precise consumer elasticities, merchant elasticities, and cost parameters. Table 4 contains all of the parameter estimates, and below I walk through the implications for elasticities.

The consumer parameters indicate that consumers are highly willing to substitute between payment methods, especially between payment methods with similar characteristics (e.g., credit vs. debit). This generates the model prediction that networks will raise merchant fees to fund rewards. I transform the random coefficients, unobserved characteristics, and price sensitivity into the semi-elasticities in Table 5. The first column of Table 5 shows that a 1-bp shock to Visa debit rewards, holding all else equal, increases the share of Visa debit primary card users by 2.4% with a standard error of 0.4%. The new consumers mostly come from MC debit, which declines by 2.5%. In contrast, MC credit only declines by 0.6%. The difference reflects the fact that consumers differ in their preferences for debit and credit cards. Cash use only declines by 0.3%. The small change reflects differences in consumers' valuation of cash versus cards. The third column shows a similar pattern for Visa credit. A shock to rewards steals consumers from MC credit and AmEx, while having a relatively muted effect on cash and debit users.

I estimate that merchants are price insensitive. Starting from an equilibrium in which three symmetric credit card networks charge the same price, a 1-bp increase in the fees to one credit card network leads to only a 0.16% decrease in the number of merchants who accept that card, with a standard error of only 0.01%. This is roughly one-tenth of the sensitivities I estimate for consumers. I describe how to calculate the merchant elasticity while holding consumer demand fixed in Appendix I.4.

I estimate that the average consumer would prefer to use debit cards if credit cards did not pay rewards. The average consumer is indifferent between a Visa debit card and a Visa credit

Table 4: Estimated parameters

Panel A: Consumer Parameters			Panel C: Network Parameters (bps)		
Parameter	Estimate	SE	Parameter	Estimate	SE
S.D. of Credit R.C.	2.0	0.0	Visa debit cost	43.3	0.2
S.D. of Card R.C.	4.9	0.1	Visa credit cost	13.7	0.4
Correlation of R.C.	-0.3	0.0	MC debit cost	52.3	0.1
Price sensitivity α	483.7	87.3	MC credit cost	56.1	0.3
Visa debit $\Xi \times 100$	-4.6	0.2	AmEx cost	57.7	0.4
Visa credit $\Xi \times 100$	-5.7	0.2	$\Delta\tau_{MC}$	0.1	0.0
MC debit $\Xi \times 100$	-4.8	0.2	$\Delta\tau_{AmEx}$	0.0	0.0
MC credit $\Xi \times 100$	-5.8	0.2			
AmEx $\Xi \times 100$	-5.9	0.2			

Panel B: External Estimates			Panel D: Merchant Parameters		
Parameter	Estimate	SE	Parameter	Estimate	SE
Cash cost c_0 (%)	0.30	Felt et al. (2020)	CES σ	7.2	1.9
			$\bar{\gamma}$	0.3	0.1
			$\log \frac{\sigma_\gamma}{\bar{\gamma}}$	-1.1	0.1

Notes: Consumer preferences over payment methods are determined by their payment utilities, $\log V_i^j = \log U^j + \Xi^j + \frac{1}{\alpha} (\eta_i^j + \beta_i X^j)$. S.D. refers to the standard deviation, and R.C. refers to the random coefficient. The standard deviation of the credit random coefficient, standard deviation of the card random coefficient, and correlation parameter describe the distribution of preferences β_i that consumers have over payment methods with a credit function and payment methods that are not cash. The Ξ are the unobserved characteristics. The fee adjustments $\Delta\tau_{MC}, \Delta\tau_{AmEx}$ exist because the model cannot rationalize three asymmetric networks charging identical merchant fees. The small size of the adjustments indicate the model is fitting a symmetric equilibrium between networks. A higher merchant CES elasticity σ reduces merchant margins. The distribution of γ is a Gamma distribution, with a mean $\bar{\gamma}$ and standard deviation σ_γ . I parameterize σ_γ as a log ratio to reduce correlation with the estimate of the mean.

Table 5: Estimated consumer own price and cross-price semi-elasticities.

Payment	V debit	MC debit	V credit	MC credit	AmEx
Cash	-0.3 (0.1)	-0.1 (0.0)	-0.6 (0.1)	-0.2 (0.0)	-0.2 (0.0)
V debit	+2.4 (0.4)	-1.0 (0.2)	-0.7 (0.1)	-0.3 (0.0)	-0.2 (0.0)
MC debit	-2.5 (0.4)	+3.9 (0.7)	-0.7 (0.1)	-0.3 (0.0)	-0.2 (0.0)
V credit	-0.6 (0.1)	-0.2 (0.0)	+2.8 (0.5)	-0.8 (0.1)	-0.7 (0.1)
MC credit	-0.6 (0.1)	-0.2 (0.0)	-2.0 (0.4)	+4.0 (0.7)	-0.7 (0.1)
AmEx	-0.6 (0.1)	-0.2 (0.0)	-2.0 (0.4)	-0.8 (0.1)	+4.1 (0.7)

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

Table 6: Fit of Durbin facts.

Effect On	Data	Model	Standard Error
Debit	-0.27	-0.27	0.06
Credit	0.35	0.30	0.09
All cards	-0.05	-0.04	0.05

Notes: The table compares the estimated effect of the Durbin Amendment on debit, credit, and overall card volumes against the simulated effects.

card that pays 1.1% in rewards. This preference will drive my welfare result that increases in credit card use relative to debit card use reduce welfare.

The network supply parameters are also precisely estimated. I estimate marginal cost parameters that average around 45 bps with a standard error of 0.3 bps. Because the network in the model combines issuer, acquirer, and network costs, it is reasonable given accounting estimates of issuer costs around 20–60 bps, acquirer costs of around 5–10 bps, and network costs below 5 bps.²⁴ Visa credit’s marginal cost is much lower because the model must rationalize why Visa pays such large rewards to consumers despite having significant market power, as evidenced by its large market share.

V.C Goodness of Fit

The model matches the effects of Durbin on credit and overall card volumes. The model slightly underestimates AmEx’s equilibrium fee, but otherwise matches prices and shares.

Table 6 shows how the model performs on an out-of-sample test: matching the facts on Durbin. This provides evidence that interpreting data on primary and secondary cards as first and second choices provides realistic estimates of substitution patterns in payments. The model exactly matches the percentage change in debit volumes, since it is a target moment in the estimation. However, the close match for percentage changes in credit and overall card volumes validates the substitution patterns from co-holding data with exogenous price variation.

Table 7 shows the baseline prices and quantities in my estimated model. The shares are slightly different than in Table F.6 because I have scaled Visa, Mastercard, and AmEx up to the entire card sector. The merchant prices are similar, although I slightly underpredict American Express’ merchant fee.

Section VI Counterfactuals

In my main counterfactual, I study the effects of a new payment app that shares characteristics with credit cards and emerging fintech payment apps. I show that entry increases merchants’

²⁴Issuer cost estimates come from cost-based benchmarks from interchange regulations. Analyses from NACHA suggest acquirers take around 5% of the fees of credit card acceptance, such that their costs are likely between 5–10 bps (NACHA, 2017). Visa’s operating profits are around two-thirds of revenue, and so at most has a marginal cost of around 5 bps.

Table 7: Baseline equilibrium prices and quantities

Variable (%)	Cash	Visa Debit	Visa Credit	MC Debit	MC Credit	Amex
Merchant fee	0.3	0.72	2.25	0.72	2.25	2.25
Rewards	0.0	0.00	1.30	0.00	1.30	1.36
Market share	20.0	23.88	26.27	9.55	10.75	9.55

cost of payments, as payment methods with high merchant fees and high rewards take a larger share of the market. Credit-averse consumers switch to credit cards to chase rewards. Consumer and total welfare fall.

My additional counterfactuals suggest that my results reflect excessive credit card adoption in the baseline equilibrium. Any policy or market structure change that reduces credit card use raises welfare. I find that repealing the Durbin Amendment’s restrictions on debit card interchange fees, regulating credit interchange, and merging Mastercard and American Express would all reduce credit card use and benefit consumers. I show that a revealed preference estimate of the welfare costs of excess credit card adoption quantitatively explains the welfare losses across my counterfactuals.

Across these counterfactuals, I assume that debit card merchant fees are capped at 0.72% unless otherwise specified. This is to be consistent with the Durbin Amendment’s effect on debit card interchange fees. Table 8 shows all of the counterfactual changes in payment prices, market shares, and the welfare effects for consumers who do not switch. Table 9 shows the overall consumer and total welfare effects.

VI.A Credit Payment App Entry

In this counterfactual, I show that the entry of a new payment network that shares characteristics with credit cards and emerging fintech payment apps increases merchant fees and consumer rewards and decreases consumer and total welfare. The value of this counterfactual is not that competition is always bad, but that given a realistic model of the U.S. payments market, plausible entrants can lower consumer and total welfare. This stands in contrast with our usual intuitions about the benefits of competition, especially in concentrated markets.

VI.A.1 Characteristics of the Entrant

Introducing a new product requires specifying the characteristics X^j, Ξ^j that enter consumer utility, the type χ^j of the payment method, and network costs. I give the app consumer characteristics X^j that are the same as a credit card and the same unobserved characteristic Ξ^j as AmEx. Consumers who dislike credit cards will therefore dislike the product, and this is important for the welfare results. I assume the new app is a new payment type $\chi^j = A$, so that a merchant who only accepts credit cards—but not the app—loses some sales from app users. Given these

characteristics and costs, I can solve for the new equilibrium after the app enters.

The assumption that the entrant is a new payment type is consistent with studies of e-commerce that consumers who prefer alternative payment methods are unwilling to substitute to cards when their preferred method is not available (Berg et al., 2022). The assumption can also be justified by the way new platforms are combining commerce and other financial services with payments into “superapps.” Not accepting the app would reduce demand from consumers who use the app even if those consumers own credit and debit cards.²⁵ In Appendix E, I show that this assumption is not essential for the welfare results.

VI.A.2 Effects on Prices and Shares

The new entrant pursues a high-merchant-fee, high-rewards strategy because consumers are price sensitive, whereas merchants are not. While consumers can substitute to traditional credit cards, merchants cannot serve app consumers by accepting credit cards. The entrant charges merchant fees of 2.64% and pays rewards of 1.64%. These are 39 bps and 28 bps higher than American Express’ baseline fees and rewards, respectively.

In response, incumbent credit card networks raise their fees by 8 bps to fund 15 bps more rewards. Incumbent debit cards raise rewards by only 8 bps because they are unable to raise their merchant fees due to the Durbin Amendment. After equilibrium price responses, incumbent credit networks lose 3 percentage points (pp) of market share, incumbent debit networks lose 3 pp of market share, and the market share of cash falls by 4 pp.

VI.A.3 Distributional Effects

Entry exacerbates regressive transfers from cash and debit consumers to credit consumers and hurts all consumers who do not switch to the new platform. These results show that the findings on redistribution by Felt et al. (2020) hold in an equilibrium framework. This step requires that merchants charge the same price to consumers who use different payment methods and pass on merchant fees to retail prices. Merchants’ costs of payments increase both because fees have risen and because more consumers are using high-merchant-fee payment options. On average, merchant prices rise by 16 bps.

For consumers who do not switch, the change in welfare is simply the change in subsidies less the change in the price index. The welfare of cash users who do not switch falls the most. Their consumption falls by 16 bps due to higher retail prices. Debit card users lose 9 bps of consumption as debit networks can slightly increase rewards, and incumbent credit card users lose 4 bps. Debit rewards rise by less because debit networks cannot raise merchant fees under Durbin. Scaling by the market shares of each of these payment instruments in the baseline equilibrium results in losses of \$3 billion for cash consumers, \$3 billion for debit consumers, and \$2 billion for incumbent credit card consumers.

²⁵For example, in their 2021 financial results “buy now pay later” platform, Klarna argues that “the Klarna app is now the single largest driver of [gross merchandise volume] across the Klarna ecosystem, fueling growth for Klarna and its retail partners through consumer acquisition and referrals... our app is becoming a central place in our consumers’ financial lives.”

Table 8: Changes in market shares, prices, and welfare of users of incumbent payment methods across counterfactuals.

	Counterfactual			
	Credit App Entrant	Repeal Durbin	Cap Credit Interchange	Merge AmEx/MC
Δ Shares (pp)				
Cash	-4	-2	12	2
Debit	-3	10	18	2
Credit	-3	-8	-29	-4
Δ Merchant Fees (bps)				
Debit	0	28	0	0
Credit	8	4	-98	3
Δ Rewards (bps)				
Debit	8	21	-12	-3
Credit	15	2	-71	-9
Δ Welfare (bps)				
Cash	-16	-3	62	7
Debit	-9	18	50	3
Credit	-4	-1	-6	-3
Δ Welfare (\$ billion)				
Cash	-3	-1	16	1
Debit	-3	7	21	1
Credit	-2	-1	-2	-1

Notes: Welfare in bps measures changes in rewards, less increases in retail prices on a per-capita basis. This welfare metric applies to any consumer who does not switch. Welfare in billions multiplies the per-capita measure by the share of consumers who use each payment method in the baseline equilibrium, and then scales up to the \$10 trillion in annual consumer-to-business payments.

VI.A.4 Consumer Welfare Effects

To study the consumer welfare effects of entry, I decompose consumer welfare into three terms—retail prices, the average subsidy paid, and non-pecuniary utility. This step requires revealed preference, as well as the assumption that the new app is also disliked by consumers who dislike traditional credit cards. Let E_i^k be an indicator that consumer i chooses payment method k . I decompose consumer welfare²⁶ as:

$$\mathbb{E} \left[\max_k \log V_i^k \right] = \underbrace{-\log P^0}_{\text{Retail Prices}} + \underbrace{\sum_k \mu^k f^k}_{\text{Rewards}} + \underbrace{\mathbb{E} \left[\sum_k E_i^k \left(-\log \frac{P^k}{P^0} + \Xi^k + \frac{1}{\alpha} (\eta_i^k + \beta_i X^k) \right) \right]}_{\text{Non-Pecuniary Utility}}$$

where μ^k is the insulated market share of instrument k as a primary payment method.

The first term captures the loss to all consumers from higher retail prices. In contrast to a standard model that normalizes the value of the outside option to zero, I set the value of the outside option to the welfare of a cash consumer. The welfare of the cash user is low if retail prices are high. The second term captures the average level of subsidies paid to consumers, weighted by the market share of each payment instrument. The third term is then the residual and captures the extent to which consumers choose payment methods that offer high non-pecuniary utility.

In practice, changes in non-pecuniary utility primarily reflect some consumers' distaste for credit cards. The marginal debit consumer could use a credit card that pays rewards, but chooses not to.²⁷ By revealed preference, this marginal consumer must be credit averse. Credit aversion could reflect a fear of overspending on a credit card, psychic costs of using a more complicated payment instrument, or a general aversion to debt.²⁸ When more consumers use credit cards, this non-pecuniary term falls.

Aggregate consumer welfare falls by 7 bps. Scaled up to the \$10 trillion in consumer-to-business payments, this represents \$7 billion per year in lost consumption. The decline in consumer welfare is surprising because entry typically raises consumer welfare by reducing markups and increasing variety (Petrin, 2002). However, because entry raises retail prices, worsening the outside option, and because credit card adoption is already excessive, the introduction of a new network with similar characteristics to credit cards makes consumers worse off in equilibrium. Table 9 shows how the three terms contribute to consumer welfare. Higher retail prices reduce welfare by \$16 billion, higher subsidies increase welfare by \$20 billion, but the shift to payment instruments with lower non-pecuniary utility hurts consumers by \$10 billion. Non-pecuniary

²⁶Aggregating consumer welfare requires a strong assumption that the planner puts equal welfare weights on credit and debit users, which is unlikely given that credit card consumers are much higher income. Given that we already saw that entry exacerbates the regressive transfers, my calculation should be considered a lower bound on the harms to consumers.

²⁷I interpret the marginal consumer between debit and credit as a debit consumer who uses credit cards more than the median debit consumer, but who nonetheless prefers debit. Table 1 shows that 76% of these consumers own rewards credit cards, yet still put the majority of transactions on a debit card.

²⁸I discuss the survey evidence for this in Appendix D.

Table 9: Decomposing the consumer and total welfare effects across counterfactuals.

	Counterfactual			
	Credit App Entrant	Repeal Durbin	Cap Credit Interchange	Merge AmEx/MC
Consumer Welfare (\$ billion)				
Retail prices	-16	-3	62	7
Rewards	20	0	-51	-11
Non-pecuniary utility	-10	8	28	6
Consumers	-7	5	38	1
Total Welfare (\$ billion)				
Merchants	0.5	-0.4	1.1	-0.6
Networks	-4	1	-11	5
Total	-10	6	28	6
Revealed preference	-9	10	29	6

Notes: Declines in non-pecuniary utility mostly capture the losses from credit-averse consumers using credit cards. Revealed preference refers to the approximation discussed in Section VI.C.

utility falls because credit-averse consumers switch to credit cards for the rewards. The ultimate loss is \$7 billion of consumption.

The retail price externality changes the sign of welfare calculations. If I ignored the equilibrium effect of retail prices, a standard discrete choice analysis based on observed market shares would lead to a \$10-billion increase in consumer welfare from entry. However, after including the retail price externalities, I arrive at a loss of \$7 billion in consumer welfare.

VI.A.5 Total Welfare Effects

Total welfare declines because network profits fall as well. To measure total welfare, I assume all of the profits from either merchants or the networks are rebated to consumers equally. Table 9 decomposes the total welfare effects. Merchant profits rise by a negligible amount because consumers have higher incomes from higher network subsidies that offset higher transaction fees. Total network profits, including the entrant, fall by \$4 billion, or 12% of industry profits. Profits fall because networks compete harder to attract consumers and merchants. The net result is that total welfare falls by \$10 billion.

Another way to understand the total welfare decline is that each credit-averse consumer who switches to credit cards lowers total surplus. The switcher bears a non-pecuniary cost from credit aversion in order to earn rewards. But while credit aversion is a social loss, the rewards are merely transfers paid for with higher retail prices. Total welfare falls.

VI.B Regulating Interchange Fees and Payment Antitrust

I consider three other counterfactuals to demonstrate that the welfare effects that I find for entry reflect a broader theme: credit card use is excessive, and anything that decreases credit card use increases welfare. I repeal the Durbin Amendment, regulate credit card interchange, and merge Mastercard and American Express. In each of these cases, total welfare rises because credit card use falls. The model is valuable because it highlights that the consumer welfare effects arise due to changes in consumer payment choices, not solely changes in prices.

VI.B.1 Repealing Durbin

Repealing the Durbin Amendment creates a progressive transfer from credit to debit consumers and increases consumer welfare. I repeal the Durbin Amendment in the model by raising the cap on debit card fees to 1% from their current level at 0.72%. This generates approximately the same level of debit rewards as in the pre-Durbin data. Merchant fees for debit cards rise by 28 bps, and debit rewards rise by 21 bps. Consumers switch to debit cards. The market share of debit cards rises by 10 pp, and the market share of credit cards falls by 8 pp.

Repealing Durbin increases consumption of debit card users by 18 bps but reduces consumption of credit card and cash users by 1 and 3 bps, respectively. After scaling by market shares, this is a gain of \$7 billion for debit consumers and losses of \$1 billion each for cash and credit consumers.

Consumers as a whole gain \$5 billion of consumption. Although higher retail prices cost consumers \$3 billion of consumption, slightly higher subsidies and \$8 billion in gains from reduced debt aversion more than compensate. Total welfare thus rises by \$6 billion as networks enjoy higher profits from stealing market share from cash.

VI.B.2 Regulating Credit Card Interchange

Regulating credit card interchange creates a progressive transfer from credit consumers to cash and debit consumers and increases consumer welfare. I cap merchant fees for Visa and MC credit cards at 1%. I do not regulate AmEx to be consistent with interchange regulations in practice. Credit card rewards fall by 71 bps. The fall in credit card rewards is muted because American Express is able to continue to charge merchant fees of 1.93% to fund rewards.²⁹ Consumers switch to debit cards. The market share of debit cards rises by 18 pp, and the market share of credit cards falls by 29 pp.

Consumption of cash and debit card users rises by 62 and 50 bps, respectively. Consumption of credit card users falls by 6 bps. Scaled up by market shares, these are gains of \$21 billion and \$16 billion for debit and cash consumers, respectively, and a loss of \$2 billion for credit card consumers.

²⁹After Visa and MC credit cards were regulated in Australia in 2003, American Express' merchant fees stayed around 1pp higher than Visa and MC, even 8 years later (Chan et al., 2012).

Consumers as a whole gain \$38 billion of consumption. Although the fall in rewards costs \$51 billion in consumption, lower retail prices generate \$62 billion of gains, and reducing the cost of debt aversion generates \$28 billion of gains. Total welfare rises by only \$28 billion as network profits fall.

VI.B.3 Merger Counterfactual

Merging AmEx and Mastercard without any cost efficiencies generates a small increase in consumer and total welfare. This result illustrates how the effects of competition in two-sided markets differ starkly from one-sided markets. Whereas mergers without efficiencies in one-sided markets always hurt consumers (Nocke and Whinston, 2022), merging two payment platforms can increase consumer and total welfare. Credit card networks create a retail price externality when they raise rewards rates to induce consumers to use more credit cards. Adoption is excessive. A merger reduces output, reduces the externality, and thereby raises welfare.

When AmEx and MC merge, merchant fees for credit cards rise by 3 bps, but more importantly, credit card rewards fall by 9 bps. Consumers switch to cash and debit cards. The market share of cash rises by 2 pp, and the market share of debit cards rises by 2 pp. Merchant fees fall when competition is reduced through a merger because both AmEx and MC credit are the same payment type χ . Therefore, merchants are more price sensitive to their relative prices. This is different than the entry counterfactual, in which the entrant is a different payment type χ .

The merger creates progressive transfers. Cash and debit consumers gain 7 and 3 bps of consumption, respectively, whereas credit users lose 3 bps. All consumers benefit from lower retail prices, but only the credit card users are hurt by a large decline in rewards. Scaled up by market shares, these are gains of \$1 billion each for debit and cash consumers, and a loss of \$1 billion for credit card consumers.

Consumers as a whole gain \$1 billion of consumption. Although lower rewards cost consumers \$11 billion of consumption, reduced debt aversion and lower retail prices more than compensate. Total welfare rises by \$6 billion as networks enjoy higher profits from the reduction in competition.

The merger counterfactual shows that prices are not sufficient for understanding welfare effects in two-sided markets. Merchant fees rise and consumer rewards fall, so both sides of the market face worse prices. Nonetheless, consumer and total welfare fall as fewer credit-averse consumers use credit cards in the counterfactual.

VI.C Revealed Preference Accounting of Welfare Effects

The total welfare effects across the counterfactuals are close to a revealed preference estimate for the aggregate loss from credit aversion. This shows that changes in credit aversion drive my total welfare results. By revealed preference, the marginal cash or debit user that switches to credit cards has an aversion toward credit cards equal to the value of credit card rewards. Thus, the estimated total welfare change from credit aversion is the difference between credit and debit

card rewards multiplied by the share of consumers who switch to cash and debit, i.e.:

$$\Delta W \approx (f^{\text{Credit}} - f^{\text{Debit}}) \times (\Delta \tilde{\mu}^{\text{Debit}} + \Delta \tilde{\mu}^{\text{Cash}})$$

The revealed preference approximation highlights that the contribution of the model is primarily to offer accurate predictions of how market shares change in response to regulations or competition. Conditional on the changes in shares, the welfare effects I calculate follow from revealed preference. The last row of Table 9 compares the output of the revealed preference argument with the actual effects I calculate with the model. This approximation fits well for almost all counterfactuals. The revealed preference estimate overstates the welfare benefits of repealing Durbin because the simple revealed preference argument does not incorporate some cash users' aversion to debit cards.

Given the centrality of revealed preference in generating my welfare results, a natural question to ask is whether revealed preference applies to consumer payment choice. Incorporating constraints does not affect the estimated welfare results. Because all models need to match the reduced-form fact on the effect of the Durbin Amendment, models with constraints would still need to predict the same changes in market shares as a function of rewards. Because the above revealed preference argument still applies for each person who switches, incorporating constraints would not change the total estimated welfare loss.

If the revealed preference argument fails, then the total welfare effects are reduced but the distributional effects remain. Revealed preference fails if consumers have access to credit cards with different rewards. Potentially, the reason debit consumers do not use credit cards is because they cannot access the same kinds of high-rewards credit cards as credit consumers. This changes the revealed preference argument by reducing the inferred value of credit aversion. The revealed preference argument also fails if consumers are generally inattentive but change payment methods in response to changes in rewards. In that case, a shock like Durbin may prompt consumers to switch, but the steady-state shares of people using debit and credit are not informative of preferences.

VI.D Summary of Counterfactual Results

An important theme from the counterfactuals is that credit card use is currently excessive, and this one fact shapes whether market structure or regulatory changes increase or decrease welfare. Entry makes credit cards more attractive, decreasing welfare. Either relaxing the Durbin Amendment or capping credit card merchant fees makes credit cards less attractive and thus raises consumer welfare. Mergers without efficiencies in one-sided markets always reduce consumer welfare. Yet because an MC and AmEx merger lowers credit card rewards, it raises consumer welfare.

Section VII Conclusion

In this paper, I study how competition from new payment networks would affect prices and welfare in the U.S. payment market. I find that payment markets are inefficient because of too much credit card use, not too little competition. Thus, a payment app that shares characteristics with credit cards and emerging fintech payment apps increases the total fees merchants pay to process payments, increases consumer rewards, and lowers consumer and total welfare. Entry reduces consumer welfare, as credit-averse consumers switch to using credit cards to take advantage of rewards. Such switching behavior inflates the aggregate price level and generates social losses. Unlike in standard antitrust settings in which competition benefits consumers through low prices and high output, payment network competition can cause harm through high prices and high output.

More broadly, my work relates to a range of questions about two-sided markets, such as the welfare effects of price discrimination in two-sided markets, competition between two-sided markets in dynamic settings, and the welfare effects of platform competition under price coherence. Consumer rewards depend on income levels, and merchant fees vary by sector. What are the welfare effects of this form of price discrimination? Payment networks take time to form. How do interchange regulations affect dynamic competition? More broadly, my empirical approach that uses variation on one side of the market to identify both sides' preferences can be used to study the welfare effects of network competition in other two-sided markets with price coherence. For example, online platforms like Facebook and Google fund large investments in consumer apps with high advertising prices. To what extent does competition between such platforms inflate retail prices and encourage excess app adoption? I hope to study some of these questions in future work.

References

- Agarwal, Sumit, Andrea F Presbitero, Andre F Silva, and Carlo Wix**, “Who Pays For Your Rewards? Cross-Subsidization in the Credit Card Market,” May 2022, p. 51.
- , **Souphala Chomsisengphet, Neale Mahoney, and Johannes Stroebel**, “Regulating Consumer Financial Products: Evidence from Credit Cards *,” *The Quarterly Journal of Economics*, February 2015, 130 (1), 111–164.
- , –, –, and –, “Do Banks Pass through Credit Expansions to Consumers Who Want to Borrow?,” *The Quarterly Journal of Economics*, February 2018, 133 (1), 129–190.
- , **Sujit Chakravorti, and Anna Lunn**, “Why Do Banks Reward Their Customers to Use Their Credit Cards?,” December 2010.
- Anderson, Simon P., Øystein Foros, and Hans Jarle Kind**, “Competition for Advertisers and for Viewers in Media Markets,” *The Economic Journal*, February 2018, 128 (608), 34–54.
- Arango, Carlos, Kim P. Huynh, and Leonard Sabetti**, “Consumer Payment Choice: Merchant Card Acceptance versus Pricing Incentives,” *Journal of Banking & Finance*, June 2015, 55, 130–141.
- Armstrong, Mark**, “Competition in Two-Sided Markets,” *The RAND Journal of Economics*, September 2006, 37 (3), 668–691.
- Bakos, Yannis and Hanna Halaburda**, “Platform Competition with Multihoming on Both Sides: Subsidize or Not?,” *Management Science*, December 2020, 66 (12), 5599–5607.
- Benetton, Matteo**, “Leverage Regulation and Market Structure: A Structural Model of the U.K. Mortgage Market,” *The Journal of Finance*, 2021, 76 (6), 2997–3053.
- Berg, Tobias, Valentin Burg, Jan Keil, and Manju Puri**, “On the Rise of Payment Firms,” *Working Paper*, May 2022, p. 55.
- Berry, Steven, James Levinsohn, and Ariel Pakes**, “Differentiated Products Demand Systems from a Combination of Micro and Macro Data: The New Car Market,” *Journal of Political Economy*, February 2004, 112 (1), 68–105.
- Blakeley, Scott and Ruth Fagan**, “A History of Credit Card Transaction Costs and the Suppliers Newly Minted Right to Surcharge to Make Credit Cards a More Competitive Payment Channel,” *The Credit and Financial Management Review*, December 2015.
- Boehm, Jennifer White**, “Credit Cards US,” Technical Report, Mintel July 2018.
- Buchak, Greg, Gregor Matvos, Tomasz Piskorski, and Amit Seru**, “Beyond the Balance Sheet Model of Banking: Implications for Bank Regulation and Monetary Policy,” *Working Paper*, January 2020, p. w25149.

- Budish, Eric, Peter Cramton, and John Shim**, “The High-Frequency Trading Arms Race: Frequent Batch Auctions as a Market Design Response*,” *The Quarterly Journal of Economics*, November 2015, 130 (4), 1547–1621.
- Caddy, James, Luc Delaney, and Chay Fisher**, “Consumer Payment Behaviour in Australia: Evidence from the 2019 Consumer Payments Survey,” *RBA Discussion Paper*, June 2020.
- Caillaud, Bernard and Bruno Jullien**, “Chicken & Egg: Competition among Intermediation Service Providers,” *The RAND Journal of Economics*, 2003, 34 (2), 309.
- Chan, Iris, Sophia Chong, and Stephen Mitchell**, “The Personal Credit Card Market in Australia: Pricing over the Past Decade,” *RBA Bulletin*, March 2012, pp. 55–64.
- Chan, Lester T.**, “Divide and Conquer in Two-sided Markets: A Potential-game Approach,” *The RAND Journal of Economics*, December 2021, 52 (4), 839–858.
- Chang, Howard, David S. Evans, and Daniel D. Garcia Swartz**, “The Effect of Regulatory Intervention in Two-Sided Markets: An Assessment of Interchange-Fee Capping in Australia,” *Review of Network Economics*, January 2005, 4 (4).
- Cohen, Alma and Liran Einav**, “Estimating Risk Preferences from Deductible Choice,” *American Economic Review*, June 2007, 97 (3), 745–788.
- Commission, DG Comp European**, “Survey on Merchants’ Costs of Processing Cash and Card Payments: Final Results, March 2015.,” Technical Report, Publications Office, LU March 2015.
- , “Study on the Application of the Interchange Fee Regulation: Final Report.,” Technical Report, Publications Office, LU 2020.
- Constantine, Lloyd**, *Priceless: The Case That Brought Down the Visa/Mastercard Bank Cartel*, Skyhorse Publishing, 2012.
- Crouzet, Nicolas, Apoorv Gupta, and Filippo Mezzanotti**, “Shocks and Technology Adoption: Evidence from Electronic Payment Systems,” *Working Paper*, November 2020, p. 97.
- Edelman, Benjamin and Julian Wright**, “Price Coherence and Excessive Intermediation*,” *The Quarterly Journal of Economics*, August 2015, 130 (3), 1283–1328.
- Egan, Mark, Ali Hortaçsu, and Gregor Matvos**, “Deposit Competition and Financial Fragility: Evidence from the US Banking Sector,” *American Economic Review*, January 2017, 107 (1), 169–216.
- Emmerton, Kelly**, “Credit Card Rewards Schemes Devalued as Interchange Fee Changes Come into Effect,” June 2017.
- Farboodi, Maryam and Gregor Jarosch**, “The Emergence of Market Structure,” *The Review of Economic Studies*, February 2022, p. 32.

- , – , and Ursula Wiriadinata, “Intermediation as Rent Extraction,” *Working Paper*, 2019, p. 75.
- Felt, Marie-Hélène, Fumiko Hayashi, Joanna Stavins, and Angelika Welte**, “Distributional Effects of Payment Card Pricing and Merchant Cost Pass-through in the United,” Federal Reserve Bank of Boston Research Department Working Papers, Federal Reserve Bank of Boston December 2020.
- Gabaix, Xavier and David Laibson**, “Shrouded Attributes, Consumer Myopia, and Information Suppression in Competitive Markets,” *Quarterly Journal of Economics*, May 2006, 121 (2), 505–540.
- Gans, Joshua S**, “Evaluating the Impact of the Payment System Reforms,” Technical Report January 2007.
- Gowrisankaran, Gautam and Joanna Stavins**, “Network Externalities and Technology Adoption: Lessons from Electronic Payments,” *The RAND Journal of Economics*, 2004, 35 (2).
- Gunn, Emma**, “As M&S Slashes Credit Card Perks Are Reward Cards Worth It?,” <https://www.thisismoney.co.uk/money/cardsloans/article-3469425/As-M-S-Bank-latest-provider-slash-perks-credit-cards-lucrative-rewards-cards-left-worth-considering.html> February 2016.
- Guthrie, Graeme and Julian Wright**, “Competing Payment Schemes,” *Journal of Industrial Economics*, March 2007, 55 (1), 32.
- Hayashi, Fumiko**, “The New Debit Card Regulations: Initial Effects on Networks and Banks,” *Federal Reserve Bank of Kansas City Economic Review*, 2012, p. 38.
- Higgins, Sean**, “Financial Technology Adoption,” *Working Paper*, December 2020, p. 80.
- Honka, Elisabeth, Ali Hortaçsu, and Maria Ana Vitorino**, “Advertising, Consumer Awareness, and Choice: Evidence from the U.S. Banking Industry,” *The RAND Journal of Economics*, August 2017, 48 (3), 611–646.
- Huynh, Kim, Gradon Nicholls, and Oleksandr Shcherbakov**, “Equilibrium in Two-Sided Markets for Payments: Consumer Awareness and the Welfare Cost of the Interchange Fee,” *Bank of Canada Working Paper*, March 2022.
- Huynh, Kim P, Jozsef Molnar, Oleksandr Shcherbakov, and Qinghui Yu**, “Demand for Payment Services and Consumer Welfare: The Introduction of a Central Bank Digital Currency,” *Bank of Canada Currency Department Working Paper*, March 2020, p. 34.
- Issa, Erin El**, “Americans Favor Debit Over Credit for Their Go-To Card,” Technical Report, Nerdwallet September 2017.
- Jensen, Austen**, “Lack of Payments Competition Only Benefits Visa & Mastercard,” May 2022.

- Koijen, Ralph S. J. and Motohiro Yogo**, “The Cost of Financial Frictions for Life Insurers,” *American Economic Review*, January 2015, 105 (1), 445–475.
- Koulayev, Sergei, Marc Rysman, Scott Schuh, and Joanna Stavins**, “Explaining Adoption and Use of Payment Instruments by US Consumers,” *RAND Journal of Economics*, 2016.
- Li, Bin Grace, James McAndrews, and Zhu Wang**, “Two-Sided Market, R&D, and Payments System Evolution,” *Journal of Monetary Economics*, November 2020, 115, 180–199.
- Liu, Chunchun, Tat-How Teh, Julian Wright, and Junjie Zhou**, “Multihoming and Oligopolistic Platform Competition,” *SSRN Working Paper*, 2021, p. 47.
- Mukharlyamov, Vladimir and Natasha Sarin**, “Price Regulation in Two-Sided Markets: Empirical Evidence from Debit Cards,” *Working Paper*, September 2022.
- NACHA**, “Understanding the Cost of Processing Card Payments,” Technical Report, Optimized Payments Consulting 2017.
- Nelson, Scott T**, “Private Information and Price Regulation in the US Credit Card Market,” *Working Paper*, 2020, p. 63.
- Nilson, Report**, “Card Fraud Losses Reach \$28.65 Billion,” *Nilson Report*, December 2020, (1187).
- , “Merchant Processing Fees in the United States,” May 2020, (1176).
- , “U.S. Consumer Payment Systems,” *Nilson Report*, December 2020, (1188).
- , “Visa and Mastercard – U.S. 2019,” *Nilson Report*, February 2020, (1169).
- Nocke, Volker and Michael D. Whinston**, “Concentration Thresholds for Horizontal Mergers,” *American Economic Review*, June 2022, 112 (6), 1915–1948.
- Orem, Tina**, “Credit Unions Revive Debit Rewards,” *Credit Union Times*, January 2016.
- Petrin, Amil**, “Quantifying the Benefits of New Products: The Case of the Minivan,” *Journal of Political Economy*, 2002, 110 (4).
- Prelec, Drazen and George Loewenstein**, “The Red and the Black: Mental Accounting of Savings and Debt,” *Marketing Science*, February 1998, 17 (1), 4–28.
- Read, John R, Meagan K Bellshaw, Cory Brader Leuchten, and Sarah H Licht**, “United States of America v. Visa Inc. and Plaid Inc.,” November 2020.
- Reserve Bank of Australia**, “Review of Retail Payments Regulation - Conclusions Paper,” Technical Report October 2021.
- Reserve, Board Federal**, “Money and Payments: The U.S. Dollar in the Age of Digital Transformation,” *Federal Reserve Discussion Paper*, January 2022.

- Robles-Garcia, Claudia**, “Competition and Incentives in Mortgage Markets: The Role of Brokers,” *Working Paper*, May 2022.
- Rochet, Jean-Charles and Jean Tirole**, “Cooperation among Competitors: Some Economics of Payment Card Associations,” *The RAND Journal of Economics*, 2002, 33 (4), 549.
- **and —**, “Platform Competition in Two-Sided Markets,” *Journal of the European Economic Association*, June 2003, 1 (4), 990–1029.
- Ru, Hong and Antoinette Schoar**, “Do Credit Card Companies Screen for Behavioural Biases?,” *BIS Working Paper*, 2020, p. 53.
- Rysman, Marc**, “AN EMPIRICAL ANALYSIS OF PAYMENT CARD USAGE,” *Journal of Industrial Economics*, March 2007, 55 (1), 1–36.
- Schneider, James and S.K. Prasad Borra**, “The Future of Finance: Redefining “The Way We Pay” in the Next Decade,” Technical Report, Goldman Sachs Equity Research March 2015.
- Shin, Hyun Song**, “CBDCs: An Opportunity for the Monetary System,” *BIS Annual Economic Report*, June 2021.
- Sidel, Robin**, “Amex-Costco Divorce Shakes Up Card Industry; Costco Cards Account for One Out of Every 10 Amex Cards in Circulation,” *Wall Street Journal*, February 2015.
- Stavins, Joanna**, “Consumer Preferences for Payment Methods: Role of Discounts and Surcharges,” *Journal of Banking & Finance*, September 2018, 94, 35–53.
- tsin Huang, Tien**, “Meeting Takeaways: Ready for Challenges Ahead,” Equity Research Report, JP Morgan November 2010.
- Usher, Andrew, Edona Reshidi, Francisco Rivandeneira, and Scott Hendry**, “The Positive Case for a CBDC,” *Bank of Canada Banking and Payments Department Discussion Paper*, July 2021, p. 20.
- Valverde, Santiago Carbó, Sujit Chakravorti, and Francisco Rodríguez Fernández**, “The Role of Interchange Fees in Two-Sided Markets: An Empirical Investigation on Payment Cards,” *Review of Economics and Statistics*, May 2016, 98 (2), 367–381.
- Weyl, E. Glen**, “A Price Theory of Multi-Sided Platforms,” *American Economic Review*, September 2010, 100 (4), 1642–1672.
- White, Alexander and E. Glen Weyl**, “Insulated Platform Competition,” *SSRN Electronic Journal*, 2016.

A Additional Model Details

A.1 Deriving the Consumer Demand Function for Merchants

Each consumer has symmetric CES preferences over merchants, and payment acceptance enters into quality. There is 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 has income y^w . The consumer chooses a consumption vector $q^w(\omega)$ to maximize utility subject to a budget constraint:

$$U^w = \max_{q^w} \left(\int_0^1 \left(1 + \gamma(\omega) v_{M^*(\omega)}^w \right)^{\frac{1}{\sigma}} q^w(\omega)^{\frac{\sigma-1}{\sigma}} d\omega \right)^{\frac{\sigma}{\sigma-1}}$$

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

The presence of $v_{M^*(\omega)}^w$ means that a consumer derives higher utility from consuming at a merchant that accepts a card the consumer wants to use. I assume 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^w , 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:

$$q^w(\gamma, p, M, y^w, P^w) = (1 + \gamma v_M^w) p^{-\sigma} \frac{y^w}{(P^w)^{1-\sigma}} \quad (16)$$

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

In this demand curve, only γ, v_M^w , and p vary across merchants. The price index P^w and the income y^w are not affected by any one merchant's actions.³⁰

The CES assumption underpins my welfare analysis. I infer from card consumers' higher consumption at merchants who accept cards as indicating that consumer utility goes up from card acceptance. CES provides a disciplined framework for adding up the utility benefits across merchants to arrive at an aggregate value of card acceptance.

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

³⁰This 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.

A.2 Deriving Merchant Optimal Pricing

The profit function as a function of the price is:

$$\Pi(p, \gamma, M, P, \tau, \tilde{\mu}) = \sum_{w \in \mathcal{W}} \tilde{\mu}^w \left[\underbrace{q^w p (1 - \tau_M^w)}_{\text{Net Revenue}} - \underbrace{q^w}_{\text{Costs}} \right] \quad (17)$$

Where the fee τ_M^w for wallet $w = (w_1, w_2)$ is the fee of the payment method that is finally used. Formally, it is $\tau_M^w = \sum_{j \in \mathcal{J}} I_{j,M}^w \tau_j$, where the indicators $I_{j,M}^w$ are defined in Equation 3 and detect if payment method j is used.

The expression for profit in Equation 17 is a wallet weighted average of revenues, net of transaction fees, less production costs, which have been normalized to 1. The merchant's optimal pricing problem is:

$$\hat{p}(\gamma, M^*(\gamma), P, \tau, \tilde{\mu}) = \underset{p}{\operatorname{argmax}} \Pi(p, \gamma, M, P, \tau, \tilde{\mu}) \quad (18)$$

The optimal price passes on the average transaction fee to the consumer. To solve the optimal pricing problem, note that each q^{w*} is still a CES demand curve that satisfies the property:

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

Let the optimal price for the firm, holding fixed the pricing and adoption decisions of other merchants, be \hat{p} . Then the first-order condition is:

$$\sum_{w \in \mathcal{W}} \left[\frac{\partial q^w}{\partial p} (\hat{p} (1 - \tau^w) - 1) + q^w (1 - \tau^w) \right] = 0$$

Rearranging terms yields and the expression for the optimal price as a function of the average transaction fee $\hat{\tau}$. This average transaction fee in turn depends on the merchant's type γ , the merchant's payment options M , the vector of transaction fees τ , and the aggregate price indices P^* . The realized transaction fee is:

$$\begin{aligned} \hat{\tau} &= \frac{\sum_w \tilde{\mu}^w q^w \tau_M^w}{\sum_w \tilde{\mu}^w q^w} \\ &= \frac{\sum_w \frac{\tilde{\mu}^w y^w}{(p^w)^{1-\sigma}} (1 + \gamma v_M^w) \tau_M^w}{\sum_w \frac{\tilde{\mu}^w y^w}{(p^w)^{1-\sigma}} (1 + \gamma v_M^w)} \end{aligned}$$

An important contribution of CES is that the relative composition of consumers does not depend on the price.

A.3 Calculating Network Profits

Below, I describe how to calculate network profits. First, note that the total dollars can also be expressed in terms of insulated shares μ^w and a new expression for insulated dollars, d_j^w , that does not depend on the normalizing constant C .

$$\tilde{d}_j^w = \frac{\mu^w}{C} d_j^w, d_j^w = \int I_{M^*(\gamma),j}^w \left(1 + \gamma v_{M^*(\gamma)}^w\right) p^*(\gamma)^{1-\sigma} dG(\gamma)$$

The profits networks earn from merchants can then be re-expressed as a sum involving insulated dollars:

$$T_j = \frac{1}{C} \times (\tau_j - c_j) \sum_{w \in \mathcal{W}} d_j^w \quad (19)$$

To calculate the cost of consumer rewards, I assume that consumers receive rewards according to a fixed percent of their equilibrium spending.³¹ This assumption is equivalent to assuming networks pay all consumers the same rewards per transaction but pay these rewards in a lump sum fashion with knowledge of equilibrium payment volumes. I calculate the total rewards that card j pays as:

$$S_j = f^j \tilde{\mu}^j \left(\frac{\sum_{k \neq j} d_j^{(j,k)} + d_j^{(k,j)}}{d_j^{(j,0)}} \right) \quad (20)$$

where $\tilde{\mu}^j \equiv \mu^{(j,0)}$ is the share of consumers who only use card j . Intuitively, the network must pay out $f^j \tilde{\mu}^j$ to these agents. I then scale this by the ratio of spending on j by all agents relative to the amount of spending the agents who use only j spend on j . The total spending iterates over the wallets in which j is either the primary or secondary card.

There is one last fixed point between the normalizing constant C , the actual market shares $\tilde{\mu}$, and the rewards paid to each type of agent. To get around this issue, I make a simplifying assumption that, for the purpose of calculating network profits, the agents who carry multiple cards can be assumed to receive the reward of their primary card. This is a small adjustment since it reflects a second-order effect of differences in rewards causing consumers to have differences in income, changing spending, and thus affecting transaction fee income. Thus, I approximate

³¹If a single-homing American Express user spends \$0.50 on American Express and earns \$0.02 in rewards, and a single-homing Visa user spends \$1 on Visa and earns \$0.02 in rewards, a multihoming consumer who spends \$0.50 on Visa and \$0.50 on American Express should earn \$0.03 of rewards.

the profits from merchants \tilde{T}_j and the reward bill \tilde{S}_j as:

$$\tilde{T}_j = \frac{1}{\tilde{C}} \times (\tau_j - c_j) \sum_{w \in \mathcal{W}} d_j^w \quad (21)$$

$$\tilde{S}_j = \frac{1}{\tilde{C}} f^j \frac{\mu^{(j,0)} (P^j)^{1-\sigma}}{1 + f^j} \left(\frac{\sum_{k \neq j} d_j^{(j,k)} + d_j^{(k,j)}}{d_j^{(j,0)}} \right) \quad (22)$$

$$\tilde{C} = \sum_{w=(w_1, w_2) \in \mathcal{W}} \frac{\mu^w (P^w)^{1-\sigma}}{1 + f^{w_1}}$$

A.4 Solving for Equilibrium Profits

To compute the equilibrium, I first assume the promised utility levels U are satisfied. The utility levels give insulated shares μ^w by Equation 11. Merchant adoption then follows from solving for the upper envelope of quasiprofit functions from Equation 26. The merchant adoption strategy yields the CES price indices P according to Equation 4. The CES price indices combined with the CES utility levels U give how much rewards f the networks need to pay from Equation 10. Equations 13, 21, and 22 then yield the network profits.

B A Micro-Foundation for Interpreting Co-Holding Data as Hypothetical First and Second Choices

This note outlines a micro-foundation by which consumers' secondary cards can be used to identify hypothetical second choices for primary card. I assume consumers have wallets with two cards: a primary card and a secondary card. The consumer usually uses the primary card and with some small probability uses the secondary card. Periodically, consumers re-assess their primary card and choose primary cards of different brands with some probabilities. If the brand of the primary card changes, the consumer then downgrades the existing primary card to secondary status, and the new card becomes the primary card.

The conditional distribution of the secondary card conditional on the brand of the primary card will then have the same distribution as second choices for primary cards conditional on the primary card. In other words, the fact that Visa cards are often found in wallets of primary AmEx users will mean that Visa is a close substitute for AmEx.

B.1 Environment and Proof

Let time be discrete $t = 1, 2, \dots$. For consumer i at time t , suppose that the utility from choosing a card $j \in \{1, \dots, J\} \equiv \mathcal{J}$ is

$$u_{ijt} = \delta_{ij} + \epsilon_{ijt}$$

Suppose her wallet at time t contains two cards, $w_t = (p_t, s_t)$, where $p_t \in J$ is the primary card and s_t is the secondary card. Then at time $t + 1$, the consumer draws new utilities and chooses a new primary card $p_{t+1} \in J$ that yields the highest utility. If $p_{t+1} = p_t$, then the wallet does not change and $w_{t+1} = w_t$. Otherwise, the new primary card changes, and then the old primary card becomes the new secondary card $s_{t+1} = p_t$. Hence $w_{t+1} = (p_{t+1}, s_{t+1})$.

Theorem 1. *The joint stationary distribution of w_t is the same as the joint distribution of first and second choices, that is*

$$P \left(\left(u_{ijt} = \max_{l \in \mathcal{J}} u_{ikt} \right) \cap \left(u_{ikt} = \max_{l \in \mathcal{J} \setminus \{j\}} u_{ilt} \right) \right) = P(p = j, s = k)$$

Proof. Suppress i for clarity. The probability of choosing j is

$$q(j) = \frac{\exp(\delta_j)}{\sum_{l \in \mathcal{J}} \exp(\delta_l)}$$

The joint distribution of first and second choices comes from a standard result on logit choice probabilities:

$$P \left(\left(u_{jt} = \max_{l \in \mathcal{J}} u_{lt} \right) \cap \left(u_{kt} = \max_{l \in \mathcal{J} \setminus \{j\}} u_{lt} \right) \right) = q(j) \times \frac{q(k)}{\sum_{l \neq j} q(l)}$$

Next we calculate the joint stationary distribution of the wallets w_t . Denote this stationary distribution with P_i . Fix the wallet $w_{t+1} = (p_{t+1}, s_{t+1})$ at time $t + 1$. For this to have occurred, there are two possibilities for the wallet at time t . In the first case, the wallet did not change and $w_{t+1} = w_t$. This happens with probability $q(p_{t+1}) P(w_{t+1})$. In the second case, a new primary card was chosen at time $t + 1$ such that the primary card is p_{t+1} and the secondary card was s_{t+1} . This happens with probability

$$\begin{aligned} q(p_{t+1}) \sum_{k=1}^J P(w_t = (s_{t+1}, k)) &= q(p_{t+1}) q(s_{t+1}) \sum_{w_{t-1}} P(w_{t-1}) \\ &= q(p_{t+1}) q(s_{t+1}) \end{aligned}$$

We can then drop time subscripts, and the stationary distribution P must then be determined by:

$$\begin{aligned} P(w) &= q(p) P(w) + q(p) q(s) \\ P(w) &= \frac{q(p) q(s)}{1 - q(p)} \\ &= q(p) \times \frac{q(s)}{\sum_{l \neq p} q(l)} \end{aligned}$$

Which is the same as Equation B.1. □

B.2 Discussion

This works because an IIA assumption holds conditional on i . For a given i , if a particular card p is the primary card, then the probability a different card is the second choice is determined by just dividing the probabilities.

The assumption that the primary card changes only if the new primary card is a different brand helps to map the thought experiment to my empirical work. In my empirical work, the secondary card counts any card brand with any amount of positive spending. Therefore, if a Visa/Mastercard multihomer decides to add a new Visa card to her wallet, provided that she puts some positive spending on Mastercard, I will count her secondary card as Mastercard. Adding a new card does not change primary/secondary status if the new card has the same brand as the old primary card.

A key behavioral assumption is that the consumer does not choose the new primary card based on the network of the secondary card. This is equivalent to assuming there are no complements or substitution effects that would make cards from different networks attractive or unattractive to hold together.

The model is consistent with different cards being complements for each other because they have different rewards categories, provided that the different networks have similar coverage of the rewards categories. For example, the trigger for getting a new card may be a desire to

get a credit card in a new rewards category. But provided that the choice probabilities for each network do not depend on rewards category, the above micro-foundation shows that primary and secondary cards can still reveal hypothetical first and second choices.

C Estimation Details

C.1 Consumer Substitution

I first discuss how I use the Homescan data. Let cash be the outside option, and order the choice set in Homescan as debit, Visa credit, MC credit, and AmEx. For each possible wallet (j, k) where j is not cash, let s_{jk} be the estimated probability that a Homescan consumer is a primary j user and a secondary k user. Stack these shares as s . I use the simplified representation in Equation 15 to calculate model implied probabilities. Since there is no price variation in Homescan I normalize $f^j \equiv 0$. The probability of a given combination of primary and secondary cards equals

$$\hat{s}_{jk}(\Sigma, \delta) = \int \frac{\exp(\delta_j + \beta_i X^j)}{\sum_l \exp(\delta_l + \beta_i X^l)} \times \frac{\exp(\delta_k + \beta_i X^k)}{\sum_{l \neq j} \exp(\delta_l + \beta_i X^l)} dH(\beta_i) \quad (23)$$

where H is the joint distribution of β_i (Berry et al., 2004). I compute this with Monte Carlo integration. Stack the model implied shares as \hat{s} .

Next, I describe how I use the Nilson data. I order the choice set of payment methods as cash, signature debit, and credit cards to match the data provided.³² Let the mean utilities in this model be $\tilde{\delta}$ to distinguish from the mean utilities used in the Homescan data. Let $\Delta f = 25$ bps, which is the change in debit rewards as a result of Durbin. The model implied moments are

$$\hat{m}(\Sigma, \alpha, \phi) = \left(\begin{array}{c} \log \int \frac{\exp(\tilde{\delta}_1 - \alpha \Delta f + \beta_i X^1)}{\sum_k \exp(\tilde{\delta}_k - \alpha \Delta f I_{\{k=1\}} + \beta_i X^k)} - \log \int \frac{\exp(\tilde{\delta}_1 + \beta_i X^1)}{\sum_k \exp(\tilde{\delta}_k + \beta_i X^k)} \\ \int \frac{\exp(\tilde{\delta}_1 + \beta_i X^1)}{\sum_k \exp(\tilde{\delta}_k + \beta_i X^k)} \times \left(\int \frac{\exp(\tilde{\delta}_1 + \beta_i X^1)}{\sum_k \exp(\tilde{\delta}_k + \beta_i X^k)} + \int \frac{\exp(\tilde{\delta}_2 + \beta_i X^2)}{\sum_k \exp(\tilde{\delta}_k + \beta_i X^k)} \right)^{-1} \\ \int \frac{1}{\sum_k \exp(\tilde{\delta}_k + \beta_i X^k)} \end{array} \right)$$

where all integrals are against the distribution H of random coefficients β_i .

I estimate the consumer substitution parameters with GMM with the optimal weight matrix. I estimate the covariance matrices of the micro-moments in s , m with the Bayesian bootstrap. I assume that the aggregate cash moment is independent of the other moments and is observed with only a small 1 bps standard error. Denote the estimated covariances as \hat{S}_1, \hat{S}_2 respectively. Since the empirical moments are from different datasets, the optimal weight matrix W is block diagonal with \hat{S}_1^{-1} and \hat{S}_2^{-1} . Stack the model moments as $\hat{g}(\Sigma, \alpha, \delta, \phi) = \left(\hat{s}(\Sigma, \delta) \quad \hat{m}(\Sigma, \alpha, \tilde{\delta}) \right)^T$ and the data moments as $g = \left(s \quad m \right)^T$. Stack the parameters as $\theta_1 = \left(\Sigma \quad \alpha \quad \delta \quad \tilde{\delta} \right)^T$. I estimate θ_1 by solving

$$\hat{\theta}_1 = \underset{\theta_1}{\operatorname{argmin}} (\hat{g}(\theta_1) - g)^T W (\hat{g}(\theta_1) - g)$$

I use the estimates $\hat{\alpha}, \hat{\Sigma}$ in the next step, but the mean utility levels $\delta, \tilde{\delta}$ are nuisance parameters.

³²The crucial assumption is that the customers of these small regional banks consider only cash, their bank's debit card, and their bank's credit cards in their choice set. If borrowers substitute across banks, I over-estimate substitution. Yet in Figure G.1 I do not observe asset substitution across banks.

C.2 Merchant Benefits and Network Costs

Let the first data moment ϕ_1 be the share of card consumers' spending at card stores (97%). Let the second data moment ϕ_2 be the logistic regression coefficient of how consumers' card preference relates to whether a transaction is done at a card merchant (Table 3). Stack these data moments as ϕ .

To calculate the analogous model moments, define expenditure at all merchants with types $\gamma \geq \gamma'$ for a consumer with wallet w as $e^w(\gamma')$. This is an integral of expenditure at each type of merchant:

$$e^w(\gamma') = \int_{\gamma > \gamma'} q^{w*}(\gamma) p^*(\gamma) dG(\gamma)$$

Let $\mathcal{M} = \{w \in \mathcal{W} : w_1 \in \{\text{Visa Credit, MC Credit, AmEx}\}\}$ be the set of wallets that are primary credit card consumers. Let $\mathcal{C} = \{w \in \mathcal{W} : w_1 = \text{Cash}\}$ be the set of wallets of primary cash users. Let γ^* be the lowest merchant type that accepts all credit cards.³³ The two model moments are

$$\begin{aligned} \hat{\phi}_1 &= \frac{\sum_{w \in \mathcal{M}} e^w(\gamma^*)}{\sum_{w \in \mathcal{M}} e^w(0)} \\ \hat{\phi}_2 &= \ell(\hat{\phi}_1) - \ell\left(\frac{\sum_{w \in \mathcal{C}} e^w(\gamma^*)}{\sum_{w \in \mathcal{C}} e^w(0)}\right) \\ \ell(p) &= \log \frac{p}{1-p} \end{aligned}$$

The first moment is the expenditure share of credit card consumers at card stores. The second moment is the difference in the logits of two expenditure shares: the shares of credit and cash consumers' spending at card stores. Stack these two model moments as $\hat{\phi}$.

I make an assumption on fees. First, I assume that the aggregate fees are observed with error because my model cannot rationalize three credit card networks of different sizes charging identical fees. Instead of matching the surveyed fees in Table F.6, I instead assume that MC credit charges a fee $\tau_{\text{Visa Credit}} + \Delta\tau_{\text{MC}}$ and that AmEx charges a fee $\tau_{\text{Visa Credit}} + \Delta\tau_{\text{MC}} + \Delta\tau_{\text{AmEx}}$, where $\Delta\tau_{\text{MC}}$ and $\Delta\tau_{\text{AmEx}}$ are fee adjustment parameters to be estimated.

I can then jointly estimate the parameters by finding the 15 parameters to match 2 moment conditions $\hat{\phi} = \phi$, 8 first-order conditions, and 5 share constraints. The 15 parameters are the average $\bar{\gamma}$ and standard deviation σ_γ of merchant benefits, the 5 marginal cost parameters c for each card, the 5 utility intercepts Ξ for each card, the two fee adjustments $\Delta\tau_{\text{MC}}, \Delta\tau_{\text{AmEx}}$, and the CES substitution parameter σ . The 8 first-order conditions are the 3 first-order conditions of each credit card network with respect to its merchant fee and the 5 first-order conditions of each card with respect to the promised utility U^j to the consumer. Debit card fees are not at a first-order condition due to the Durbin Amendment. The 5 share constraints require that at the profit maximizing promised utility for each card, the resulting aggregate shares $\tilde{\mu}$ from Equation

³³I treat credit card acceptance as the sign of accepting all cards because some merchants in the model accept debit but not credit.

12 match the data.³⁴ I solve the moment conditions and the first-order conditions jointly because the distribution of merchant types affects the networks' first-order conditions.

I calculate the standard errors through the delta method. Denote all the parameters to be estimated in this step as θ_2 . Stack all the first-order conditions and moment conditions into a function F . The estimate $\hat{\theta}_2$ solves the equation:

$$F(\hat{\theta}_2, \hat{\theta}_1, \hat{\phi}) = 0$$

The implicit function theorem gives a representation of $\hat{\theta}_2$ as $\hat{\theta}_2(\hat{\theta}_1, \hat{\phi})$ with a known Jacobian. I calculate the covariance matrix of $(\hat{\theta}_1, \hat{\phi})$ by using the Bayesian bootstrap for the distribution of $\hat{\phi}$ and the GMM formula for $\hat{\theta}_1$. The delta method converts the covariance matrix and the Jacobian into a full covariance matrix for $\hat{\theta}_2$.

³⁴Here I use true market shares rather than insulated shares because the wedge between the two depends on the CES price index, which can change across parameter specifications.

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

Table D.1: Survey data on why consumers choose their preferred payment instrument

	Cash	Debit, Low Credit Share	Debit, High Credit Share	Credit
Budget Control	0.15	0.09	0.09	0.04
Convenience	0.31	0.40	0.41	0.28
Rewards	0.00	0.02	0.03	0.28

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

Fear of overspending is a significant concern for many consumers. Table D.1 summarizes data from the SCPC 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).

There is also some evidence that some consumers find debit cards simpler to use. Table D.1 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 likely refers to any concerns about making sure to make on-time payments with a credit card. 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., 2015, 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 28% 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.

E Merchant Substitution Between the Entrant and Credit Cards

In this counterfactual I relax the assumption that consumers who use the entrant's payment network shop less at stores that only accept credit cards but not the entrant. After relaxing the assumption, the entrant can be thought of as a fourth credit card network, like Discover, becoming as large as AmEx. In this case I obtain qualitatively similar welfare results. The main difference is that credit card merchant fees fall by less than one bp. However, credit card rewards still increase by 5 bps and debit card rewards rise by a smaller 3 bps. The entrant still causes more consumers to adopt high-cost payment methods, which generates similar welfare results.

Entry still exacerbates regressive transfers. The higher cost of payments causes the retail price level to rise by 6 bps. Cash users therefore lose 6 bps of consumption, debit users lose 3 bps, and credit users on average lose 1 bp.

Consumer and total welfare still fall. Consumers as a whole lose \$2 billion of consumption. Although the net effect of higher subsidies and higher prices still puts consumers \$2 billion ahead, the \$4-billion cost from more debt-averse consumers using credit cards results in lower consumer welfare after entry. Total welfare falls by \$4 billion as networks compete down profits.

F Additional Tables

Table F.1: Summary statistics of Nilson Report panel

	N	Mean	P25	P50	P75
Assets	309	29126.09	4207.34	9673.76	34162.04
Credit	296	1431.63	365.44	554.50	1455.00
Debit	294	4928.75	1237.25	2526.00	5435.00
Signature Debit	292	3035.46	783.75	1270.50	2715.25
Treated	309	0.48	0.00	0.00	1.00

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

Table F.2: Average of transaction characteristics in the payment diary sample

	Ticket Size	Use Cash	Use Debit	Use Credit	Merchant Accepts Card
Mean	21.86	0.38	0.34	0.28	0.95

Table F.3: Summary statistics of the Homescan sample

	N	Mean	P25	Median	P75
Years per Household	92107	3.06	1.00	2.00	5.00
Transactions	92107	500.49	134.00	306.00	669.00
Average Tx Size	92107	56.62	35.41	49.56	69.43

Table F.4: Comparing Homescan payment shares to aggregate shares

Payment Method	Homescan	Nilson
Amex	0.04	0.10
Cash	0.24	0.20
Debit	0.37	0.33
MC	0.11	0.11
Visa	0.24	0.26

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

Table F.5: Aggregate shares and cost of card acceptance derived from the Nilson Report

Payment Method	Volume in 2019 (Tr)	Share of Total
Total	9.6	
Cash + Check	1.9	20%
Cards	7.7	80%
Credit	4.0	42%
Visa	2.1	22%
MC	0.9	9%
AmEx	0.8	8%
Discover	0.1	1%
Debit	3.3	34%
Visa	1.9	20%
MC	0.8	8%
Other	0.6	6%
o/w Other Cards	0.4	4%

Notes: The data in this table combines both aggregate payment data from Nilson (2020c) and data on individual networks from Nilson (2020d,b). “Other Cards” captures private label credit cards, SNAP EBT cards, and prepaid cards

Table F.6: Aggregate prices for merchants and consumers and estimates of acceptance locations.

Card	Average Merchant Discount	Rewards	Number of Acceptance Locations (Mln)
Visa + MC Credit	2.25%	1.30%	10.7
AmEx	2.27%	1.36%	10.6
Visa + MC Debit	0.72%	0%	

Notes: I calculate rewards for Visa + MC Credit from Agarwal et al. (2018), who report that typical consumer banks pay out around 1.4% of purchase volume for rewards and fraud expense. In the US, banks typically pay around 10 bps of fraud expense (Nilson, 2020a). Therefore rewards are around 1.3%. From American Express’s 2019 10k, I calculate that American Express earned around \$26 billion in gross discount revenue but paid out around \$15.7 billion in net rewards. This yields a rewards rate of 1.36%. Debit cards no longer offer rewards checking in the wake of Durbin (Hayashi, 2012). Hence a rewards rate of 0%. Merchant discount fees are calculated from a survey of acquirers. Acceptance locations are also estimates obtained from the Nilson Report (Nilson, 2020d).

Table F.7: 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	-0.034 (0.086)	-0.007 (0.051)	-0.100 (0.104)	-0.111+ (0.060)
Treat, t=-3	0.103 (0.084)	0.050 (0.032)	0.002 (0.098)	-0.006 (0.050)
Treat, t=-2	-0.104 (0.073)	0.016 (0.016)	-0.084* (0.038)	-0.016 (0.027)
Treat, t=0	0.005 (0.055)	-0.119 (0.079)	0.168** (0.057)	-0.006 (0.056)
Treat, t=1	-0.449*** (0.101)	-0.103* (0.044)	0.176* (0.075)	0.020 (0.048)
Treat, t=2	-0.363** (0.116)	-0.198** (0.056)	0.285** (0.085)	0.002 (0.057)
Treat, t=3	-0.358** (0.105)	-0.274*** (0.059)	0.352*** (0.095)	-0.048 (0.057)
N	292	292	296	281
Bank FE	X	X	X	X
Year FE	X	X	X	X
Cluster N	39	39	39	39

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

Table F.8: Subgroup analysis for the effect of card preference on the likelihood the consumer shops at a store that accepts card

	Credit vs Debit	Singlehome	Singlehome CC	Income Group
Prefer Credit	0.25* (0.11)			
Prefer Debit	0.33*** (0.09)			
Singlehome X Prefer Card		0.11 (0.13)	0.06 (0.09)	
Prefer Card		0.27** (0.09)	0.28** (0.09)	0.45*** (0.13)
High Income X Prefer Card				-0.26 (0.17)
N	29661	29101	29253	29661
State, year FE	X	X	X	X
Transaction controls	X	X	X	X
Consumer controls	X	X	X	X

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

Notes: Standard errors are clustered at the consumer level. Transaction Char. FE refers to FE's for the ticket size, the merchant type (e.g., restaurant or retail),. Consumer Char. FE refers to FE's for the consumer's income, education, credit score, and age

Table F.9: 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	MC	Visa
AmEx	N	11568	111	142	527
	% row	93.7	0.9	1.1	4.3
Debit	N	639	132097	1422	2670
	% row	0.5	96.5	1.0	2.0
MC	N	444	426	26806	1057
	% row	1.5	1.5	93.3	3.7
Visa	N	871	910	1079	61791
	% row	1.3	1.4	1.7	95.6

Table F.10: 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	0.76	0.18	0.95
Visa	0.81	0.15	0.97
MC	0.77	0.18	0.95
Debit	0.86	0.11	0.97

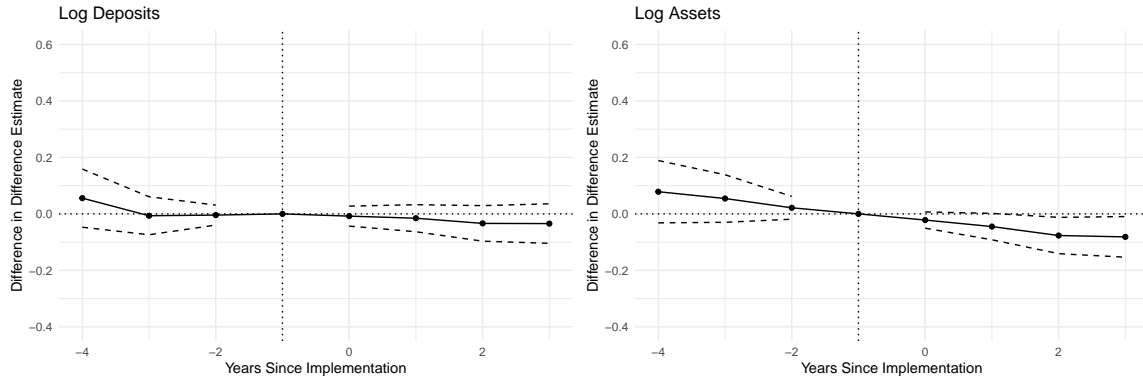
Table F.11: Number of credit cards and debit cards carried by typical consumer

	Rysman (2007)	DCPC	Homescan
Share of credit card single-homers	0.51	0.39	0.38

Notes: The number for Rysman (2007) is the conditional probability of owning only one of a Visa, MC, or AmEx credit card conditional on owning at least one. This is different than the number he reports for single-homing because I ignore Discover. The probability from the DCPC is the share of Visa, MC, or AmEx credit card holders who hold only one of the three. The Homescan probability is the share of consumers who, over the course of a year, have transactions on only one of Visa credit, MC credit, or AmEx, conditional on having transactions on at least one of the three.

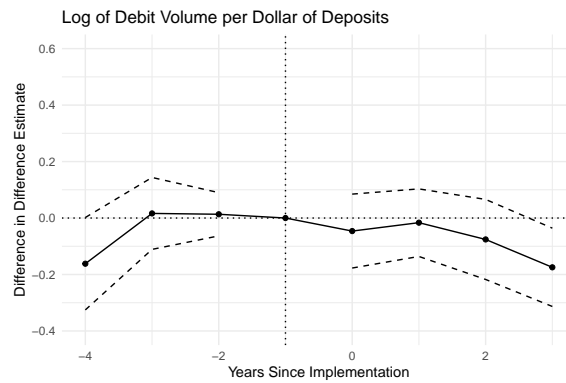
G Additional Figures

Figure G.1: The effect of the Durbin Amendment on deposits and assets



Notes: The vertical line marks the year before the policy announcement. The policy went into full effect in year 2012, which is at $t = 1$.

Figure G.2: The effect of the Durbin Amendment on overall debit volumes



Notes: The vertical line marks the year before the policy announcement. The policy went into full effect in year 2012, which is at $t = 1$.

H A Method for Calculating Derivatives of Expectations of Non-differentiable Functions

Suppose $f : \mathbb{R}^N \rightarrow \mathbb{R}$ is continuous but non-differentiable. Then by a standard convolution theorem

$$h : \mathbb{R}^N \rightarrow \mathbb{R}$$

$$\mu \mapsto \mathbb{E}[f(X)], X \sim N(\mu, \sigma^2 I)$$

is differentiable. This note explains how to efficiently compute an approximation to the partial derivatives of h . This is non-trivial because the standard Monte Carlo approximation of h as $\hat{h} = N^{-1} \sum_{i=1}^N f(X_i)$ where $X_i \sim N(\mu, \sigma^2 I)$ does not generate a differentiable function in μ .

The key trick is to use the fact that convolution and differentiation commute. Let $g(x) = \mathbb{E}[f(X_1, \dots, X_N) | X_1 = x]$. Then by the law of iterated expectations,

$$\mathbb{E}[f(X)] = \mathbb{E}[g(X_1)]$$

By the law of iterated expectations, we have that

$$\mathbb{E}[f(X)] = \mathbb{E}[g(X_1)]$$

$$= \frac{1}{\sqrt{2\pi\sigma^2}} \int_{\mathbb{R}} g(z) \exp\left(-\frac{1}{2\sigma^2}(z - \mu_1)^2\right) dz \quad (24)$$

where μ_1 is the first term in μ . Interchanging differentiation and integration yields

$$\frac{\partial}{\partial \mu_1} \mathbb{E}[f(X)] = \frac{1}{\sqrt{2\pi\sigma^2}} \int_{\mathbb{R}} g(z) \frac{z - \mu_1}{\sigma^2} \exp\left(-\frac{1}{2\sigma^2}(z - \mu_1)^2\right) dz \quad (25)$$

Equations 24 and 25 provide integral expressions for the expectation and the derivative of the expectation. To approximate these expectations, one can simulate g with standard Monte Carlo techniques as \hat{g} . While \hat{g} will not be differentiable, by the convolution theorem expressions 24 and 25 will both be differentiable even if g is replaced by \hat{g} . The remaining integral can then be calculated efficiently by Gauss-Hermite quadrature.

I Quasiprofits

I.1 Proof of Approximation

Theorem 2. For any γ, M, P, τ ,

$$\hat{\Pi} - \bar{\Pi} = (1 + \gamma) O\left((\tau^{\max})^2\right)$$

where

$$\bar{\Pi}(\gamma, M, P, \tau) \equiv \frac{1}{C} \left(\frac{\sigma}{\sigma - 1} \right)^{1-\sigma} \left\{ -a_M + b_M \gamma + \frac{1}{\sigma} \right\} \quad (26)$$

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

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

$$\tau^{\max} = \max_j \tau_j \quad (27)$$

Proof. I first prove the theorem for $\gamma = 0$, and when $\tau = 0$. I then use the envelope theorem to extrapolate to small values of τ . From the definition in Equation 17, profits in general are

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

Suppress the \mathcal{W} and leave out the $\frac{1}{C}$ normalizing factor. When $\gamma = 0$, profit simplifies to

$$\hat{\Pi} = \sum_w \mu^w \hat{p}^{-\sigma} (\hat{p}(1 - \tau_M^w) - 1)$$

$$\hat{p} = \frac{\sigma}{\sigma - 1} \frac{1}{1 - \hat{\tau}}$$

At a fee of zero, $\hat{\tau} = 0$. Hence profits are

$$\begin{aligned} \hat{\Pi}(0) &= \frac{1}{\sigma - 1} \times \hat{p}^{-\sigma} \left(\sum_w \mu^w \right) \\ &= \left(\frac{\sigma}{\sigma - 1} \right)^{1-\sigma} \frac{1}{\sigma} \left(\sum_w \mu^w \right) \end{aligned}$$

We next establish the result for small τ . By the envelope theorem, the derivative of the

optimized profit for a $\gamma = 0$ firm with respect to the transaction fees τ at zero is

$$\begin{aligned} \left. \frac{\partial \hat{\Pi}}{\partial \tau_j} \right|_{\tau_j=0} &= \sum_w \mu^w \hat{p}^{-\sigma} \left(-\hat{p} I_{j,M}^w \right) \\ &= - \left(\frac{\sigma}{\sigma-1} \right)^{1-\sigma} \sum_w \mu^w I_{j,M}^w \end{aligned}$$

where the indicator $I_{j,M}^w$ is an indicator capturing whether payment method j is used by the wallet w when the merchant accepts M . Crucially, we have that the indicators multiplied by the fees gives the card fee that the consumer will cause the merchant to pay $\sum_{j=1}^J I_{j,M}^w \tau_j = \tau_M^w$. We can then compute profits at a generic level of fees with a Taylor approximation. Up to second-order terms in τ , this should equal:

$$\begin{aligned} \hat{\Pi}(\tau) &= \hat{\Pi}(0) + \sum_{j=1}^J \frac{\partial \hat{\Pi}}{\partial \tau_j} \tau_j + O((\tau^{\max})^2) \\ &\approx \sum_w \mu^w \left[\left(\frac{\sigma}{\sigma-1} \right)^{1-\sigma} \frac{1}{\sigma} - \left(\frac{\sigma}{\sigma-1} \right)^{1-\sigma} \tau_M^w \right] \\ &= \left(\frac{\sigma}{\sigma-1} \right)^{1-\sigma} \left[- \sum_w \mu^w \tau_M^w + \frac{1}{\sigma} \right] \end{aligned}$$

This establishes the theorem for $\gamma = 0$ and small τ .

Next we prove the result for generic γ . Recall that $\hat{\tau}$ is the realized average card fee that the merchant incurs and enters into optimal pricing. Drop terms that are of order $O(\tau^2)$. By the envelope theorem we can ignore the effect of changing γ on the optimal price. Hence the derivative of optimized profit with respect to γ is

$$\begin{aligned} \frac{\partial \hat{\Pi}}{\partial \gamma} &= \sum_w \mu^w v_M^w \hat{p}^{-\sigma} (\hat{p} (1 - \tau^w) - 1) \\ &\approx \sum_w \mu^w v_M^w \left(\frac{\sigma}{\sigma-1} \right)^{-\sigma} (1 - \sigma \hat{\tau}) \left(\frac{\sigma}{\sigma-1} (1 + \hat{\tau}) (1 - \tau^w) - 1 \right) \\ &\approx \left(\frac{\sigma}{\sigma-1} \right)^{-\sigma} \frac{1}{\sigma-1} \times \sum_w \mu^w v_M^w (1 - \sigma \hat{\tau}) (1 + \sigma \hat{\tau} - \sigma \tau^k) \\ &\approx \left(\frac{\sigma}{\sigma-1} \right)^{1-\sigma} \frac{1}{\sigma} \sum_w \mu^w v_M^w (1 - \sigma \tau^k) \end{aligned}$$

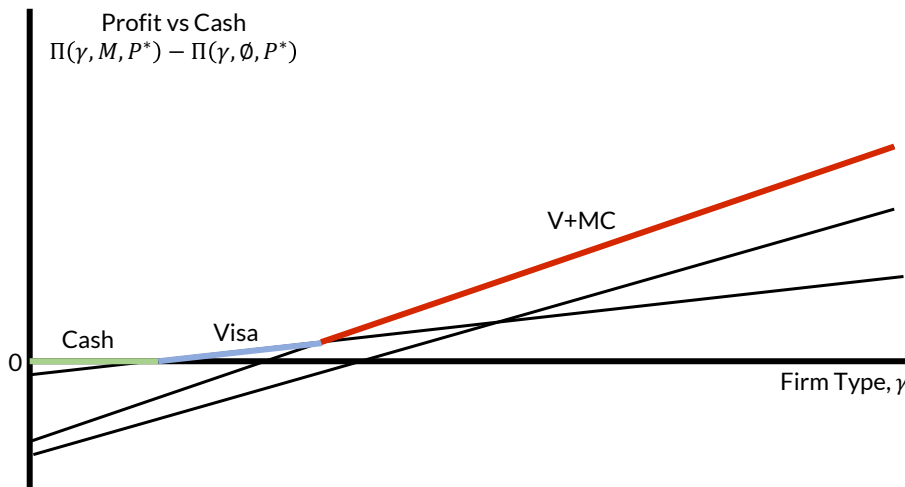
Integrating the derivative from 0 to γ gives the desired result. \square

Linearity means the adoption equilibrium for the continuum of merchants can be computed by solving for the upper envelope of a collection of linear functions. I use this fact to illustrate the similarities between my model of merchant adoption and that of Rochet and Tirole (2003). I elaborate on these issues below.

I.2 Example of Calculating the Equilibrium

Figure I.1 shows an example of computing an equilibrium when Visa charges merchants low fees but has a low market share among consumers, MC charges high fees and has a high market share, and cash is free. At $\gamma = 0$, because cards cost more than cash, all of the quasiprofit functions for bundles M that include cards are less than the quasiprofit for cash. Therefore, merchants with low benefit parameters γ choose to only accept cash. However, because Visa's fee is lower, its y -intercept is closer to zero and its quasiprofit function crosses zero first. The crossing point marks the start of a region of merchants who only accept Visa. When the quasiprofit function for the combination of Visa plus MC exceeds the quasiprofit function for Visa, all merchants of that type or higher will then accept both.

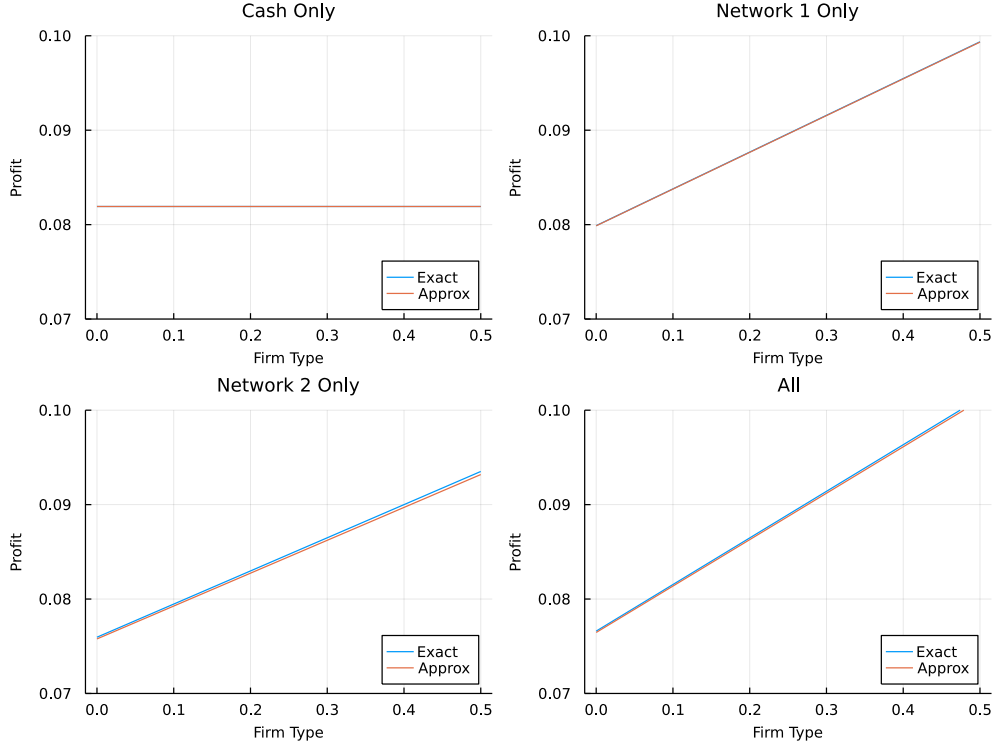
Figure I.1: Illustration of how to compute the merchant adoption subgame.



I.3 Quality of Approximation

A natural question is whether the quasiprofit functions are a good approximation of true profits. Figure I.2 compares exact and approximate profits in a case with two networks with symmetric market shares, differentiated only by the two networks charge different fees. The fit is very close for all values of the merchant type γ .

Figure I.2: Numerical example of how quasiprofit functions approximate true profit functions for a case of two networks with symmetric consumer parameters but who set merchant fees of $\tau_1 = 0.02$ and $\tau_2 = 0.04$



I.4 Comparison with Rochet and Tirole (2003)

The linearity of quasiprofits also reveals how the extent to which consumers hold one card or two will shape 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.

I.5 Calculating the Derivative of Merchant Acceptance

If all other credit card networks charge a fee of τ^* and one network deviates to a fee of τ , the lowest merchant type that accepts the deviating network is γ' where

$$\gamma'(\tau) = \begin{cases} \frac{\sigma\tau}{1-\sigma\tau} & \tau < \tau^* \\ \frac{\sigma\rho\tau + \sigma(1-\rho)(\tau-\tau^*)}{\rho(1-\sigma\tau) - \sigma(1-\rho)(\tau-\tau^*)} & \tau \geq \tau^* \end{cases} \quad (28)$$

and ρ is the share of credit card holders that only carry one card. This expression is continuous but not differentiable at τ^* . To be consistent with the equilibrium refinement I use to solve the model I calculate the percentage change in acceptance by averaging the effects of deviations to higher and lower fees. Formally, I calculate the percentage change as:

$$\frac{1}{2} \times \frac{G(\gamma'(\tau^* - 10^{-4})) - G(\gamma'(\tau^* + 10^{-4}))}{1 - G(\gamma'(\tau^*))}$$

where G is the CDF of merchant types. I calculate the standard error of this change with the delta method.

I.6 Implications for The Effects of Surcharges on Payment Choice

The linearity of quasiprofits means that I can show that no merchant that accepts credit cards is able to change a credit card consumer's payment choice by passing on the transaction fee. If the symmetric credit card fee is τ , then by Equation 28 all merchants with types $\gamma > \gamma^* \equiv \frac{\sigma\tau}{1-\sigma\tau}$ adopt credit cards. At a merchant of type γ , consumers value card usage at γ percent of sales. A credit card consumer would therefore need to be charged a $1 - (1 + \gamma)^{-\frac{1}{\sigma}} \approx \frac{\gamma}{\sigma}$ percent fee to switch to cash. But for $\tau \in [0, \frac{1}{\sigma})$, we have that $(1 + \gamma^*)^{-\frac{1}{\sigma}} \leq 1 + \frac{\gamma^*}{\gamma^*+1} (-\frac{1}{\sigma})$. Plugging in γ^* yields that $\frac{\gamma^*}{\gamma^*+1} = \sigma\tau \implies 1 - (1 + \gamma^*)^{-\frac{1}{\sigma}} \geq \tau$, and so the required fee to get the consumer to switch exceeds the merchant fee. If the type γ^* firm cannot induce consumers to switch, all higher types would also be unable to do so.