An Empirical Analysis of Payment Card Usage

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Abstract: This paper exploits a unique data set on the payment card industry to study issues associated with network effects and two-sided markets. We show that consumers concentrate their spending on a single payment network (single-homing), although many maintain unused cards that allow the ability to use multiple networks (multi-homing). Further, we establish a regional correlation between consumer usage and merchant acceptance within the four major networks (Visa, Mastercard, American Express and Discover). This correlation is suggestive of the existence of a positive feedback loop between consumer usage and merchant acceptance. JEL L140, L800
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1. Introduction

This paper exploits a unique data set on the payment card industry to explore the ways in which consumers use payment cards. The payment card industry is subject to increasing attention by economists and policy-markers. The interaction of consumer usage and merchant acceptance of payment cards is widely recognized as an example of network effects (Katz and Shapiro; 1994). Payment cards have also been a major motivation for recent research on the related topic of two-sided markets (see Armstrong, 2004 and Rochet and Tirole, 2004 for overviews), which focuses on the determinants of pricing by intermediaries between two related markets. In addition, partly guiding this new research, are a series of recent antitrust cases associated with the payment card industry.

These sources of inquiry have led to a number of important and unresolved empirical questions that we explore here. One important issue is the prevalence of "multi-homing" (Rochet and Tirole, 2003), the use of more than one payment card network. The level of multi-homing affects the market power that a network has over merchants that would like to interact with the network's consumers. While it is clear that consumers can hold payment cards from more than one system (for instance, American Express and Visa), it is unclear how often they do or how they use the cards they hold.

A second important issue is whether there exists a positive feedback loop between consumer usage and merchant acceptance of a payment network. Although not necessary for a market to exhibit "two-sidedness" (see Rochet and Tirole 2004), the presence of a positive feedback loop establishes the importance of the theory on indirect network effects and two-sided markets for the payment card industry. At some level, consumer

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usage and merchant acceptance must be interdependent: consumers place no value on a network for which there is no merchant acceptance and vice versa. However, given that the payment card industry is long established, the extent to which card usage actually responds to changes in the level of merchant acceptance today is up for debate. The existence of multi-homing or a positive feedback loop have important implications for analysis of these markets, but have gone previously unstudied.

To answer these questions, we exploit a novel data set that is well suited to these issues. We observe a panel of consumer usage from 1998 to 2001 in which consumers record how they make every monetary transaction for a month. We observe whether the consumer uses cash or a payment card (or many other options) and the brand of the payment card. In addition, a separate data set records the dollar value of transactions on the Visa network for all merchant transaction. We have these data monthly from 1998-2001. Because some charges for the other networks (Mastercard, American Express and Discover) appear on the Visa network, we have proxies for network acceptance by month and locale for each major network.

We find mixed results with regards to multi-homing. With regards to usage, relatively few consumers actually use multiple networks. A majority of consumers put all of their payment card purchases on a single network. However, with regards to ownership, most consumers do maintain cards from different networks, which would allow them to take advantage of different networks quickly if they chose to do so.

Based on these results, we turn to the question of a positive feedback loop. In this paper, we seek only to establish a correlation (not causality) between consumer usage and merchant acceptance. We estimate a logit model of the choice of "favorite" network and are interested in the role of local merchant acceptance in guiding this choice. To proxy for merchant acceptance, we use both counts of the number of local firms that accept a payment network as well as the value of merchant transactions on a network. We establish a positive and significant within network correlation between merchant acceptance and consumer usage. Showing this correlation suggests that there may be a positive feedback loop between the two.

2. Related Literature

The broader issue of network effects is a well-studied phenomenon with early theoretical papers dating back to Rolffs (1978), Katz and Shapiro (1985) and Farrell and Saloner (1985). See Shy (2001) for an introduction and overview of this literature. Recently, a related theoretical literature has appeared on two-sided markets. This literature focuses on the role of intermediaries in matching and pricing for two inter-related markets. An early paper is Baxter (1983). Schmalensee (2002), Wright (2002), Caillaud and Julien (2003) and particularly Rochet and Tirole (2002, 2003) are important recent contributions. Armstrong (2004) and Rochet and Tirole (2004) present overviews of the recent literature.

An early empirical study that addresses a two-sided market is Rosse (1970), which studies cost curves for the newspaper industry. A recent contribution is Rysman (2004), which analyzes the feedback loop between advertising and consumer usage in the

Yellow Pages market.[2] Evans (2003a, 2003b) discusses a number of issues associated with two-sided markets in applied and antitrust settings. With regards to payment networks, Borzekowski and Kiser (2004) use a simultaneous equations approach to search for a positive feedback loop in the use of point-of-sale networks.

There are a number of empirical papers on other aspects of the payment card industry. Ausubel (1991) provides an excellent overview of the industry and argues that consumers underestimate the probability that they will make interest payments on their purchases, leading to high interest rates and persistent industry profits. Ausubel (1999) works with a randomized credit card offers by a major industry participant and confirms the role of adverse selection in the market. Calem and Mester (1995) provide evidence from the Survey of Consumer Finance in favor of Ausubel's hypothesis.

There are separate literatures discussing the role of payment cards in consumer debt and bankruptcy (e.g. Gross and Souleles, 1998) and the substitution of electronic payments for cash (e.g. Snellman, Vesala and Humphrey, 2000). We do not pursue these issues here. Stango (2000) and Stango (2002) studies the interaction between issuing banks over their choice of fixed or variable interest rates and their pricing in the face of consumers with switching costs. Our paper studies consumer use and takes the decisions of banks as exogenous to individuals.

3. Industry

Payment cards provide an alternative method to cash and checks for making transactions. In many cases, they also provide lines of credit and some other services or benefits. The four major payment card providers, and the ones we focus on in this paper, are Visa, Mastercard, Discover and American Express. During the time of this study, Visa and MasterCard were set up as cooperatives of banks, referred to as associations. Member banks issue cards to consumers and acquire merchants willing to accept the association's payment card. In any given exchange, a good or service goes from a merchant to a consumer. Then, the consumer is billed for that product by the issuing bank. The price the consumer pays is transferred to the acquiring bank and then to the merchant. The merchant pays a *merchant discount* to the acquiring bank and the acquiring bank pays an *interchange fee* to the issuing bank. The card associations serve as clearinghouses for each of these transactions and extract a small transaction fee from both sides. The card associations set the interchange fee. Member banks set the terms they charge to consumers and the merchant discount, as well as contract for extra benefits such as rewards programs.

In this sense, member banks cooperate to set the interchange fee but compete to set the terms received by consumers and merchants. The cooperative determination of the interchange fee has been the subject of antitrust scrutiny, with the card associations arguing that the importance of consumer and merchant interaction creates a two-sided market in which the interchange fee is an important instrument for achieving the efficient level of pricing to both sides. Rochet and Tirole (2002) and the citations therein provide extensive analysis of this issue.

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[2] Elements of a two-sided market story appear in the study of the radio market by Berry and Waldfogel (2000). Gandal, Kende and Rob (2000) identify a positive feedback loop between the production of CD and CD players. They do not analyze an intermediary, which characterizes recent work on two-sided markets.

American Express and Discover are closed, proprietary networks. They operate in a similar way to the associations except that they determine all prices internally and perform marketing themselves.[3] Typically, Visa, Mastercard and Discover extend lines of credit along with their cards. American Express offers both credit cards and charge cards for which the entire bill must be paid monthly.

The payment card industry has recently witnessed rapid growth in the area of debit cards. With a debit card purchase, the price of the product is extracted directly from the consumer's bank account. Many banks now brand what used to be their ATM cards with the Visa or Mastercard logo, in which case the consumer can use the card to make purchases at all accepting merchants. Because in many cases banks replaced ATM cards with debit cards without an explicit choice on the part of the consumer, we regard the choice of debit card network to be different than the choice of credit/charge card network.[4] We separate or we exclude debit cards in much of what follows. Alternative payment cards are telephone cards and proprietary cards set up by retailers and gasoline companies. We largely ignore these types of cards as there is no two-sidedness to the interaction: merchant acceptance does not depend meaningfully on consumer usage. Much more complete industry descriptions are available elsewhere. For instance, see Hunt (2003).

4. Data

This study exploits two unique data sets. The first is the Payment Systems Panel Study, from Visa International. The PSPS is a random sample of 23,492 people that hold at least one payment card.[5] The data are drawn from the years 1994 to 2001. Respondents record their entire spending activity for one month in each quarter. Respondents record the merchant name, location and amount of any purchases and the payment method, be it cash, traveler check, credit card, gas card or store card (or a number of other classifications). In the case of a payment card, respondents record the brand (Discover, American Express Green, Visa Checkcard, Mastercard Platinum etc.,-- there are over 50 categories.). Furthermore, respondents record a list of all cards they own, whether or not they use them. We observe the interest rate, the annual fee associated with each card and the issuing bank. Because transaction side data is not available before 1998, we use only the years 1998 to 2001. This limits us to 13,467 individuals. The drop is so large because there is frequent entry and exit from the sample. In the data set we use (1998 and later), the mean number of quarters that a person is in the data set is 5.74 and the median is 3. Of individuals in the data set, 24% are in the sample for only one quarter. Only 8.5% are in for the entire sample, 16 quarters. We observe 77,349 consumer-quarter observations. The PSPS provides weights that allow us to compute results that are representative of the U.S. population. These weights are used in all following tables and computations.

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[3] Recently, American Express has been negotiating with banks to issue their cards.

[4] In most cases, consumers may request an ATM card without debit features from their bank. However, the default is for the bank to replace an ATM card with a debit card.

[5] According to the Survey of Consumer Finance, 81.4% of households hold at least one payment card (including all debit and credit cards, store cards, ATM cards, etc.) Comparing the PSPS to the SCF typically finds lower card holdings in the SCF. This may be because the PSPS has a slightly more inclusive definition of who is a member of a household or because the PSPS is more rigorous about determining card ownership than the broader SCF.

The second major element of the data set is the Visa Transactions database. This data set provides the number and amount of authorizations by month for every card reader on the Visa network. Authorizations for payment do not always lead to payments but track payments very closely. For each reader, it provides the name of the merchant, the zip code and a detailed industry code. Because of system break-downs or other surprising occurrences, some authorizations for networks besides Visa are handled by the Visa network. Payments are not handled across networks but each networks is set up to handle authorizations for all of the networks. The Transactions Database reports authorizations for each network separately. Assuming the likelihood of such an incident does not vary geographically, this feature gives us a measure of how much merchant usage there is of each of the four networks (Visa, Mastercard, American Express and Discover).[6] We have this data monthly from 1998 to the present, but use only up to 2001 when the PSPS ends.

There are a few problems with the Transactions data set. First, what the data set regards as the merchant name is entered by hand at each card reader. Many stores have multiple card readers so as few as 50% of the merchant names at a zip code may be distinct. We cannot tell if the repeated names are from the same store or repeated at different brand outlets in the same zip code. Furthermore, some "merchant names" may differ across card readers in the same store (e.g. Walmart #23, Aisle 1, Walmart #23, Aisle 2, etc.). We make no attempt to correct for this "merchant name" problem. We expect that its prevalence does not vary in systematic ways across zip codes in such a way that would affect our empirical results.

Another problem is that the zip code is missing or is something other than 5 numerals for a large number of observations. We drop these merchants – about 20% of the data. Note that many such "merchants" have no relevant location. For instance, telephone calls through AT&T charged to credit cards have missing zip codes. We also drop observations that are from the industry code that reflects automatic recurring payments. Finally, there are three (out of 48) missing months for this data set. This seems to be due simply to the fact that the data is old (by Visa's standards). As the PSPS is based on quarterly observations, we compute monthly averages of the Transactions data for each quarter. Missing months are simply dropped from these averages.

We now present some simple statistics characterizing these data, starting with the PSPS. Our data show that people average 36.3 transactions per month, with a median of 34. Table 1 presents the number of cards per person per month for the years 1994 to 2001. The number of cards that a person holds is decreasing over time, mostly driven by decreases in the number of proprietary store cards and gasoline cards. While the number of credit cards has stayed stable over the time period, there has been rapid growth in the number of debit cards, especially for Visa. Network payment cards (those associated with Visa, Mastercard, Discover or American Express) represent about 40% of the cards in circulation.

With regards to transactions and spending, we can see starkly the increasing use of payment cards. Table 2 shows that percentage of transactions conducted with payment

[6] A potential problem is that we cannot observe any activity at merchants that do not accept Visa cards. This problem is significant if a large number of retailers do not accept Visa and retailers that do not accept Visa accept non-Visa cards at different rates than ones that do accept Visa. We cannot evaluate the extent of this problem with our data but hope that it is not important, particularly for the first reason.

cards has increased from 12.4% to 28.9%. Weighted by the value of transactions, this number has gone from 17.5% to 29.6%. This increase has taken place at the expense of both cash and check transactions.

Table 3 presents market shares for the payment card networks. We see rapid growth in debit card usage, with Visa being much more successful than Mastercard. Credit cards account for less and less of the market, particularly when measured by transactions. But much of the gain by debit cards has come at the expense of proprietary and gasoline cards.

Table 4 reports summary statistics from the Transactions data: the number of merchants transacting on each network per month and the total dollar amounts of those transactions. These numbers are summed over debit and credit. The table reports quarterly averages. Table 4 exhibits a strong seasonal trend with high usage in the fourth quarter of each year. Conditional on seasonality, the table exhibits strong growth for each of the four networks in both merchants and transaction amounts. The fact that these data come from the Visa network is readily apparent as the numbers for Visa are much higher than the other networks. To get a sense of the magnitude, the PSPS (Table 3) shows that Visa's market share in dollars is about 4.5 times that of American Express and Discover. However, Table 4 shows Visa to be 30-40 times greater. Note in terms of shares on Table 4, there is a slight decline for Visa over time (from about 85% to 80%). Given that Visa's share is not shrinking according to Table 3, it suggests an increased use of the Visa network to place authorizations for other cards.

5. Multi-homing

This section considers the prevalence of multi-homing. Theoretical work highlights the importance of multi-homing but there is little previous research documenting its existence. For our purposes, multi-homing is defined to be the ownership or use of cards from two separate networks, where networks are Visa, Mastercard, American Express and Discover. We do not count holding two cards from the same network as multi-homing. Throughout this section, we look only within credit cards and not debit cards, although the results are similar when we include debit cards.

First, we consider multi-homing from the perspective of card ownership. Afterwards, we discuss card usage. Table 5 shows the portion of person-months from 1994 to 2001 in which cards from each possible combination of networks appear. For instance, the first row tells us that 23.49% of our observations hold a card (or multiple cards) from the Visa network and no other. The second row shows that months in which we observe a consumer holding cards from both the Visa and Discover networks but neither the Mastercard nor the American Express network represent 5.72% of the data set. By this measure, single-homing represents 36% of the data set (the sum of market shares in the starred rows).

Strikingly, 69% of consumers hold cards from the Visa network in a given month. Note that many consumers may regard the Visa and Mastercard networks as interchangeable as they are marketed in similar ways and have almost identical merchant acceptance. Table 5 says that 83.7% of consumers hold a card from either the Visa or the Mastercard network in a month. Given that about 13% of the observations hold no network card at all, that means that practically every consumer holding a card holds one from either the Visa or Mastercard network. Therefore, to the extent that consumers "single-home", it is almost exclusively with the Visa or Mastercard networks.

Another way to evaluate whether consumers multi-home is to look at spending amounts on different networks as opposed to just how many cards consumers hold. Table 6 analyzes the percentage of spending that consumers place on their most used card or network. The first row looks at people for a single month and presents this percentage measured at various percentile cut-offs. For instance, the median person puts all of his or her spending on a single network in given month. In 75% of consumer-months, consumers place more than 97% of their spending on a single network. The numbers are similar when we measure by card instead of network. We see that 75% of people put more than 87% of their spending on a single card in a given month. Over longer periods of time, there is some evidence that consumers switch between networks. The second and fourth rows shows that among people in the sample more than 6 years, the median person puts 80.6% of their spending for the entire period on a single network and 65.9% on a single card.

To further explore the issue of switching, Table 7 exploits the panel nature of the data set to presents a transition matrix for the most used network in a month. The first row presents the share of consumer-months that each network is chosen as the "favorite," the network with the greatest transaction volume. In order to avoid spurious favoritism, we restrict our analysis in this table to consumer-months where the favorite network has at least 60% of the network transaction volume. Table 7 shows that Visa is most often chosen favorite: 50.3% of consumer months. The next four rows present the probability of picking one network as "favorite" conditional on the network chosen in the previous observation. For instance, in the cases where a consumer uses the Visa network the most, they choose Visa again in the following observation in 85.4% of cases. Only 2.4% of the time, they switch to Discover. By multiplying the diagonal of the transition matrix times the market shares and summing, we see that there is an 81.4% of a consumer remaining on the same network between observations. While high, there is some switching.

Together, Table 6 and Table 7 suggest that there is very little multi-homing in terms of usage. Instead, consumers concentrate their spending on a single network and periodically switch their most used network. However, Table 5 indicates that many consumers maintain the ability to switch networks on short notice by keeping cards from multiple networks. It is unclear which effect dominates from the perspective of the merchant. That is, if a merchant dropped a network affiliation, would the merchant lose sales from consumers who concentrate their spending on a single network or would consumers simply switch to using multiple networks? This question gets at the heart of the issue multi-homing, but is unresolved in the current analysis.

6. Determinants of Choice

In this section, we estimate a model of how consumers choose between networks. We are particularly interested in the role of local merchant acceptance in affecting consumer decisions. For instance, in areas where more merchants accept Visa cards, do we observe that consumers are more likely to use Visa cards?

Based on the results in previous section, it seems inappropriate to model how consumers decide on a payment method for each transaction. Furthermore, we believe that issues determining the choice of card to use, such as which cards the consumer has on hand, their fees and the consumer's balances, would be difficult to incorporate properly and would not contribute substantially to the questions of interest in the paper. Instead, we treat a consumer-month as an observation and determine a "favorite network" for each observation. The favorite network is the one most used by a consumer in that month, as measured by the value of transactions. If we do not observe at least 60% of the value of transactions in a month on a single network, we drop that observation. We model the discrete choice between the four payment networks, assuming a consumer can choose between each of the four in each period.[7]

We denote the options for consumers with $j=(1,2,3,4)$ representing Visa, Mastercard, American Express and Discover respectively. Utility to consumer i from choosing network j in period t is defined as follows:

$$U_{ijt} = X_{it}\beta_j + \gamma_j \ln(M_{ijt}) + \varepsilon_{ijt}$$

In this equation, X_{it} represents consumer demographic information and β_j captures the effect of demographics on an individual network (e.g. if wealthier people prefer American Express). Merchant acceptance of network j near consumer i is represented by M_{ijt}. The construction of this variable is discussed below. We allow the parameter on merchant acceptance, γ_j , to vary across networks so networks may differ in the importance of their positive feedback loop. The variable ε_{ijt} represents idiosyncratic taste for a particular network. We assume that ε_{ijt} is *iid* extreme value over time and across people so the model takes on the familiar form of the logit model.

Note that the level of utility is not identified in a discrete choice model. We normalize $U_{i1t}=\varepsilon_{i1t}$ (mean utility to the Visa network is zero) and estimate the utility to the other networks relative to Visa. That is, for $j=2,3,4,$ we estimate:

$$\widetilde{U}_{ijt} = X_{it}(\beta_j - \beta_1) + \gamma_j \ln(M_{ijt}) - \gamma_1 \ln(M_{i1t}) + \varepsilon_{ijt} \qquad (1)$$

Therefore, we estimate three sets of parameters, one for each of the non-Visa networks. Merchant acceptance for Visa shows up in each equation and we expect it to enter negatively. This set-up suggests that the coefficient on Visa merchant acceptance should be constrained to be the same in each equation, although we experiment with this restriction.

Before moving forward, we discuss our measures of merchant acceptance. We use two measures, both at the level of the 3-digit zip code. The first measure is the number of merchant names appearing in the payment network. While this is a natural measure, it has the drawback that it puts substantial weight on potentially unimportant (even spurious) merchants.[8] As an alternative, our second measure is the sum of sales on a network for a month. While this measure puts weight on the most important retailers, it is problematic to the extent that consumer usage mechanically raises local sales. If consumers in a location use a particular network extensively for some unobserved reason, then naturally

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[7] Obviously, we have greatly simplified the choices involved in determining payment card behavior in order to focus on issues of network choice. See Carow and Staten (1999) for a study of the choice between using a network payment card or a prorietory store card. See Min and Kim (2003) for a study of the choice of how much to borrow with a credit card. See Zinman (2004) for a study of the choice of debit versus credit card and Hyytinen and Takalo (2004) for a study using multiple payment types.

[8] A potential problem is that merchants that accept a card but do not use the network for a month do not appear in our data set. So areas where consumers use a network extensively may drive up the number of merchant names by visiting more potential stores. We expect that this effect is not very important.

merchant transactions on that network will be high even if there is no positive feedback. The two measures are similar but not identical: their correlation in our regression data set is 0.76, 0.67, 0.34 and 0.45 for Visa, Mastercard, American Express and Discover. However, the two measures lead to similar results, providing validity to our overall conclusions. As an alternative to 3-digit zip codes, we tried computing these measures by summing over zip codes whose population centers were within 25 miles of a consumer's zip code center and found very similar results.

Given this definition of M_{ijt}, what is the source of identification in our approach? From equation 1, we see that we will find $\gamma_j>0$ if consumers more often choose network j in regions where merchant acceptance on network j is high relative to merchant acceptance on Visa (with the ratio of acceptance on two networks being captured by their difference in logs). Similarly, we find $\gamma_1>0$ if consumers choose Visa in regions where the ratio of acceptance on other networks to Visa acceptance is low.

Clearly, the ratio of merchant acceptance that we construct varies across locations simply because of the noisy signals we observe of the true merchant acceptance (particularly noisy for networks other than Visa). However, to the extent that we find strong results, we conclude that there is some signal in the variables we observe.

This approach also means that we cannot find a correlation simply driven by scale effects. Clearly, in areas where economic activity is high for some exogenous reasons, we may find both that there are many consumers who use payment cards and many merchants who accept them but we would not want to conclude that there is necessarily a positive feedback loop. But if this high activity affects each network symmetrically, it will not impact our estimation, which is based on the choice *among networks*.[9] Consider doubling the size of a given zip code so merchant acceptance for each network doubles and consumer usage shares remain the same. In the case where $\gamma_1=\gamma_2=\gamma_3=\gamma_4$, this change will have no impact on the left-hand or right-hand side. That is, if this scaling is the only type of variation in the data, we will not find $\gamma_j>0$. Note that in practice, we do not require that $\gamma_1=\gamma_2=\gamma_3=\gamma_4$, which we believe provides a more stringent test of the issues of interest. But doing so does not change the major results.

Furthermore, this identification strategy allows us to proceed although we observe only retailers that accept cards, not those who do not. One might think to use the ratio of the number of merchants accepting a network to the total number of merchants in an area for M_{ijt}. However, in our setup, a variable such as the total number of retailers in an area affects each network equally and so should not impact our estimation. Again, this statement is formally true only if $\gamma_1=\gamma_2=\gamma_3=\gamma_4$. Also, this estimation approach is robust to observing different proportions of merchant acceptance for each network, as long as that proportion is constant for the network across locations.

We see three economic reasons why we may find that $\gamma_j>0$. First, high merchant acceptance may cause high consumer usage. Second, consumer usage may cause high merchant acceptance. That is, consumer choice may be driven by exogenous variables and merchants respond. For instance, we show that consumers with high income are more likely to use American Express. Also, Sears introduced the Discover card by replacing the Sears store card, so consumers that live near a Sears may be more likely to

[9] We can see the equations we estimate as the second nest in a nested logit model where in the first nest, consumers choose between using a payment card or not. Issues that affect all networks equally can be restricted to the first nest and so do not affect results based only on the second nest.

hold a Discover card. The form of the response by retailers may be entry by retailers that accept that card to areas where the card is popular. For instance, stores that cater to high income consumers also typically accept American Express and may be attracted to areas with high-income, American Express-using consumers. Alternatively, retailers that would be in an area regardless may accept a card that is in heavy use in that area.

If consumer usage causes high merchant acceptance, M_{ijt} is endogenous because of reverse causality. Our approach does not allow us to distinguish whether consumer usage causes merchant acceptance, merchant acceptance causes consumer usage or both. However, we feel that simply establishing a correlation between acceptance and usage is a contribution. Finding a positive γ suggests the existence of some part of the feedback loop between consumers and merchants, which we take as new evidence in favor of the theoretical work on two-sided markets and its application to the payment market.

A third explanation for finding $\gamma_j>0$ may be an omitted variable. But an advantage of the discrete choice framework is that it focuses on within-network correlation and so leaves little room for explanations based on omitted variables. Explanations that lead us to wrongly find $\gamma_j>0$ must affect both consumers and firms for each network separately and directly, and in some regions but not others. For instance, it is possible that high retail activity affects one network differentially. Another example that would be problematic for our approach would be if a network starts a promotional campaign in a particular region. If the campaign was aimed at both consumers and retailers in a particular region, so both U_{ijt} and M_{ijt} are high for consumers subject to the campaign, then we may find $\gamma_j>0$ although there is no feedback.[10] This may be the case for American Express. Presumably, the popularity of American Express with the travel and leisure industry is in part due to marketing by American Express directly to both consumers and retailers that participate in this industry, although it is probably also due in part to a positive feedback loop between consumers and retailers.

In order to guard against this sort of endogeneity, we introduce regional demographic variables. We match each consumer to demographic data from the 2000 Census based on the consumer's 5-digit zip code.[11] For demographic controls, we include median household income, the percent of the population owning their own home, the percent that has graduated college, the percent of the population in an urban area (as classified by the Census), the percent of the population taking public transportation to work and population density.

7. Results

This section presents results from predicting individual's choice of "favorite network" for a month as a function of merchant acceptance and other control variables. Again, we construct the favorite network based only on credit and charge card usage, ignoring debit card usage. Results were similar when we used debit card usage. In Table 8, the measure

[10] If the campaign is aimed only at consumers and retailers respond to greater consumer usage with greater acceptance, then we would want to conclude that merchants respond. The omitted variable explanation must affect both sides of the market directly.

[11] There were a small number of observations where we could not match 5 digit zip codes in the Census and the PSPS and instead used demographics for the 3 digit zip code. Some observations (7) are dropped because of a failure to match even at the 3-digit level.

of merchant acceptance is the total number of merchant names appearing on a network in the consumers' 3-digit zip code. In this table and those following, we compute standard errors accounting for the fact that individuals' decisions may be correlated over time (clustered standard errors). The standard errors we report are much higher than if we did not account for this issue, as individuals do not switch their favored network very often.[12]

We consider the first three columns of Table 8 to be the main results of the paper. High Visa acceptance enters negatively and significantly into the American Express and Discover equations suggesting that high Visa acceptance in a region makes consumers more likely to use Visa. Similarly, American Express and Discover acceptance enter positively into their respective equations, implying that greater merchant acceptance makes consumers more likely to use these cards relative to Visa. In contrast, the effects of Visa and Mastercard in the Mastercard equation are insignificant. This result on Mastercard can be explained by the special relationship between Visa and Mastercard. For instance, the very great majority of retailers that accept Visa also accept Mastercard, and vice versa. That suggests that variation in the ratio of merchant acceptance is driven by noisy measurement. Not surprisingly, we do not discern consumers substituting between them based on local acceptance.

As control variables, we have included education level and age of the head of the household, household income, household size (number of people) and a time trend. Almost none of these variables enter significantly except, as might be expected, high income households are more likely to choose American Express. Low education and large households are more likely to choose Mastercard. The time trend is negative in all cases and significant in American Express, suggesting that Visa is getting more popular over time. We also experimented with dummies for each quarter and found similar results.

As discussed above, unobserved regional effects that directly affect both consumer usage and merchant acceptance may cause us to find $\gamma_j>0$ when there is no direct relationship between acceptance and usage. In the second set of columns in Table 8, we attempt to address this issue by introducing regional demographics. Only a few of these variables turn up significant and the main results remain unchanged, although the parameter on Discover acceptance is now significant at a 90% rather than 95% level of confidence.

Next, we consider using total amounts transacted on a network to proxy for merchant acceptance. Table 9 presents the results in the same manner as Table 8. In the first three columns, we see that more Visa acceptance has a negative and significant impact on all three other networks. And acceptance at each of the three networks is associated with usage of those networks. The results are similar in sign and magnitude when we enter local demographics as controls (columns 4-6). The fact that we can now see an impact of Visa on Mastercard and vice versa may indicate that the accounting relationship between consumer usage and transaction amounts may cause this proxy for merchant acceptance to be unreliable. Alternatively (and we believe, less plausibly), it

[12] The number of observations is much less than the 77,349 consumer-month observations in the data from 1998 to 2001. The great majority of lost observations (30,747) are due to consumer-month in which there is no use of a network credit or charge card for an entire month. A further 2,629 observations are dropped because a consumer did not put at least 60% of their spending on a single network. An additional 7 observations a dropped due to a failure to match zip codes in the Transaction and PSPS data.

may be that consumers and merchants really do distinguish between the two networks and that the "amounts" proxy is superior to the "count" proxy of merchant acceptance.

We consider one further robustness check. The results in Table 8 as well as our knowledge of the industry suggest that competition with regards to merchant acceptance between Visa and Mastercard is quite different than between the other networks. We capture this issue by grouping Visa and Mastercard into a single choice that responds only to Visa's merchant acceptance.[13] Table 10 presents results using counts of merchant names to proxy for merchant acceptance. The main results are confirmed: acceptance at each network is positively correlated with usage at the network.

Finally, we consider magnitudes. Table 11 computes the change in probability of picking a given network from a percentage change in the explanatory variable. Note that we do not interpret these parameters as causal and this exercise is useful for evaluating the size of the parameters, not for determining a causal effect. Formally, we compute $dP_j/dln(X_k)$, where P_j is the probability of a consumer picking network j and X_k is the average value of the k^{th} explanatory variable in levels. We do this for the parameter estimates from the first three columns of Table 8. We find reasonable effects from the variables of interest. For instance, doubling the number of merchants accepting Visa increases the probability of choosing Visa by 3.6 percentage points over the predicted probability of market share of 53%. The gain comes at the expense of American Express and Discover rather than Mastercard. Note that each row in Table 11 sums to zero. The effects of merchant acceptance on American Express and Discover seem particularly strong relative to their market shares, which supports the intuition that positive feedback loops should be stronger for networks that are less widespread.

Overall, the results provide support for the hypothesis that network merchant acceptance and network consumer usage are correlated. Visa, American Express and Discover acceptance each are associated with more consumers on their networks. It is unclear whether Visa acceptance draws consumers from the Mastercard network, which is not surprising given our prior knowledge of the industry and the data.

8. Conclusion

This paper exploits a unique data set on the payment card industry to explore empirically issues that are important in the recent theoretical work on two-sided markets. We show that very few consumers multi-home in the sense that they place almost all of their spending on a single payment network. However, about two-thirds of consumers maintain cards from different networks so they may switch to multi-homing for relatively small benefits.

We also show that consumer's choice of a favorite network is correlated with the amount of local merchant acceptance of that network, where merchant acceptance is measured by either counts of merchant names transacting in a given month or transaction volume for the month. As the correlation is within each payment network, it is difficult to construct an explanation for why we observe this correlation other than some form of

[13] An alternative would be to group Visa and Mastercard into a nest of a nested logit model. However, given we believe that variation in the ratio of merchant acceptance between these two reflects only noisy data, our approach seems cleaner.

causality, but we do not establish the nature of the causality with this approach. Certainly, the result is consistent with the presence of a positive feedback loop.

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Table 1: Number of Cards Per Person

	Total	Credit Visa	Credit MC	Credit Disc	Credit Amex	Debit Visa	Debit MC	store	atm	Gas	phone	other
1994	7.20	1.01	0.79	0.27	0.18	0.06	0.02	2.63	0.61	0.82	0.28	0.54
1995	6.92	1.13	0.81	0.37	0.19	0.07	0.02	2.35	0.66	0.68	0.32	0.33
1996	6.95	1.17	0.77	0.32	0.19	0.19	0.05	2.21	0.49	0.61	0.32	0.64
1997	6.69	1.13	0.73	0.25	0.17	0.12	0.03	2.13	0.56	0.58	0.31	0.67
1998	6.49	1.14	0.76	0.27	0.19	0.20	0.07	2.02	0.50	0.55	0.30	0.50
1999	6.35	1.13	0.70	0.26	0.17	0.27	0.09	1.94	0.42	0.50	0.27	0.59
2000	6.20	1.14	0.73	0.22	0.16	0.33	0.12	1.92	0.37	0.46	0.23	0.52
2001	5.96	1.16	0.83	0.23	0.15	0.38	0.13	1.80	0.34	0.46	0.19	0.29
Avg.	6.61	1.13	0.76	0.27	0.18	0.21	0.07	2.12	0.49	0.58	0.28	0.54

Table 2: Payment Method Market Shares

	Percentage of Transactions				Percentage of Spending			
	Cash	Check	Card	Other	Cash	Check	Card	Other
1994	48.5	35.8	12.4	3.3	21.3	51.4	17.5	9.9
1995	47.0	34.9	15.7	2.3	20.0	51.0	21.2	7.7
1996	45.1	34.7	17.7	2.5	18.0	50.7	21.5	9.8
1997	45.4	33.1	18.8	2.7	19.6	49.0	23.2	8.3
1998	43.2	33.1	20.5	3.2	18.6	49.0	23.2	9.3
1999	42.4	31.2	23.1	3.3	18.6	46.9	25.0	9.5
2000	40.5	30.1	26.0	3.4	18.0	45.6	28.2	8.2
2001	38.9	28.6	28.9	3.5	16.9	44.8	29.7	8.6
Avg.	43.7	32.5	20.8	3.0	18.7	48.3	24.1	8.9

Table 3: Payment Card Network Market Shares

	% of Card Transactions							% of Card Amount						
	Credit				Debit			Credit				Debit		
	Visa	MC	Amex	Disc	Visa	MC	Other	Visa	MC	Amex	Disc	Visa	MC	Other
1994	26.7	22.0	7.6	15.1	3.7	0.7	24.2	32.9	24.2	9.7	14.3	1.9	0.4	16.6
1995	30.3	22.0	6.6	12.6	4.7	0.9	22.8	33.0	25.0	10.9	12.1	2.5	0.5	16.1
1996	29.5	20.7	6.1	8.1	14.7	3.1	17.8	33.7	23.9	10.5	8.4	8.5	1.8	13.2
1997	30.2	19.3	6.7	9.6	11.0	2.4	20.8	34.7	21.7	11.3	9.6	6.7	1.4	14.7
1998	27.9	18.1	5.6	10.2	14.8	5.0	18.4	33.8	20.9	9.4	10.4	9.0	3.0	13.5
1999	28.4	15.0	5.5	8.4	21.2	6.1	15.5	34.9	18.0	8.7	8.5	13.2	4.2	12.5
2000	26.5	14.1	4.8	9.2	25.6	6.0	13.7	32.9	17.5	7.5	9.7	16.7	4.3	11.5
2001	23.9	16.1	5.3	8.7	27.1	7.1	11.9	30.1	18.7	8.5	9.7	17.8	4.7	10.4
Avg.	27.5	17.6	5.8	9.7	17.9	4.6	16.9	33.1	20.6	9.3	10.0	11.0	3.0	13.1

Table 4: Transactions over the Visa network

		Amounts ($000,000,000)				Merchants (000,000)			
Year	Qtr	Visa	MC	Amex	Disc	Visa	MC	Amex	Disc
1998	1	38.66	4.64	1.24	0.53	5.65	0.57	0.16	0.23
	2	43.86	5.20	1.36	0.58	6.02	0.60	0.17	0.26
	3	46.11	5.53	1.42	0.63	6.37	0.64	0.20	0.25
	4	51.05	6.32	1.59	0.71	6.01	0.65	0.22	0.24
1999	1	44.98	5.73	1.46	0.63	5.72	0.66	0.19	0.23
	2	52.12	6.65	1.64	0.73	6.46	0.77	0.21	0.24
	3	54.32	7.14	1.86	0.85	6.29	0.77	0.24	0.28
	4	60.44	8.04	2.31	0.97	5.51	0.76	0.33	0.33
2000	1	52.82	7.00	2.21	0.88	5.46	0.81	0.30	0.31
	2	62.18	8.50	2.65	1.01	5.93	0.87	0.35	0.35
	3	63.31	8.88	2.38	1.02	5.67	0.81	0.41	0.36
	4	68.40	11.00	2.61	1.19	5.68	0.88	0.39	0.37
2001	1	61.67	9.23	2.46	1.04	5.69	0.91	0.38	0.37
	2	66.84	10.48	2.26	1.14	6.00	0.88	0.42	0.40
	3	72.52	12.29	2.86	1.19	6.05	0.85	0.45	0.42
	4	88.89	17.68	1.62	1.87	6.11	0.93	0.36	0.42

Table 5: Probability of holding a combination of cards

	Visa	MC	Amex	Disc	%	cum %
*	Y	N	N	N	23.49	23.49
	Y	N	N	Y	5.72	29.21
	Y	N	Y	N	3.06	32.27
	Y	N	Y	Y	1.21	33.48
	Y	Y	N	N	18.52	52.00
	Y	Y	N	Y	9.83	61.83
	Y	Y	Y	N	3.86	65.69
	Y	Y	Y	Y	3.22	68.91
*	N	Y	N	N	9.79	78.70
	N	Y	N	Y	3.22	81.92
	N	Y	Y	N	1.18	83.10
	N	Y	Y	Y	0.56	83.66
*	N	N	Y	N	1.10	84.76
	N	N	Y	Y	0.23	84.99
*	N	N	N	Y	1.80	86.79
	N	N	N	N	13.22	100.00

Notes: * indicates single homing

Table 6: Concentration of Spending

	Percentile				
% on most used network	75	50	25	5	Obs.
Spending per person per month	100	100	97.4	59.3	87,893
Spending per person	99.1	80.6	62.0	48.0	528
% on most used card					
Spending per person per month	100	100	87.8	54.4	87,893
Spending per person	92.7	65.9	45.9	30.2	528

Spending per person is computed only for people in the data set greater than 6 years.

Table 7: Transition matrix for most used network

	Visa	MC	Amex	Disc
share	50.3	29.8	7.3	12.5
	Transition matrix			
Visa	85.4	9.1	2.4	3.1
MC	15.6	78.4	2.2	3.8
Amex	15.0	9.3	73.1	2.6
Disc	12.2	9.2	1.6	77.0

Table 8: Choice of favorite network based on merchant counts

	MC	Amex	Disc	MC	Amex	Disc
Visa count	-0.051	-0.296	-0.296	-0.027	-0.291	-0.291
	(0.075)	(0.086)	(0.086)	(0.079)	(0.091)	(0.091)
MC count	-0.037			-0.061		
	(0.075)			(0.075)		
Amex count		0.353			0.230	
		(0.074)			(0.081)	
Disc count			0.197			0.168
			(0.091)			(0.090)
High School	-0.202	0.438	-0.057	-0.188	0.469	-0.048
	(0.130)	(0.411)	(0.170)	(0.133)	(0.415)	(0.173)
College	-0.272	0.809	0.084	-0.255	0.845	0.105
	(0.137)	(0.411)	(0.177)	(0.141)	(0.418)	(0.182)
ln(HH Inc)	-0.012	0.882	-0.078	0.009	0.892	-0.072
	(0.052)	(0.109)	(0.070)	(0.055)	(0.112)	(0.073)
ln(Age)	0.020	-0.309	0.268	0.028	-0.309	0.232
	(0.087)	(0.167)	(0.130)	(0.088)	(0.166)	(0.129)
time trend	0.003	-0.139	-0.087	0.008	-0.110	-0.083
	(0.028)	(0.046)	(0.037)	(0.028)	(0.047)	(0.037)
ln(HH size)	0.195	-0.321	0.121	0.192	-0.294	0.100
	(0.064)	(0.160)	(0.094)	(0.065)	(0.159)	(0.095)
% pop urban				-0.098	-0.050	-0.041
				(0.160)	(0.337)	(0.248)
% diff county				0.178	0.015	-0.291
5 years prev.				(0.392)	(0.710)	(0.542)
% pub. Transp				-1.794	-2.583	-2.271
				(1.334)	(1.560)	(2.093)
ln(med HH inc)				0.043	0.025	-0.238
				(0.169)	(0.338)	(0.240)
% grad college				-0.736	-0.839	0.453
				(0.837)	(1.610)	(1.139)
ln(density)				0.037	0.194	0.077
				(0.035)	(0.064)	(0.054)
% own home				-0.219	-0.274	0.786
				(0.318)	(0.626)	(0.462)
Constant	0.246	-9.991	-0.116	-0.47	-10.795	1.635
	(0.632)	(1.343)	(0.850)	(1.576)	(3.339)	(2.221)
Observations		43966			43466	

Notes: Dependent variable is choice of favorite network (Visa, MC, Amex, Disc)
Count is number of merchant names on that network in the 4-digit zip code.
Clustered standard errors in parentheses

Table 9: Choice of favorite network based on transaction amounts ($)

	MC	Amex	Disc		MC	Amex	Disc
Visa $	-0.264	-0.302	-0.302		-0.292	-0.329	-0.329
	(0.062)	(0.060)	(0.060)		(0.068)	(0.067)	(0.067)
MC $	0.195				0.199		
	(0.062)				(0.063)		
Amex $		0.305				0.230	
		(0.051)				(0.058)	
Disc $			0.213				0.208
			(0.061)				(0.061)
High School	-0.203	0.418	-0.060		-0.187	0.451	-0.052
	(0.131)	(0.410)	(0.171)		(0.133)	(0.414)	(0.174)
College	-0.266	0.787	0.087		-0.254	0.828	0.102
	(0.138)	(0.410)	(0.177)		(0.141)	(0.417)	(0.183)
ln(HH Inc)	0.005	0.886	-0.066		0.012	0.898	-0.065
	(0.052)	(0.108)	(0.070)		(0.055)	(0.111)	(0.073)
ln(Age)	0.022	-0.310	0.269		0.038	-0.309	0.240
	(0.087)	(0.167)	(0.130)		(0.088)	(0.166)	(0.129)
time trend	-0.016	-0.045	-0.047		-0.011	-0.022	-0.040
	(0.026)	(0.043)	(0.034)		(0.026)	(0.044)	(0.035)
ln(HH size)	0.188	-0.325	0.107		0.190	-0.302	0.089
	(0.064)	(0.161)	(0.095)		(0.065)	(0.159)	(0.095)
% pop urban					-0.134	-0.060	-0.078
					(0.160)	(0.337)	(0.249)
% diff county					0.284	0.065	-0.169
5 years prev.					(0.396)	(0.703)	(0.542)
% pub. Transp					-1.366	-2.558	-2.211
					(1.296)	(1.552)	(2.075)
ln(med HH inc)					0.121	0.041	-0.193
					(0.171)	(0.340)	(0.244)
% grad college					-0.787	-0.834	0.470
					(0.837)	(1.612)	(1.147)
ln(density)					0.061	0.202	0.095
					(0.036)	(0.065)	(0.054)
% own home					-0.204	-0.252	0.742
					(0.322)	(0.622)	(0.464)
Constant	1.011	-9.743	0.701		-0.108	-9.879	2.361
	(0.678)	(1.400)	(0.922)		(1.578)	(3.313)	(2.231)
Observations		43610				43466	

Notes: Dependent variable is choice of favorite network in a month (Visa, MC, Amex, Disc)

$ is amount of transactions in dollars on that network in 4 digit zip code.

Clustered standard errors in parenthesis

Table 10: Visa and Mastercard as a single choice

Visa count	-0.27	-0.27		-0.261	-0.261
	(0.074)	(0.074)		(0.079)	(0.079)
Amex count	0.394			0.278	
	(0.066)			(0.072)	
Disc count		0.224			0.199
		(0.078)			(0.079)
High School	0.719	0.012		0.741	0.008
	(0.412)	(0.159)		(0.424)	(0.159)
College	1.108	0.117		1.123	0.126
	(0.417)	(0.164)		(0.432)	(0.165)
ln(HH Inc)	0.898	-0.047		0.864	-0.057
	(0.088)	(0.060)		(0.092)	(0.063)
ln(Age)	-0.272	0.394		-0.25	0.371
	(0.140)	(0.111)		(0.141)	(0.112)
time trend	-0.108	0.016		-0.076	0.019
	(0.040)	(0.027)		(0.041)	(0.027)
ln(HH size)	-0.195	0.067		-0.156	0.043
	(0.114)	(0.079)		(0.112)	(0.080)
% pop urban				-0.085	0.065
				(0.269)	(0.203)
% diff county				0.263	-0.144
5 years prev.				(0.609)	(0.468)
% pub. transp				-0.995	-2.439
				(1.247)	(1.713)
ln(med HH inc)				0.051	-0.004
				(0.280)	(0.203)
% grad college				-0.178	-0.312
				(1.283)	(0.999)
ln(density)				0.173	0.037
				(0.054)	(0.045)
% own home				0.059	0.584
				(0.516)	(0.374)
Constant	-11.802	-1.707		-12.755	-1.989
	(1.131)	(0.734)		(2.709)	(1.865)
Observations	43966			43466	

Notes: Visa and MC are treated as a single choice, which depends on Visa merchant acceptance

Table 11: Marginal effects

	Visa	MC	Amex	Disc
Visa count	0.036	0.005	-0.013	-0.027
	(0.016)	(0.015)	(0.004)	(0.008)
MC count	0.006	-0.008	0.001	0.001
	(0.012)	(0.016)	(0.001)	(0.003)
Amex count	-0.011	-0.006	0.020	-0.002
	(0.002)	(0.001)	(0.004)	(0.001)
Disc count	-0.012	-0.007	-0.001	0.021
	(0.006)	(0.003)	(0.001)	(0.009)
High School	0.021	-0.048	0.028	-0.002
	(0.032)	(0.025)	(0.023)	(0.017)
College	0.010	-0.074	0.052	0.012
	(0.033)	(0.026)	(0.025)	(0.017)
ln(HH Inc)	-0.021	-0.015	0.050	-0.014
	(0.011)	(0.010)	(0.006)	(0.007)
ln(Age)	-0.010	0.000	-0.019	0.029
	(0.020)	(0.017)	(0.009)	(0.013)
time trend	0.009	0.006	-0.007	-0.008
	(0.006)	(0.006)	(0.002)	(0.004)
ln(HH size)	-0.028	0.042	-0.022	0.008
	(0.015)	(0.013)	(0.009)	(0.009)
Pred. Prob	0.53	0.30	0.06	0.12

Pred. Prob is the predicted probability of choosing that network
Calculated as dP/dlnX at mean of X. Standard errors in parenthesis.
Computations based on results in Table 8