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 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. Further, we establish a regional correlation between consumer usage of one of the four major networks (Visa, Mastercard, American Express and Discover) and merchant acceptance of these cards. This correlation is suggestive of the existence of a positive feedback loop between consumer usage and merchant acceptance. JEL L140, L800

Very preliminary

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. One reason is the recent increase in theoretical research on two-sided markets (see Armstrong 2002 for an overview), which focuses on the determinants of pricing by intermediaries between two related markets. A second reason, partly guiding this new research, is a series of recent antitrust cases associated with the payment card industry.

These sources of inquiry have lead to a number of important and unresolved empirical questions that I explore here. One important issue is the prevalence of "multi-homing" (Rochet and Tirole, 2003), the use of more than one payment card network. 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 how consumers respond to merchant acceptance of a card network. It is obvious that consumers place no value on a network for which there is no merchant acceptance. 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. Both of these issues have important implications for analysis of these markets, but have gone previously unstudied.

To answer these questions, I exploit a novel data set that is well suited to these issues. I 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

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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 that despite the theoretical importance of multi-homing, relatively few consumers actually use multiple networks. A majority of consumers put all of their payment card purchases on a single network. However, 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 estimate a logit model of the choice of "favorite" network. We are interested in the role of merchant acceptance in guiding this choice. To proxy for merchant acceptance, we use both measures of local spending on a network as well as counts of the number of local firms that accept a payment card network. We establish a positive and significant correlation between merchant acceptance and consumer usage. Showing this correlation suggests that there may be 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 differs from the work on network effects in that its focus is on pricing as opposed to technology adoption. Its motivating examples tend to be payment card markets and media rather than hardware/software 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 (2002) presents an overview 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 (2003), 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. To my knowledge, there is no formal empirical work that studies issues associated with two-sided markets in the payment card industry.

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 by showing that low quality credit card offers

[2] Elements of a two-sided market story appear in the study of the radio market by Berry and Waldfogel (2000) but they lack the detailed station-level data to explore these issues fully. Gandal, Kende and Rob (2000) also identify a positive feedback loop between the production of CD and CD players. Note that in their case, they do not analyze an intermediary that characterizes recent work on two-sided markets.

draw pools of respondents with worse observable and unobservable characteristics, leading to more defaults. 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

See Hunt (2003). To be completed.

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 who hold at least one payment card from 1994 to 2001.[3] Once per quarter, a respondent records their entire spending activity for one month. 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.) and the issuing bank. Furthermore, respondents record a list of all cards they own, whether or not they use them. We observe the interest rate and annual fee associated with each card. Because of the availability of transaction side data, 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 second major element of the data set is the Visa Transactions database. This data set provides the number and amount of transactions by month for every card reader on the Visa network. 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 charges for networks besides Visa are reported over the Visa network. The Transactions Database reports these numbers 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

[3] 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.

Express and Discover). 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 numerous missing months for this data set – 13 out of 48. 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. There is only one quarter for which we are missing all three months (Year 2000, first quarter). We drop these observations in the PSPS.

Here, we present some simple statistics characterizing these data. 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 proprietary store cards and gasoline cards. At the same time, the number of Visa and Mastercard cards is increasing, while the number American Express and Discover cards are decreasing or staying the same. Network payment cards (those associated with Visa, Mastercard, Discover or American Express) represent about 40% of the cards in circulation.

Table 1: Number of Cards Per Person

	Total	Visa	MC	Disc	Amex	Store	ATM	Gas	Phone	other
1994	7.20	1.08	0.81	0.37	0.19	2.63	0.61	0.82	0.28	0.42
1995	6.92	1.20	0.83	0.32	0.19	2.35	0.66	0.68	0.32	0.38
1996	6.95	1.36	0.82	0.25	0.17	2.21	0.49	0.61	0.32	0.73
1997	6.69	1.25	0.76	0.27	0.19	2.13	0.56	0.58	0.31	0.64
1998	6.49	1.33	0.83	0.26	0.17	2.02	0.50	0.55	0.30	0.53
1999	6.35	1.40	0.80	0.22	0.16	1.94	0.42	0.50	0.27	0.64
2000	6.20	1.48	0.85	0.23	0.15	1.92	0.37	0.46	0.23	0.52
2001	5.96	1.53	0.96	0.24	0.20	1.80	0.34	0.46	0.19	0.23
Avg.	6.61	1.33	0.83	0.27	0.18	2.12	0.49	0.58	0.28	0.54

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 cards has increased from 12.4% to 20.8%. Weighted by the value of transactions, this number has gone from 17.5% to 29.6%. Much of this increase has taken place at the expense of cash transactions. Transactions by check have declined, but not when measured in terms of dollar spending. Table 3 presents market shares for the payment card networks. Visa has increased market share in usage tremendously. While market shares for American Express and Discover have decreased somewhat, much of Visa's gain is at the expense of proprietary and gasoline cards.

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				
	Visa	MC	Amex	Disc	Other	Visa	MC	Amex	Disc	Other
1994	30.4	22.7	7.6	15.1	24.2	34.8	24.6	9.7	14.3	16.6
1995	35.0	22.9	6.6	12.6	22.8	35.5	25.4	10.9	12.1	16.1
1996	44.1	23.8	6.1	8.1	17.8	42.2	25.7	10.5	8.4	13.2
1997	41.2	21.6	6.7	9.6	20.8	41.4	23.1	11.3	9.6	14.7
1998	42.8	23.0	5.6	10.2	18.4	42.8	23.9	9.4	10.4	13.5
1999	49.5	21.1	5.5	8.4	15.5	48.1	22.3	8.7	8.5	12.5
2000	52.2	20.2	4.8	9.2	13.7	49.6	21.8	7.5	9.7	11.5
2001	51.0	23.1	5.3	8.7	11.9	48.0	23.5	8.5	9.7	10.4
Avg.	45.4	22.2	5.8	9.7	16.9	44.1	23.5	9.3	10.0	13.1

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. 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 of the payment card market is not shrinking, it suggests an increased use of the Visa network to place payments for other cards.

Table 4: Transactions over the Visa network

		Amounts ($000,000,000's)				# of Merchants (000,000's)			
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
1998	2	43.86	5.20	1.36	0.58	6.02	0.60	0.17	0.26
1998	3	46.11	5.53	1.42	0.63	6.37	0.64	0.20	0.25
1998	4	53.17	6.64	1.61	0.75	6.04	0.63	0.19	0.24
1999	1	44.98	5.73	1.46	0.63	5.72	0.66	0.19	0.23
1999	2	52.97	6.80	1.69	0.74	6.52	0.72	0.22	0.24
1999	3	54.32	7.14	1.86	0.85	6.29	0.77	0.24	0.28
1999	4	55.07	7.15	2.10	0.85	5.59	0.79	0.31	0.33
2000	1	.	.	.	.	.	.	.	.
2000	2	62.18	8.50	2.65	1.01	5.93	0.87	0.35	0.35
2000	3	63.31	8.88	2.38	1.02	5.67	0.81	0.41	0.36
2000	4	70.87	11.00	2.61	1.19	5.62	0.88	0.39	0.37
2001	1	63.69	9.53	2.51	1.07	5.73	0.88	0.39	0.37
2001	2	66.58	10.34	2.06	1.12	5.91	0.87	0.42	0.40
2001	3	71.29	11.76	2.74	1.24	6.14	0.86	0.46	0.42
2001	4	88.89	17.68	1.62	1.87	6.11	0.93	0.36	0.42

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.

First, we consider multi-homing from the perspective of card ownership. Afterwards, we discuss card usage. Table 5 shows the portion of person-months in which cards from each possible combination of networks appear. For instance, the first row tells us that 25.49% 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 the Visa and Discover network but not the Mastercard and American Express network represent 5.75% of the data set. By this measure, single-homing represents 36.9% of the data set (the sum of market shares in the starred rows).

Strikingly, 75% 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 88.8% of consumers hold a card from either the Visa or the Mastercard network in a month. Given that about 9% 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.

Table 5: Probability of holding a combination of cards

	Visa	MC	Amex	Disc	%	cum %
*	Y	N	N	N	25.49	25.49
	Y	N	N	Y	5.75	31.24
	Y	N	Y	N	3.11	34.35
	Y	N	Y	Y	1.15	35.5
	Y	Y	N	N	21.48	56.98
	Y	Y	N	Y	10.66	67.64
	Y	Y	Y	N	4.35	71.99
	Y	Y	Y	Y	3.44	75.43
*	N	Y	N	N	9.21	84.64
	N	Y	N	Y	2.74	87.38
	N	Y	Y	N	0.99	88.37
	N	Y	Y	Y	0.45	88.82
*	N	N	Y	N	0.74	89.56
	N	N	Y	Y	0.17	89.73
*	N	N	N	Y	1.43	91.16
	N	N	N	N	8.84	100

Notes: * indicates single homing

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 95% of their spending on a single network. The numbers are similar when we measure by card instead of network. 75% of people put more than 80% 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 81.1% of their spending for the entire period on a single network and 65.8% 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 that where the favorite network has at least 60% of the network transaction volume. Table 7 shows that Visa is most often chosen favorite: 55.9% 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 87.7% of cases. Only 2.4% of the time, they switch to Discover. In order to avoid spurious switching, this table drops all of consumer-months in which less than 60% of spending is on a single network. By multiplying the diagonal of the transition matrix times the market shares and summing, we see that there is an 80.2% 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 practice. 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.

Table 6: Concentration of Spending

	Percentile				
% on most used network	75	50	25	5	Obs.
Spending per person per month	100	100	95.2	58.4	97,951
Spending per person	99.0	81.1	62.2	47.9	575
% on most used card					
Spending per person per month	100	100	81.9	52.9	97,951
Spending per person	91.0	65.8	45.9	29.9	575

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	55.9	28.2	5.9	10.1
	Transition matrix			
Visa	87.7	8.0	1.9	2.4
mc	16.4	78.3	1.9	3.3
Amex	17.4	9.7	70.6	2.3
Disc	13.3	8.9	1.4	76.4

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. 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 payment networks.

A potential pitfall in this estimation problem is finding spurious correlation between merchant acceptance and consumer usage. For instance, in areas where economic activity is high for some exogenous reasons, we may find both that there are many consumers who use Visa cards and many merchants who accept them but we would not want to conclude that there is necessarily a positive feedback loop. In order to avoid this problem, we look only at the choice between networks among consumers who have chosen to use a network. The following model makes this explicit.

Consider a nested logit model in which consumers choose whether or not to use a payment card in the first stage and choose which of the four networks to use in the second stage. We denote the options for consumers with $j=(0,1,2,3,4)$ representing (outside option, Visa, Mastercard, American Express, Discover) respectively. These five options are grouped into two nests $g=(0,1)$ where the outside option is in group 0 and the four networks are in group 1. Utility to consumer i from choosing network j in period t is defined as follows:

$$U_{ijt} = X_{it}\beta + X_{it}\beta_j + M_{ijt}\gamma_j + \xi_{igt} + \zeta_{igt} + \varepsilon_{ijt}$$

In this equation, X_{it} represents consumer demographic information, β captures the effect of demographics on all payment cards 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 ξ_{igt} represents unobservable appeal of using a payment card. The variable ζ_{igt} represents consumer idiosyncratic taste for all payment cards and ε_{ijt} represents idiosyncratic taste for a particular network. We assume that ε_{ijt} and $\zeta_{igt} +\varepsilon_{ijt}$ are distributed iid extreme value over time and across people so the model takes on the familiar form of the nested logit model. Although all of the unobservable variables are indexed by i, we think of ξ_{igt} as representing location characteristics and might be constant across consumers in the same location whereas ζ_{igt} and ε_{ijt} represent true individual preferences.

Endogeneity enters the model through ξ_{igt} . For instance, if consumer i is a big shopper, consumer i may also like to use a payment card so ξ_{igt} would be high. If other consumers lives in a neighborhood of similar consumers, retail activity may be high in the area and we may observe high merchant activity on the payment networks, which (depending on our measure of merchant acceptance) my lead to high M_{ijt} for each network j. We avoid this type of spurious correlation by using the fact that high commercial activity should affect each of the networks symmetrically and focusing on the decision among networks. In the nested logit model, consider consumers who have chosen to use one of the networks (chosen to use group 1). The consumer chooses between networks based on conditional utility:

$$U_{ijt|g=1} = X_{it}\beta_j + M_{ijt}\gamma + \varepsilon_{ijt}$$

This utility function generates a simple logit model of the decision among networks. Only factors that affect networks differently enter this decision. The term ξ_{igt} drops out. Intuitively, areas with high retail activity may have high payment card usage but the effect should be symmetric across payment networks. To the extent that it is not, we attempt to control for by allowing demographics to differentially affect networks, as measure by β_j.

Note that the level of utility is not identified in a discrete choice model. We normalize $U_{i1t|g=1}=0$ (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:

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

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.

We see three 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, M_{ijt} may be 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.

A third explanation for finding $\gamma_j>0$ may be an omitted variable. For instance, suppose that Mastercard starts a promotional campaign aimed at both consumers and retailers in a particular region, so both U_{i2t} and M_{i2t} are high for consumers subject to the campaign. Then we may find $\gamma_j>0$ although there is no feedback loop. Note that 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. That is, explanations that lead us to wrongly find $\gamma_j>0$ must affect both consumers and firms separately and directly, and in some regions but not others.

This problem is equivalent to introducing an unobservable quality variable that varies not only across locations and consumers but also networks, say ξ_{ijt}. If it is correlated with M_{ijt}, we have an endogeneity problem. 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.[4] 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.

Before moving forward, we discuss our measures of merchant acceptance. We use two measures, both at the level of the zip code. The first is the sum of sales on a network for a month. While this is a natural measure, it is problematic to the extent that consumer

[4] There were a small number of observations where we could match 5 digit zip codes in the Census and the PSPS and instead used demographics for the 3 digit zip code. Some observations are dropped because of a failure to match even at the 3-digit level.

usage mechanically raises local sales. If consumers in a location use a particular network extensively for some unobserved reason, then naturally merchant transactions on that network will be high even if there is no positive feedback. As an alternative, our second measure is the total number of merchant names appearing in the payment network. This has the advantage that it does not depend on how much consumers spend. However, it has the drawback that it puts substantial weight on potentially unimportant (even spurious) merchants.[5] We determine the merchant acceptance that a consumer faces by taking the sum over merchant names and transaction amounts within 25 miles of the consumer. More specifically, we take the sum over both variables over zip codes with population centers within 25 miles of the population center of the consumer's zip code.

6. 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. In Table 8, the measure merchant acceptance is total dollars transacted on a network within 25 miles of a consumer. In this table and those following, we compute standard errors accounting for the fact that individuals may have correlated errors 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.[6]

We consider the first three columns of Table 8 to be the main results of the paper. High Visa acceptance enters negatively into the other three networks, suggesting that high Visa acceptance in a region makes consumers more likely to use Visa. Similarly, Mastercard, American Express and Discover acceptance all enter positively into their respective equations, implying that greater merchant acceptance makes consumers more likely to use these cards. Note that we have allowed the affect of Visa acceptance to differ at Mastercard and the other two networks but the size of these two parameters looks similar.

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 and high education households are more likely to choose American Express.

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 in any of the regressions and the main results are unchanged.

[5] There is a problem similar to the previous one in the sense 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.

[6] The number of observations is much less than the 77,349 consumer-quarter observations in the data from 1998 to 2001. The great majority of lost observations is due to consumers who do not use a network payment card for an entire month. There is small loss due to dropping consumers who do not put at least 60% of their network spending on a single network due to dropping observations from the first quarter of 2000, and a very small loss due a failure to match zip codes in the Transaction and PSPS data.

Next, we consider using counts of merchant names instead of transactions values 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 American Express and Discover but not on Mastercard. The inconclusive result on Mastercard might 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. Higher acceptance of American Express implies consumers are more likely to use that network. The effect for Discover is significant at a 90% confidence level. The results are similar in sign and magnitude when we enter local demographics as controls (columns 4-6) although now the effect of Discover acceptance on Discover usage is significant at a 95% confidence level.

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 draw consumers to their networks, although it is unclear whether Visa acceptance draws consumers from the Mastercard network. The American Express result seems particularly strong and robust, which might not be surprising if one believes that positive feedback loops should be stronger for networks that are less widespread.

Another concern with these results is that we measure merchant acceptance for all four networks based on transactions recorded on the Visa network. As discussed earlier, we therefore have much more complete data for the Visa network than the other three. As a robustness check, we present results treating network choice as a binary variable: either the consumer chooses the Visa network or the consumer chooses one of the other three. We predict choice based on individual demographics, regional demographics and the measures of Visa acceptance, ignoring the merchant data on the other networks.

Results appear in Table 10. Column 1 does not include regional demographics and the effect of the merchant acceptance (measured by total dollars transacted on the Visa network within 25 miles of the consumer) is positive but significant only at a 90% level of confidence. However, with this set-up, we should be much more interested in the results including regional demographics. Regional demographics can control for the fact that Visa transactions will be high in regions with high commercial activity.[7] Column 2 introduces regional demographics and indeed, the coefficient on Visa acceptance is larger in magnitude and significant at a 95% confidence level. The same is true when we use merchant name counts to measure acceptance. In columns 3 and 4, we see that the parameter is positive and, when regional demographics are introduced, significant.

6. 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 although multi-homing is important theoretically, very few consumers multi-home in the sense that they place almost all of their spending on a single payment network.

[7] In Table 8 and Table 9, we could expect that transactions would be high at all four networks simultaneously, so it was not clear what further information was captured by the regional demographics.

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 transaction volume on the network or counts of merchant names transacting in a given month. This result is consistent with the presence of a positive feedback loop, although we cannot discern the nature of causality with this approach.

Table 8: Choice of favorite network based on transaction amounts ($)

	MC	Amex	Disc	MC	Amex	Disc
Visa $	-0.350	-0.295	-0.295	-0.397	-0.294	-0.294
	(0.057)	(0.053)	(0.053)	(0.061)	(0.061)	(0.061)
MC $	0.335			0.327		
	(0.059)			(0.060)		
Amex $		0.364			0.277	
		(0.051)			(0.058)	
Disc $			0.275			0.274
			(0.053)			(0.056)
High School	-0.018	0.607	0.028	-0.009	0.597	0.028
	(0.107)	(0.424)	(0.166)	(0.108)	(0.427)	(0.167)
College	-0.017	1.047	0.214	-0.002	1.046	0.232
	(0.113)	(0.430)	(0.172)	(0.115)	(0.435)	(0.173)
ln(HH Inc)	0.048	1.015	0.047	0.034	1.017	0.038
	(0.043)	(0.101)	(0.065)	(0.044)	(0.103)	(0.067)
ln(Age)	0.343	0.233	0.897	0.345	0.232	0.871
	(0.072)	(0.152)	(0.120)	(0.073)	(0.153)	(0.122)
time trend	-0.082	-0.122	-0.046	-0.065	-0.099	-0.045
	(0.020)	(0.039)	(0.025)	(0.021)	(0.041)	(0.027)
ln(HH size)	0.077	-0.213	0.042	0.063	-0.193	0.004
	(0.052)	(0.128)	(0.083)	(0.053)	(0.126)	(0.085)
% pop urban				-0.233	-0.194	-0.078
				(0.134)	(0.293)	(0.219)
% diff county				-0.767	-0.582	-0.582
5 years prev.				(0.323)	(0.637)	(0.502)
% pub. Transp				0.273	-0.524	-1.771
				(0.995)	(1.313)	(1.836)
ln(med HH inc)				0.622	0.113	0.146
				(0.158)	(0.334)	(0.243)
% grad college				-1.637	0.062	-0.577
				(0.709)	(1.395)	(1.092)
ln(density)				0.044	0.162	0.019
				(0.035)	(0.066)	(0.057)
% own home				-0.614	-0.005	0.427
				(0.260)	(0.572)	(0.401)
Constant	-1.382	-14.928	-3.952	-6.298	-15.759	-5.47
	(0.493)	(1.209)	(0.794)	(1.405)	(3.109)	(2.137)
Observations	48118			47553		

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

$ is amount of transactions in dollars on that network within 25 miles.

Clustered standard errors in parenthesis

Table 9: Choice of favorite network based on merchant counts

	MC	Amex	Disc	MC	Amex	Disc
Visa count	-0.036	-0.159	-0.159	-0.070	-0.152	-0.152
	(0.057)	(0.067)	(0.067)	(0.061)	(0.075)	(0.075)
MC count	-0.003			-0.025		
	(0.061)			(0.063)		
Amex count		0.300			0.211	
		(0.062)			(0.069)	
Disc count			0.134			0.143
			(0.072)			(0.077)
High School	-0.018	0.599	0.030	-0.009	0.591	0.032
	(0.106)	(0.424)	(0.166)	(0.107)	(0.427)	(0.166)
College	-0.019	1.039	0.211	0.000	1.041	0.234
	(0.112)	(0.430)	(0.172)	(0.114)	(0.435)	(0.173)
ln(HH Inc)	0.041	1.012	0.040	0.031	1.014	0.034
	(0.043)	(0.100)	(0.065)	(0.044)	(0.103)	(0.067)
ln(Age)	0.339	0.235	0.896	0.340	0.233	0.868
	(0.072)	(0.152)	(0.120)	(0.073)	(0.153)	(0.121)
time trend	-0.040	-0.205	-0.047	-0.034	-0.175	-0.049
	(0.022)	(0.043)	(0.028)	(0.022)	(0.044)	(0.028)
ln(HH size)	0.077	-0.204	0.050	0.062	-0.186	0.009
	(0.052)	(0.127)	(0.083)	(0.053)	(0.126)	(0.085)
% pop urban				-0.218	-0.157	-0.038
				(0.134)	(0.295)	(0.220)
% diff county				-0.939	-0.546	-0.700
5 years prev.				(0.321)	(0.636)	(0.504)
% pub. Transp				-0.395	-0.751	-1.904
				(0.999)	(1.322)	(1.832)
ln(med HH inc)				0.592	0.055	0.088
				(0.156)	(0.327)	(0.236)
% grad college				-1.611	0.091	-0.509
				(0.710)	(1.392)	(1.080)
ln(density)				0.036	0.138	0.004
				(0.035)	(0.067)	(0.058)
% own home				-0.694	0.001	0.476
				(0.258)	(0.570)	(0.399)
Constant	-1.943	-15.208	-4.76	-6.946	-16.091	-5.753
	(0.478)	(1.192)	(0.773)	(1.459)	(3.158)	(2.185)
Observations		48118			47553	

Notes: Dependend variable is choice of favorite network (Visa, MC, Amex, Disc)

Count is number of merchant names on that network within 25 miles

Clustered standard errors in parentheses

Table 10: Choice of Visa as favorite network

Visa $	0.022	0.070		
	(0.012)	(0.023)		
Visa count			0.020	0.058
			(0.015)	(0.028)
High School	-0.005	-0.009	-0.005	-0.009
	(0.098)	(0.099)	(0.097)	(0.099)
College	-0.097	-0.112	-0.096	-0.112
	(0.102)	(0.104)	(0.102)	(0.104)
ln(HH Inc)	-0.124	-0.114	-0.121	-0.113
	(0.038)	(0.039)	(0.038)	(0.039)
ln(Age)	-0.476	-0.470	-0.476	-0.470
	(0.066)	(0.067)	(0.066)	(0.066)
time trend	0.033	0.020	0.039	0.038
	(0.016)	(0.017)	(0.016)	(0.016)
ln(HH size)	-0.038	-0.020		-0.023
	(0.047)	(0.048)		(0.048)
% pop urban		0.186		0.170
		(0.124)		(0.125)
% diff county		0.784		0.804
5 years prev.		(0.285)		(0.285)
% pub. Transp		0.450		0.523
		(0.865)		(0.867)
ln(med HH inc)		-0.458		-0.388
		(0.143)		(0.141)
% grad college		1.164		1.040
		(0.637)		(0.635)
ln(density)		-0.051		-0.034
		(0.032)		(0.032)
% own home		0.319		0.298
		(0.233)		(0.233)
Constant	2.925	6.51	3.091	6.388
	(0.444)	(1.257)	(0.427)	(1.298)
Observations	48149	47584	48149	47584

Notes: Dependent variable is whether Visa is favorite network for month
Clustered standard errors in parenthesis.

6. References

Armstrong, M (2002) "Competition in Two Sided Markets," mimeo, University of College London.

Ausubel, L. (1991) "The Failure of Competition in the Credit Card Market," *American Economic Review* 81(1) pp. 50-81.

Ausubel, L. (1999) "Adverse Selection in the Credit Card Market," mimeo, University of Maryland.

Baxter, W.F. (1983) "Bank Interchange and Transactional Paper: Legal Perspectives," *Journal of Law and Economics,* 26:541-588.

Caillaud, B. and B. Jullien (2003) "Chicken and Egg: Competition among Intermediation Service Providers," *RAND Journal of Economics*, forthcoming.

Calem, P.S. and L.J. Mester (1995) "Consumer Behavior and the Stickiness of Credit-Card Interest Rates," *American Economic Review,* 85(5) 1327-1337.

Evans, D. (2003a) "Some Empirical Aspects of Multi-sided Platform Industries," *Review of Network Economics,* 2(3) 191-209.

Evans, D. (2003b) "The Antitrust Economics of Multi-sided Platform Markets," *Yale Journal on Regulation*, 20(325)327-379.

Farrell, J. and G. Saloner (1985) "Standardization, Compatibility and Innovation," *Rand Journal of Economics* 16 pp. 70-83.

Gross, D.B. and N.S. Souleles (1998) "An Empirical Analysis of Personal Bankruptcy and Deliquency," Wharton Financial Institutions Center Working Paper 98-28-b.

Hunt, R. (2003) "An Introduction to the Economics of Payment Cards Network," *Review of Network Economics* 2(2) pp. 79-96.

Katz, M. and C. Shapiro (1985) "Network Externalities, Competition and Compatibility," *American Economic Review*, 75 424-40.

Rochet J-C and J. Tirole (2002) "Cooperation among Competitors: Some Economics of Payment Card Associations," *RAND Journal of Economics*, 33: 1-22.

Rochet J-C and J. Tirole (2003) "Platform Competition in Two-Sided Markets," *Journal of the European Economic Association,* 1(4).

Rysman, M. (2003) "Competition Between Networks: A Study of the Market for Yellow Pages," *Review of Economic Studies*, forthcoming.

Schmalensee, R. (2002) "Payment Systems and Interchange Fees," *Journal of Industrial Economics,* 50: 103-122.

Shy, O. (2001) "*The Economics of Network Industries*," Cambridge University Press.

Snellman, J, J Vesala and D. Humphrey (2000) "Substitution of nancash Payment Instruments for Cash in Europe," Bank of Finland Discussion Papers.

Stango, V (2000) "Competition and Pricing in the Credit Card Market," *The Review of Economics and Statistics,* 82(3), 449-508.

Stango, V. (2002) "Pricing with Consumer Switching Costs: Evidence from the Credit Card Market," *The Journal of Industrial Economics*, L(4), 475-492.

Wright, J. (2003) "Optimal Card Payment Systems," *European Economic Review*, 47 pp. 587-612.

Wright, J. (2002) "The determinants of optimal interchange fees in payment sytems," *Journal of Industrial Economics*, forthcoming.