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Supplier Switching and Outsourcing

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Abstract

We examine supplier switching decisions using a unique database that tracks firms (credit unions) and their suppliers (data processing vendors); the data are in a panel, allowing us to track supplier switching decisions at a new level of detail. We focus on two sets of relationships. First, we estimate a model that relates supplier choices and switching to a variety of buyer- and supplier-specific characteristics. Second, we examine how switching depends on the vendor relationships that credit unions choose: one is a partial form of outsourcing while the other is more complete. This allows us to estimate how supplier switching interacts with organizational form.

Key words: switching costs, outsourcing

JEL codes: L10, L14, L24

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1. Introduction

In strategy and economics there is a widely held notion that firms face costs associated with switching suppliers. Since the work of Williamson (1979) and its follow-ons, this notion has been formalized within the theory of transaction cost economics (TCE).[2] The TCE view recognizes that buyers and suppliers must make specific investments to establish and maintain business relationships. If these investments are non-recoverable, switching (i.e., exiting the relationship and finding a new business partner) will be costly. This view of the firm has implications at several levels. First, to the extent that observable features of buyer-supplier relationships systematically correlate with switching costs, empirical analysis of switching can explain not only the frequency of switching and the equilibrium length of buyer-supplier relationships across firms and industries, but also the extent to which switching costs cause hold-up problems. And more importantly, potential switching costs would influence the organization of firms, by, for example, inducing firms to avoid market transactions and vertically integrate.

In this paper, we provide some new evidence on buyer-supplier switching, using a unique database that allows us to track buyers (credit unions) and their suppliers (data processing vendors). One of the most interesting aspects of our data is that it allows us to examine switching behavior separately for firms that partially outsource their data-processing and the firms that completely outsource their data processing (DP). Most CUs choose either an "in-house" processing system under which the CU retains substantial control over the system, or an "online" system that grants the vendor nearly complete control over the processing system. Essentially, these alternatives represent different regimes of asset ownership and control, another key feature of transaction cost economics. Our data allow us to estimate how these different patterns of ownership and control interact with CU characteristics and switching under different organizational forms. This informs our understanding of how organizational form affects switching costs, and also how firms make ex ante choices regarding their outsourcing.

We track both credit unions and their vendors over time, at half-year intervals over eight years, observing a rich set of CU-level characteristics including size, product

[2] This dates at least to Porter (1979).

mix and location. While our vendor data are less rich, we do observe some vendor features such as its size and the characteristics of its customer base.

We use nested logit framework and examine both how buyers choose suppliers conditional on switching, and how buyer and seller characteristics influence decisions to switch suppliers. This allows us to examine the link between switching costs and both credit union (CU) and vendor characteristics. The CU-level characteristics at the heart of our empirical analysis are size and product offerings. There is considerable anecdotal evidence that larger firms may find switching suppliers either easier (if there is scale economy in switching), or more difficult (if smaller firms are more "agile"). We also explore the relationship between product offerings and switching; here, most anecdotal evidence suggests that firms with more "complex" offerings (as reflected by greater breadth) face higher switching costs (Hubbard, 2001; Masten, 1984; Ono and Stango, 2005).

We first estimate a model of vendor choice by CUs conditional on switching. This allows us to estimate the benefit a CU receives from a particular vendor, conditional on vendor characteristics and the "match" between a CU and its existing vendor. Because vendors sell to multiple CUs we can use vendor fixed effects to control for unobserved vendor heterogeneity. The second stage of the empirical model estimates how CU and vendor characteristics influence switching. This second stage includes information from the first stage that allows us to control for the unobserved components of switching costs.

Our results suggest that both CU and vendor characteristics are important determinants of buyer-supplier relationships. We also find that the type of outsourcing relationship affects the relationship between CU characteristics and switching. For CUs retaining significant in-house control over their DP, there is a negative relationship between CU size and switching costs. There is no such relationship for CUs choosing to fully outsource their DP. The results highlight a link between organizational structure and transaction costs; we discuss this further later in the paper.

To our knowledge, this is the first study to examine how supplier switching behavior varies both with buyer-supplier characteristics and with organizational form. There is of course a large theoretical and empirical literature on consumer switching costs.[3] Our work complements the existing transaction cost literature related to vertical relationships, asset ownership and outsourcing.[4] Our work attempts to deepen this analysis by linking firm characteristics and outsourcing to switching costs – which are themselves drivers of equilibrium organizational form.

Credit Unions and Data-Processing

Credit unions (CUs) are financial institutions that provide banking services to their members. CUs are in principle non-profit organizations, owned by their members. In many cases, a CU will affiliate with an organization, from which it draws members. These organizations are diverse -- Boeing employees, state teachers in many states, the Navy, and the Pentagon all have CUs offering services to their members. Other CUs exist for which there is no explicit organizational affiliation. CUs vary widely in terms of size. In December 2003, 33% of credit unions had assets of less than $5 million, 16% had assets between $5 and $10 million, 39% had assets between $10 and $100 million, and 12% had assets of more than $100 million.

In many ways, the structure of the CU industry mirrors that of the commercial banking sector, which represents the primary competitor to CUs for customers.[5] Beyond offering checking and saving accounts, CUs offer a wide array of financial services, including more sophisticated saving and investment options as well as personal loans and mortgages. Because of their status as non-profit organizations, CUs are entitled to preferential tax treatment. However, CUs do face competitive pressure from commercial banks, which often offer amenities that give them quality advantages over CUs.

[3] See Farrell and Klemperer (2004) for a survey of existing work. Israel (2004) is an example of recent work that does observe switches at the individual level, in an insurance market. In marketing there is a substantial literature on brand switching by consumers. See, e.g., Keane(1998) and Chintagunta(1998).

[4] Abraham and Taylor (1996) examine business service subcontracting of U.S. manufacturing firms. Kelly and Harrison (1990) and Ono (2003) also examine the relationship between firm characteristics and outsourcing decisions. Masten (1984) studies input procurement in the aerospace industry, showing that more complex inputs are less likely to be outsourced. In more recent work, Baker and Hubbard (2003) study the decision of shippers between using private (in-house) and for-hire (outsourced) drivers as their carriers and find that market segments where drivers perform complex tasks are more likely to be served by in-house drivers and trucks.

[5] See Emmons and Schmid (2000) for a discussion.

Data Processing

Like all financial service providers, CUs need to maintain detailed records of their clients' transactions. The core data for each customer usually includes transaction records associated with a checking or savings account. Managing other financial services such as credit cards, personal loans and mortgages increase the complexity of DP requirements. Such data may come in to the CU through teller transactions, through the mail, on the phone or from deposit boxes and ATMs.

While CUs may track member/customer data manually (on paper), the vast majority of CUs use some form of computer system to handle their DP. Most firms turn to outside vendors to handle their DP operations. There are two primary forms of DP services: vendor supplied on-line service bureau (VOL), and vendor supplied in-house system (VIH). Between Dec, 1996 and Dec, 2003, on average, 92.3% relied on outside vendors for DP services, with roughly 30% choosing VOL and the remainder choosing VIH.[6]

In general the VOL option is a more complete form of outsourcing, while in the VIH system the CU retains control over more aspects of data processing. In a VOL arrangement, the hardware and software used for DP are located off-site at the vendor's service bureau, which handles DP for many or all of its customers. The CU communicates with the "service bureau" through terminals connecting to the vendor's servers. These terminals may be supplied by the vendor, or be Windows-based PCs owned by the CU. The VIH system most often consists of an "out-of-the-box" software suite, which is then installed on the CUs computers. While most software vendors provide initial training on the software, the CU has much more control of both software and hardware after that point. CUs sometimes purchase servers from the vendor for VIH data processing, and typically maintain in-house IT staffs to deal with technical problems; for VOL, such function is performed by the vendor.

[6] For the purpose of the study, we exclude observations for CUs using manual systems (used only by the smallest CUs), and also those using computer-based systems developed and operated completely internally (typically used only by the largest CUs).

2. Data

We take the data from the National Credit Union Administration (NCUA) Call Report, which surveys all CUs in the United States semi-annually in June and December. The NCUA data serve as the analogue to the FDIC's Call Reports for commercial banks, and are the source of record for balance sheet, income and other information for CUs. Among the variables collected by NCUA are questions about the mode of data-processing used by the CU, and (since 1996) the vendor used to procure DP services. In order to focus on vendor switching, here we take CUs' choice of DP mode as given; in other work we examine the mode choice itself.[7] Consequently, we drop from the sample any CUs that switch from VIH to VOL or vice versa; in any case, there are few such CUs and this does not affect our results. Table 1 shows data describing the composition of our sample and the use of these DP options by CUs.

Vendors and Switching

Each CU-period observation lists a vendor from which the CU purchases its DP system. During our study period, we identify over 100 vendors providing VIH or VOL services to CUs.[8] Of these, most are small vendors with one or two customers. To simplify the analysis, we exclude vendors who have fewer than 50 CU customers in all periods of our sample. We also exclude when vendors CU customers are fewer than 10.[9] This reduces the number of vendors supplying VIH to roughly 30 per year and the number supplying VOL to roughly 15. These remaining vendors are, generally speaking, large and, they market their products over multi-state regions or nationally. The market seems competitive: while some vendors specialize in the provision of certain services or may

[7] See Ono and Stango (2005).

[8] This is after we cleaned individual CUs' data entries for the vendor names. The number of vendors has a decreasing trend, mostly due to merger and acquisition.

[9] The first restriction serves two purposes. First, in the analysis below we allow credit unions to choose among all vendors – including the smallest dramatically increases the computational burden in estimating the model but does not add much information to the analysis, since most smaller vendors are probably not in the choice set for many other CUs. It is also more difficult to identify and track smaller vendors, particularly since there was substantial acquisition activity during the sample period. The second restriction excludes some outliers where a small vendor grew dramatically (typically through acquisition). For example, until 1999 CONCENTREX had only 5 to 9 customers in each period. In 1999, when CONCENTREX acquired MC its number of clients jumped to over 200. Such cases are rare.

target CUs with particular size and product mix, any one CU has numerous viable choices when deciding on a vendor. Nor is the market highly concentrated.

CUs typically negotiate long-term contracts for their DP services, with those for VOL services being longer – it is common for such contracts to extend four to six years. These contracts specify ongoing prices for most services such as maintenance and software upgrades. They do not cover all contingencies, however, as CUs occasionally find themselves in need of services outside the scope of the contract.

As Table 1 illustrates, vendor switching is very rare.[10] In any given six-month period, roughly two percent of CUs switch vendors.[11] The degree of switching does not change much over time, except for a downward blip (and subsequent bump) around the year 2000. It is likely that Y2K concerns caused firms to delay switching. In most cases, a switch occurs after the vendor's contract with the CU expires.

Switching is more common for CUs using VIH than VOL. It is difficult to attribute this to any one cause. Switching costs likely take several forms in this market. To that point, actual switching costs depend on the form of DP used. For a CU using a VOL system, switching requires re-training (of tellers), and may also require expenses associated with converting and transferring historical account record data to the new vendor.[12] The latter is often held by those in the industry to be a substantial deterrent to switching. In contrast, a VIH user will possess all historical account data, but may need to re-configure its on-site hardware system or convert its data for a new vendor. It also may need to re-train its internal IT staff on the new system – this appears to be a particular concern for CUs based on anecdotes from the trade press. In addition, the fact that VIH allows greater customization and flexibility by having data and software on-site may make switches less common for CUs that customized. Finally, either type of switch incurs transaction costs due to writing new contracts.

While the infrequency of switching is suggestive that switching costs are large in this industry, there are other reasons for long-term relationships to exist. It may simply be

[10] Focusing on switching further reduces the sample. We include only CUs that appear in at least two consecutive periods.
[11] There is a good deal of consolidation during our sample period. We do not treat vendor name changes following merger as switches.
[12] Often, the format that should be used to store the data is specified in the contract. But the format is not necessarily the same as what a new vendor prefers.

the case that buyers and suppliers "match" well here. As is well-known, this represents an econometric difficulty in identifying switching costs in any setting.[13] In the empirical work below, we attempt to control for some aspects of matches using vendor and CU characteristics. We are also less inclined to view matches as the primary driver of buyer-supplier tenure. While there is some differentiation in DP product offerings, the functions performed by most DP vendors are fairly similar; it is unlikely, therefore, that any one vendor provides a service that renders it a dramatically superior match relative to its competitors.

3. The Empirics of Supplier Choice and Switching

Our empirical analysis has two goals. First, we are interested in explaining how vendor and CU characteristics are associated with the utility from using a particular vendor's service. The second goal is explaining how CU characteristics affect decisions to switch. To motivate the empirical work we first discuss the characteristics we focus on in our analysis of switching.

In our previous work (Ono and Stango, 2005), we identify two primary firm-specific factors affecting DP choices: CU size and product mix (as measured by the number of financial products a CU offers). Size may affect switching costs in a number of ways. Larger firms may find it more attractive to switch if there are fixed costs associated with switching. However, smaller firms may be more nimble if large hierarchies make organizational change difficult.

The number of products offered by a CU might affect switching costs as well. CUs offer a wide array of financial services, with specific offerings varying across CUs. Offering a greater number of products may increase switching costs for a number of reasons. It is likely that additional products increase the complexity of the CU's DP requirements, particularly since the incremental product offerings (e.g., variable rate home equity lines of credit) require more intensive DP than basic services (such as checking). There are nine advanced products for which we can identify whether a CU offers or not: auto loans, fixed-rate mortgage loans, variable-rate mortgage loans, credit

[13] See Heckman (1991) for a discussion of the problem, and Israel (2004) for a recent empirical application to the insurance industry.

cards, home equity lines/loans, money market, share certificate, IRA/KEOGH accounts, and business loans. We count the number of such advanced products that are offered by each CU and use it as a measure of the complexity of the CU's DP requirements.

Table 2 shows descriptive statistics for these CU characteristics as well as other variables we employ in the empirics. We measure CU size using the log number of "members" or customers. For the VIH sample, the log number of members per CU is on average 7.87, which is equivalent of 2,618 members, and for VOL, it is 8.23 – equivalent of 3,752 members. In the VIH sample the average number of products is 4.08; vendor switchers have slightly fewer product offerings. In the VOL sample the mean number of products is 4.91, with switchers having slightly more. Generally speaking, firms choosing VOL are larger and have more products. However, there is an interaction between size and products; very large CUs with many products are more likely to choose VIH (see Ono and Stango, 2005). For this reason, in the empirical work below we not only examine the relationship between size, products and switching but allow interactions between size and number of products.

Table 2 also shows summary statistics for other variables that might also influence how CUs choose vendors or switch between them. We measure whether a vendor has its headquarters in the CU's home state; CUs may find local vendors more attractive.[14] We also measure whether the CU is in an urban area (MSA) or not; previous work on outsourcing has found that this can affect organizational form. We observe the "charter" type of the CU as well – its organization affiliation (e.g., military, educational). Finally, we construct two variables that measure the "match" between a CU and its (or any potential) vendor. These matches are based on product mix, the notion being that a CU may prefer a vendor whose DP capabilities are compatible with its product offerings. CU may also prefer a vendor whose typical customers are similar to the CU; it is possible that vendors standardize their service according to the needs of their typical customers. We measure each vendor's DP characteristics using the product offerings of its existing customers. For each vendor, we identify the median number of products for its customers,

[14] We obtain headquarter location through vendor websites and a trade publication, the *Credit Union Technology Survey.* Some vendors have multiple offices. However, identifying all the offices for all vendors is difficult. Here we focus on vendors' HQ locations.

as well as the maximum number of products offered by any one of its customers. This allows the construction of DIFF_NP, which is the difference between a CU's number of products and the median number associated with its vendor's customers.[15] We also construct DMAX_NP, which is equal to one if the CU offers a number of products equal to the maximum offered by any of the vendor's CU customers.[16] This may capture a propensity to switch due to growth; a common reason for vendor switching in the trade press is that a CU "outgrows" its existing vendor, often by expanding its product mix beyond the capabilities of the vendor. Finally, to control for the general popularity of a vendor DP system, we include the number of CUs (NCU) using the vendor's system (of the same type, VIH or VOL). We also include vendor dummies to control for time-invariant intrinsic utility or price associated with a particular vendor.

Modeling vendor choice and switching

There are two aspects related to CU switching behavior. First, a CU must assess the benefit it would receive from the alternatives it faces. Second, it must compare this benefit to the costs of switching. Let U^i_{jt} represent the present value of the utility that CU i obtains (absent switching costs) by choosing vendor j in period t. This utility has a systematic component V^i_{jt}, and a random component, i.e.

$$U^i_{jt} = V^i_{jt} + \varepsilon^i_{jt}$$

If the CU faces no switching costs, it will simply choose the vendor that maximizes its expected utility; we assume that each CU faces N^i_t alternatives to its current vendor, and evaluates the expected utility from each. Suppose, however that the CU faces switching costs C^i_t; these costs are incurred only if the CU switches vendors. We can then write the CU's utility as

$$U^i_{jt} = V^i_{jt} - D^i_t \cdot C^i_t + \varepsilon^i_{jt},$$

where $D^i_t = 1 \quad \text{if} \quad vendor^i_t \neq vendor^i_{t-1}$, and 0 otherwise.

[15] Many vendors offer both VIH and VOL services, while they are typically specialized to one of them. We calculate the median number for each mode.

[16] Again, the maximum number of products offered by a vendor's customers is identified separately for VIH and VOL.

Let Z_{jt}^{i} represent a vector of covariates determining utility that a CU receives from a particular vendor; this vector could consist of vendor characteristics or CU/vendor interactions. Let X_{t}^{i} represent a vector of CU characteristics influencing switching costs. Assuming a linear relationship between characteristics and utility, we can write utility as:

$$U_{jt}^{i} = \delta Z_{jt}^{i} - D_{t}^{i} \cdot \beta X_{t}^{i} + \varepsilon_{jt}^{i} .$$

One could in principle estimate the relationship above by multinomial logit, under the assumption that the random components are i.i.d. and follow a Type I extreme value distribution. One limitation of the above specification is that it presumes that U_{jt}^{i} is specified correctly. If not, and in particular if there is an unobserved component in C_{t}^{i}, then the utilities from alternatives to the CU's existing vendor will be correlated (conditional on observables). To account for this possibility, we estimate a nested logit model, assuming that the random components for alternatives follow a generalized extreme value distribution and allowing random components for the alternatives other than the CU's existing vendor to correlate with correlation coefficient, $1-\rho^{2}$. The probability that a given alternative vendor is chosen conditional on a switch (where $D_{t}^{i}=1$) is

$$q_{t}^{i} = \frac{e^{V_{jt}^{i}/\rho}}{\sum_{j=1}^{N_{t}^{i}} e^{V_{jt}^{i}/\rho}} .$$

The probability that a CU switches vendors is

$$P_{t}^{i}(D_{t}^{i}=1) = \frac{e^{\rho I_{t}^{i} - V_{0t}^{i} - C_{t}^{i}}}{1+e^{\rho I_{t}^{i} - V_{0t}^{i} - C_{t}^{i}}} ,$$

where $I_{t}^{i} = \log(\sum_{k=1}^{N_{t}^{i}} e^{V_{k}^{i}/\rho})$ is the inclusive value measuring the aggregate utility from all alternatives to the CU's existing vendor,[17] and V_{0t}^{i} is the expected utility from the

[17] Note that following McFadden (1978), we can write the inclusive value as;

$$I_{t}^{i} = \frac{\overline{V}_{t}^{i}}{\rho} + \log N_{t}^{i} + \log\left(\frac{1}{N_{t}^{i}} \sum_{k \neq h^{i}} e^{\frac{V_{k}^{i} - \overline{V}_{t}^{i}}{\rho}}\right)$$

existing vendor's service. When $\rho = 1$, this specification becomes a standard multinomial logit. While we could perform maximum-likelihood method to estimate the parameters, the computational burden is high when there are many parameters. Including the vendor and time dummies, we have over 100 parameters to estimate. Thus, we estimate the mode above in two stages. First, we use the subsample of "switchers" to estimate a multinomial logit relating characteristics in Z_{jt}^i to vendor choices, i.e.

$$q_t^i = \frac{e^{\delta Z_{jt}^i / \rho}}{\sum_{j=1}^{N_t^i} e^{\delta Z_{jt}^i / \rho}}.$$

In that model, the choice set for each CU is the set of vendors offering the same mode type (VIH or VOL), and also having at least one customer with as many product offerings as the CU.[18] Note that the estimated parameters are not identified separately from the correlation coefficient or the standard deviation of the distribution of the random components.

These parameters allow us to calculate the inclusive value based on the equation above. For the second stage, we then run a logit model in which the dependent variable is equal to one if the CU switches the vendor. We can write the probability of a switch as:

$$P_t^i(D_t^i = 1) = \frac{e^{\rho I_t^i - \tilde{\delta} Z_{0t}^i - \beta X_t^i}}{1 + e^{\rho I_t^i - \tilde{\delta} Z_{0t}^i - \beta X_t^i}},$$

where Z_{0t}^i includes characteristics of the CU's existing vendor (in contrast to Z_{jt}^i, which measures characteristics of alternatives to the CU's current vendor). Note that the coefficients on Z_{0t}^i will vary from those on Z_{jt}^i due to ρ; we also allow δ and $\tilde{\delta}$ to be different. Since the inclusive value is estimated from the first stage multi-nomial logit, the second stage yields coefficient estimates that are consistent but not efficient; we correct the standard errors using the approach in McFadden (1981).

The equation in the previous paragraph reveals a limitation of the empirical analysis. While in principle we have specified that the Z_{jt}^i and X_t^i vectors are those

[18] In our sample, essentially all CU chose (in t) vendors that had at least one CU clients using as many complex DP (in t-1) as the CU did in t-1.

determining utility and switching costs respectively, it is possible that a given covariate may influence both utility and switching costs. To the extent that this occurs, we will not separately identify the δ and β coefficients associated with that covariate. We discuss this in more detail below.

Covariates

In order to minimize endogeneity concerns associated with switching and its effect on CU/vendor characteristics, we use lagged values of all CU and vendor characteristics in the model.[19]

We include in the vectors Z_{0t}^{i} and Z_{jt}^{i} a set of variables measuring the attractiveness of vendors to CUs. These include DIFF_NP, the difference between a vendor's "typical" number of product offerings and the CU's number of product offerings. We also include the squared term of this variable intending to capture the "match" between CU and vendor. We also include MAX_NP, a dummy variable indicating that the vendor's maximum number of product offerings are equal to the number offered by the CU. In principle we might expect that CUs would find a vendor less attractive if it would not allow the CU to expand its product line at some point in near future. We also include a variable equal to one if the vendor is in the same state as the CU; local vendors may be more attractive. To control for other unobserved features of the vendor, we include the log of its number of CU customers; this may capture vendor quality, particularly the component that is time-varying. We also include vendor fixed effects to control for vendor-specific unobserved heterogeneity that is constant over time.

The vector X_{t}^{i} includes the CU characteristics we expect to be correlated with supplier switching costs. These include CU size (log members), number of products and their interaction, and a dummy variable equal to one if the CU is in an urban area. We also include a set of dummies for the field of membership of the CU, and a vector of time dummies.

[19] For example, a given credit union who switched between June 1999 and December 1999 will be in the December 1999 period as a switcher. Vendor and CU characteristics for that observation are from June 1999.

To examine the links between organizational form and characteristics affecting vendor choices and switching, we estimate each model separately for the subsamples of CUs using VIH and VOL DP systems.

4. Empirical Results and Discussion

Table 4 presents the results of the first stage multinomial logit model correlating vendor choices with the variables in Z_{jt}^{i}. We estimate this model for the subsample of CU/period observations in which the CU switches vendors. As you can see in Table 1, for VIH, the sample size for this multinomial logit is 1,876 and for VOL, 423.

Generally speaking, our explanatory variables are statistically related to vendor choice. While the coefficient for DIFF_NP is not significant in either subsample, DIFF_NP2 is negative and highly significant in both. This implies that CUs choose vendors with typical clients that match the CU's product mix. To understand the magnitude of the coefficients, suppose that vendor A has a probability of being chosen of 0.2 when it offers a typical number of products equal to the CU's. If it instead offered two more or less, its probability of being chosen would fall to 0.15 $(= 0.2 \times \exp(-0.0699 \times 2^2)$ for VIH; the magnitude effect is similar for VOL.

The coefficient on MAX_NP is negative in both subsamples, but only significant for CUs choosing VIH DP systems. This suggests that a CU is less likely to choose a vendor for which its DP requirements would be at the high end of the vendor's capabilities. The economic magnitude of this coefficient is quite large; when DMAX_NP=1, a vendor's probability of being chosen falls to one quarter of its value when DMAX_NP=0.

Geography also appears to matter. In both subsamples the coefficient of DSAME is positive and significant, indicating that the proximity to the vendor's headquarters matters. This effect is quite large; a vendor whose headquarters are in the same state as its potential VIH (VOL) CU customer is five (twelve) times more likely to be chosen than an out-of-state vendor. This suggests that while many industry observers view the market as national and even international in scope, there are regional submarkets, and that these are substantially more important in VOL relationships.

The vendor-specific variables are important as well. The positive coefficient on Ln(NCU) indicates that (for VIH vendors), vendors are more likely to be chosen as they become larger. It is difficult to attach any one interpretation to this coefficient; it could measure changes in unobserved quality, scale economies, or any other things. The vendor fixed effects are also important, implying that vendors have fixed characteristics that are important influences on CU choice.[20]

Table 5 shows results from our second stage analysis, which is a logit model with the inclusive value from the first stage included as a right-hand side variable.[21] The coefficient on the inclusive value is positive in both subsamples, though larger and more significant in the VIH subsample. It is also consistent with random utility theory, which implies a coefficient between -1 and 1. For VIH sample, it is .280 and significant, indicating a very high correlation (0.93) for the unobserved random component associated with the utilities for alternative vendors. The correlation is also fairly high for the VOL subsample, and is significantly different from zero (i.e., the coefficient on the inclusive value is significantly different from one).

The primary results of interest are those on the variables we think should be correlated with switching costs: size, number of products, and the interaction of these two variables. These variables are all statistically significant in both subsamples, though the signs are reversed for VIH and VOL. In the VDIH sample, the coefficient on CU size is (-.298+.0304×NP), and for any number of products (1 and 9 in our study) CU size is negatively related to switching. Thus, all else equal bigger CUs are less likely to switch if their DP system is VIH. However, the strength of this relationship is lower for CUs with more products.

In the VOL subsample the coefficient for CU size is (.638-.107×NP). For CUs with NP greater than 5.96, size is negatively related to the probability of switching – as in

[20] The vendors with the largest positive coefficients are BRADFORD (1.1**), FISERV(1.43**), and OPENSOLUTIONS(1.8***); those with the largest negative coefficients are DATAMATIC (-3.18**) and ISSI(-1.97**). These coefficients are consistent with not only market shares in the cross-section, but changes in vendor popularity over time; the market shares of BRADFORD, FISERV, and OPENSOLUTIONS increase over the study period and those of DATAMATIC and ISSI fall. As examples, BRADFORD's number of VIH clients rises from 14 to 115 over the sample, while the number of VIH clients for ISSI falls from 100 to 4.

[21] We have also estimated the model as a straight logit without the inclusive value. The results are similar.

the VIH subsample. It is only for those VOL clients with few products that the relationship is reversed.

The coefficients on the urban dummy and interaction are significant only in the VIH sample. For an urban CU the coefficient is (.656-.127×ln(NCU)). It implies that CUs buying from larger vendors are less likely to switch if they are in urban areas. The coefficients on the other variables are sensible: the year effects show no sharp trend other than the drop in switching before Y2K. The field dummies are by and large not significant. One interesting difference between VIH and VOL samples is that the size of the vendor is negatively related to switching for VIH, and positively related for VOL. We discuss possible explanations for this below.

The coefficients on the variables that are also in the first stage should measure how these variables provide utility from the CU's existing vendor. This implies that they will have signs negative to those in the first stage. This is largely borne out by the data, with the same variables generally being statistically significant in each stage. The positive coefficients for DIFF_NP2 suggest that a CU is more likely to switch when its product mix deviates from that of its vendor's typical customer. The negative coefficient for the DSAME implies that a CU is less likely to switch if the vendor's headquarters are in the same state. However, this coefficient is statistically significant only for VIH services, not VOL systems. The negative coefficient on DMAX_NP implies that being a relatively complex customer of a vendor reduces the probability of switching – this is the only result opposite to the first stage results.

Discussion and Interpretation

The results show general support for our view that firm-level and vendor-level characteristics strongly affect both vendor choices and supplier switching. The first-stage results are consistent with the idea that we can measure both the relative attractiveness of vendors, and at least part of the "match" between CU and vendor. This is important for the second stage results that correlate characteristics with switching. We now discuss possible interpretations for the patterns of coefficients that we observe, and in particular the differences across DP modes.

Including the inclusive value in the second stage has a potentially important implication. The second stage results lend support to the idea that there is unobserved correlation between the utility from alternative vendors. This is consistent with the idea that there are significant unobserved and common switching costs. Of course, there could be other explanations for such unobserved correlation.

Regarding the second stage results for firm size and product mix, we find that both are statistically significant determinants of switching. In general, we find that larger CUs are less likely to switch vendors. Though this result is somewhat dependent on product mix, in the data product mix and size are highly correlated. This implies that while one can interpret the coefficients as explaining the effects of independent variation in size or products, it is most likely that a large (small) firm will have many (few) products. With this in mind, we have calculated fitted switching probabilities for the two most typical CUs in our sample: a small CU with few products, and a large CU with many products. This more clearly illustrates our general result: in the VIH subsample, larger CUs are significantly less likely to switch than smaller CUs. In the VOL subsample, this is not true: in fact, for the VOL subsample switching is essentially independent of CU characteristics, at least for the majority of CUs. We have also estimated the models without size/product interactions and these results are similar: in the VIH sample, size is negatively and significantly related to switching, while in the VOL sample neither size nor products are related to switching.

The fact that switching costs are more sensitive to CU characteristics for VIH systems fits with our view of how each system operates. A VIH system grants the CU more control over the specific investments it makes in DP training, hardware and (to an extent) software. It is of course the size of these investments that determines switching costs, to the extent that the investments are sunk. Thus, we would expect that CUs with different characteristics to choose different optimal investments in VIH systems, leading to different switching costs and a relationship between characteristics and switching costs. On the other hand, the VOL product involves relatively little CU-specific investment. It therefore makes sense that CU characteristics are less critical in determining switching costs for this mode.

We should note, however, that the relative insensitivity of switching costs to CU characteristics for VOL does not imply that switching costs for this mode are low. To the contrary, the evidence suggests that switching costs may be higher for this mode; switching overall is less frequent for VOL than VIH. It is merely the case that across CUs choosing VOL, there is not much variation in switching costs based on CU size.

Our view of how these factors interact in equilibrium is something like this: For firms that are most typical in terms of size and product mix, a relatively thick market for DP services has arisen that allows them to outsource their DP through VOL systems. This is supported by the raw data, which shows that most VOL customers are relatively similar, and also have numbers of products and members that are typical (of the population including those who ultimately choose VIH). For these firms, switching costs may be large or small relative to VIH, but in any case the size of switching costs is relatively invariant to CU characteristics. There are many other CUs for which a VOL system is inappropriate. Our intuition is that this is either because VOL is too simple (for a large CU with many products) or too complex (for a very small CU with few products). These less typical CUs find it optimal to be flexible in how they invest in DP systems. Thus, they choose a mode of DP (VIH) that allows them discretion over their specific investments such as IT, training, and hardware. For very small CUs this is valuable because it allows them to make only a minimum investment in DP – as a consequence, they have very low switching costs. Large CUs, on the other hand, make large investments in DP because they desire flexibility and customization beyond that offered by a typical arms-length (VOL) transaction. This ultimately creates high switching costs, but yields other benefits that offset the downside of being locked in to their supplier. It may also be the case that these larger CUs have more bargaining power with their suppliers, mitigating the risk of holdup once they have made a DP investment.

This view of how switching costs and DP mode choice interact is borne out in our other work examining mode choices (Ono and Stango, 2005). In that study, we find a U-shaped relationship between size (or number of products) and the likelihood that a CU chooses a VIH system. In other words, both very small and very large CUs pick VIH. Our work here provides one explanation for that result.

Our results shed light on some other possible influences on switching. The fact that large CUs switch less often than small firm is consistent with the view that larger firms are less adaptable than smaller firm, perhaps because hierarchies make change difficult. The results are inconsistent with the view that there are fixed costs of switching vendors – which implies that larger firms should have lower (average) switching costs. The results could be indicative of scale diseconomies, in fact; it may be the case that large CUs find it disproportionately difficult to switch. This may be due to contracting costs, or retraining and infrastructure diseconomies associated with switching. Of course, these implications must be taken in light of the differences across modes in the relationship between size/products and switching – for example, if it is hierarchies that explain less frequent switching by larger firms, these hierarchies must be less flexible in CUs choosing VIH than VOL.

There are some results that remain difficult to explain. One is that conditional on size, it is generally true in our sample that CUs with more products switch more often. It may not be strictly correct to look at this margin, since size and products are so strongly correlated. Nonetheless, we would expect that if products require greater DP investments (particularly for VIH systems), then this should make switching harder. It is possible that some unobserved factor is positively correlated with both products and switching – for example, having an exceptionally skilled IT staff might increase product offerings and make switching easier. We plan to explore this further in later drafts of this paper.

Another puzzling result is that vendor size is negatively related to switching for VIH systems, and positively related for VOL systems. The former result seems intuitive, if vendor size captures unobserved quality. The latter is more difficult to explain. One possibility is that mergers among VOL vendors increase the likelihood that CUs switch away from the merged firm; this would lead to a positive correlation between within-vendor size and switching. This is something that could be controlled for.

A final counterintuitive result is that MAX_NP, the variable measuring whether a CU has more products than any of its vendor's customers, has a negative sign in both the first and second stage models. The first stage result is intuitive - it suggests that firms value switching to a vendor that allows them to expand their product offerings (because some of its existing customers already offer more products). The second stage result, however, implies that firms at the high end of their vendor's product mix capabilities switch less. One possibility for this is that in the second stage this variable is correlated with something else such as tenure, or an unobserved component of the match between CU and vendor. Again, this bears further investigation.

5. Conclusion

The empirical model we develop here can yield rich information about both how firms choose suppliers, and what influences their decision to switch suppliers. Because we track both firms and their vendors over time, we can use actual switches to estimate how cross-sectional and time-series factors influence switching. We find that switching costs appear to be important; not only is switching itself infrequent in this market, but the unobserved component of alternative vendor utility is significant – this suggests that any switch incurs some common cost.

We also find that cross-sectional differences in firm size and product mix influence switching in complex ways. Generally speaking, larger CUs, who also tend to have many products, switch less. The size/switching relationship is most relevant for firms that retain at least some control over their DP investments (by using a VIH system). In contrast, CUs who more fully outsource their DP functions appear to face the same switching costs independent of their individual characteristics (though the level of their switching costs may be higher). These results highlight a number of tradeoffs in organizational form. For example, while larger CUs may have advantages over smaller CUs because they offer more products, smaller CUs may be less locked in to their DP vendors. Another dimension of tradeoffs is that bringing some DP activities in-house may have benefits (flexibility and customization) and costs (greater lock-in, particularly for large CUs). These results can shed light on both cross-sectional and time-series variation in organizational form.

We plan to extend this work in two ways. First, under stricter assumptions about specification and functional form, our model can reveal much more about switching costs than our modest interpretation here. We can also complement our existing empirics with information on firms' DP expenditures, which will allow us to say much more about switching costs.

Another facet of switching we plan to explore is the relationship between switching costs and firms' ex ante choices regarding how to organize their DP. We could expect, for example, that firms facing high switching costs would be more likely to move DP in-house, either fully or partially. This will provide a fuller picture of the relationship between switching costs and organizational form.

Table 1. Sample composition and switching

	Vendor In-house			Vendor On-line		
Period	CUs	Vendors	switches (%)	CUs	Vendors	switches (%)
Jun, 1997	4,872	31	150 (3.09 %)	2,176	15	33 (1.52 %)
Dec, 1997	5,216	31	118 (2.26 %)	2,169	15	20 (0.92 %)
Jun, 1998	5,319	30	95 (1.79 %)	2,157	15	29 (1.34 %)
Dec, 1998	5,341	30	148 (2.77 %)	2,140	14	31 (1.45 %)
Jun, 1998	5,341	30	157 (2.94 %)	2,140	15	29 (1.36 %)
Dec, 1999	5,303	29	88 (1.66 %)	2,119	16	14 (0.66 %)
Jun, 2000	5,245	28	90 (1.72 %)	2,092	15	13 (0.62 %)
Dec, 2000	5,098	28	157 (3.08 %)	2,002	15	39 (1.95 %)
Jun, 2001	5,059	29	222 (4.39 %)	1,986	17	62 (3.12 %)
Dec, 2001	4,982	28	201 (4.03 %)	1,990	17	49 (2.46 %)
Jun, 2002	4,959	27	171 (3.45%)	1,967	16	42 (2.14 %)
Dec, 2002	4,942	25	110 (2.23 %)	1,931	16	29 (1.50 %)
Jun, 2003	4,908	27	87 (1.77 %)	1,879	15	17 (0.90 %)
Dec, 2003	4,807	26	82 (1.76 %)	1,795	13	16 (0.89 %)
	71,392		1,876	28,543		423

(Source: Authors' calculation based on NCUA data)

Table 2: CU characteristics

VIH Subsample

	Switchers		All			
Variable	Mean	S.D.	Mean	S.D.	Min	Max
Number of members (log)	7.58	0.43	7.87	1.53	4.6	13.2
No. of products	3.63	2.31	4.08	2.46	1	9
Dummy: =1 if the vendor's HQ is in the same sate as the CU	0.0944	NA	0.12	NA	0	1
Dummy: =1 a CU is in an urban area	0.76	NA	0.78	NA	0	1
Dummy: FOM = community	0.0762	NA	0.08	NA	0	1
Dummy: FOM = association	0.0778	NA	0.07	NA	0	1
Dummy: FOM = education	0.12	NA	0.11	NA	0	1
Dummy: FOM = military	0.00906	NA	0.02	NA	0	1
Dummy: FOM = government	0.138	NA	0.15	NA	0	1
DIFF_NP	-0.184	2.15	0.31	1.92	-7	8
Dummy: =1 if Max NP	0.0293	NA	0.04	NA	0	1
No. of venders	28.59	3.1	28.1	3.58	12	32
n	1,876		71,392			

VOL Subsample

	Switchers:		All			
Variable	Mean	S.D.	Mean	S.D.	Min	Max
No. of members (in log)	8.44	0.81	8.23	0.91	4.6	13
No. of products	5.27	1.83	4.91	1.95	1	9
Dummy: =1 if the vendor's HQ is in the same sate as the CU	0.195	NA	0.16	NA	0	1
Dummy: =1 a CU is in an urban area	0.844	NA	0.8	NA	0	1
Dummy: FOM = community	0.139	NA	0.11	NA	0	1
Dummy: FOM = association	0.0213	NA	0.03	NA	0	1
Dummy: FOM = education	0.085	NA	0.08	NA	0	1
Dummy: FOM = military	0.0142	NA	0.02	NA	0	1
Dummy: FOM = government	0.1466	NA	0.15	NA	0	1
DIFF_NP	0.317	1.83	-0.01	1.89	-6	5
Dummy: =1 if Max NP	0.0284	NA	0.03	NA	0	1
No. of venders	15.52	1.54	15.3	1.66	7	18
n	423		28,543			

(Source: Authors' calculation based on the NCUA data)

Table 3: Characteristics of Vendors in the Choice Sets

Variable	VIH sample				VOL sample			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Number of CU clients* (in log)	4.62	1.16	2.30	7.52	4.15	1.15	2.30	7.08
Number of Products of a typical (median) CU clients*	3.97	1.97	1	8	4.69	1.23	1	7
Maximum Number of Products	8.15	1.11	5	9	8.15	1.34	3	9

(Source: Authors' calculation based on the NCUA data)

* Many vendors provide both VDIH and VDOL services, while the degree of specialization varies. For the VDIH sample, we use the VDIH CU clients for a vendor, and for the VDOL sample, we use the vendor's VDOL CU clients.

Table 4: Results of Multi-nomial logit

Dependent variable:=1 if a vendor is chosen by a CU

	VIH sample		VOL sample	
No. of observations	1,876 CU-periods		423 CU-periods	
	Coef.	(z-stat.)	Coef.	(z-stat.)
Vendor-CU variables				
DIFF_NP	-0.0766	(-1.18)	0.122	(0.62)
DIFF_NP2	-0.0699***	(-17.53)	-0.0665***	(-2.86)
Dummy: MAX_NP	-1.47***	(-3.93)	-0.174	(-0.36)
Dummy: Same state	1.60***	(16.35)	2.50***	(12.55)
Vendor variables				
Ln(NCU) †	0.528***	(4.12)	0.146	(0.54)
Vendor Fixed-Effects	Yes		Yes	

(Source: Authors' calculation based on the NCUA data)
*** significant at 1% level.
†: For VDIH sample, we use CU clients using VDIH services of a vendor, and for the VDOL sample, we count the clients using VDOL.

Table 5: Decision to switch

Dependent variable: =1 if a CU switches a vendor between t-1 and t.

	VIH sample		VOL sample	
	Coef.	(z-stat.)†	Coef.	(z-stat.)†
Inclusive Value	0.280***	(3.30)	0.169	(1.32)
CU variables				
No. of members (in log)	-0.298***	(-5.22)	0.638***	(3.14)
No. of products (NP)	-0.152	(-1.48)	0.865**	(2.34)
No. of members (in log) × NP	0.0304***	(2.94)	-0.107***	(-3.07)
D_urban: =1 a CU is in an urban area	0.656**	(2.23)	1.267	(1.60)
D_urban × ln(NCU)	-0.127***	(-2.63)	-0.182	(-1.39)
Dummy: FOM = community	0.0438	(0.452)	0.250	(1.60)
Dummy: FOM = association	0.0713	(0.768)	-0.378	(-1.09)
Dummy: FOM = education	0.0561	(0.731)	-0.0333	(-0.183)
Dummy: FOM = military	-0.471*	(-1.87)	-0.195	(-0.462)
Dummy: FOM = government	-0.105	(-1.46)	-0.155	(-1.05)
Vendor-CU variables				
DIFF_NP	-0.0943	(-1.36)	0.105	(0.476)
DIFF_NP2	0.0495***	(13.06)	0.0413***	(2.73)
Dummy: MAX_NP	-0.347*	(-1.65)	-0.712**	(-1.98)
Dummy: Same state	-0.374***	(-2.81)	-0.108	(-0.569)
Time dummies (Omitted category: June, 1997)				
Dec, 1997	-0.335**	(-2.48)	-0.481	(-1.68)
Jun, 1998	-0.577***	(-4.04)	-0.0854	(-0.329)
Dec, 1998	-0.108	(-0.826)	0.0132	(0.0513)
Jun, 1998	-0.0421	(-0.324)	-0.0644	(-0.246)
Dec, 1999	-0.640***	(-4.36)	-0.804**	(-2.45)
Jun, 2000	-0.646***	(-4.42)	-0.868***	(-2.59)
Dec, 2000	0.0456	(0.356)	0.303	(1.20)
Jun, 2001	0.353***	(2.96)	0.787***	(3.37)
Dec, 2001	0.273**	(2.25)	0.549**	(2.24)
Jun, 2002	0.120	(0.968)	0.423**	(1.68)
Dec, 2002	-0.325**	(-2.36)	0.0491	(0.180)
Jun, 2003	-0.606***	(-4.04)	-0.437	(-1.32)
Dec, 2003	-0.636***	(-4.04)	-0.787**	(-2.24)
Constant	-3.15**	(-2.22)	-13.53***	(-5.37)
Vendor variables				
Ln(NCU)	-0.332**	(-2.48)	0.783*	(1.77)
Vendor Fixed-Effects	Yes		Yes	

(Source: Authors' calculation based on the NCUA data)

†: The standard errors of this upper-stage estimation are corrected by recursive method as presented in McFadden (1981).

***: significant at 1% level.

**: significant at 5% level.

*: significant at 10% level.

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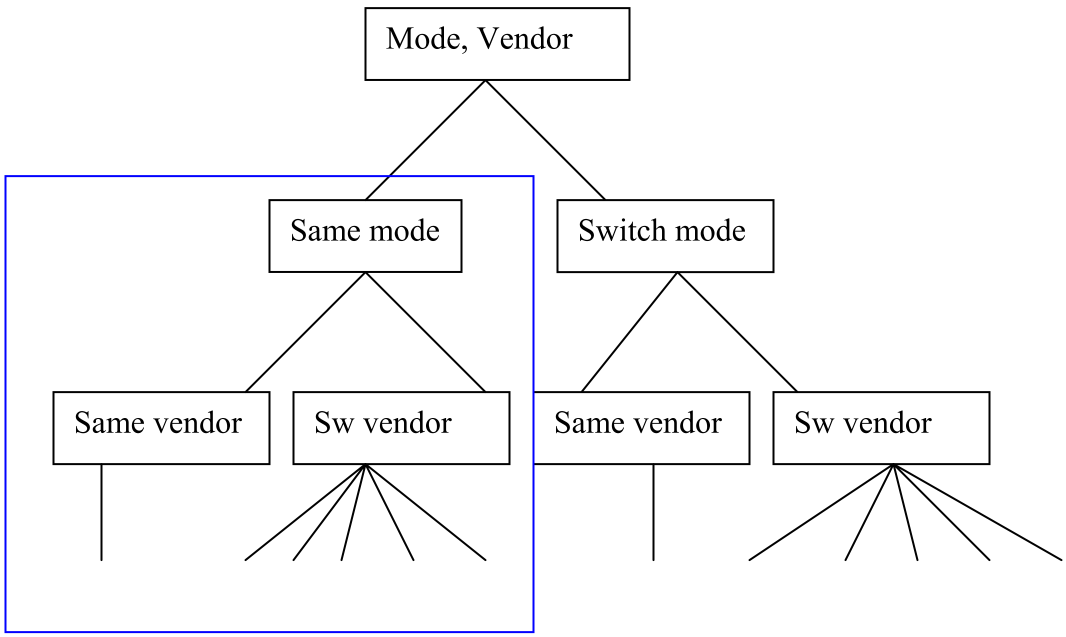
Appendix

Decision Tree



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