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SWITCHING COST AND BRAND LOYALTY IN ELECTRONIC MARKETS: EVIDENCE FROM ON-LINE RETAIL BROKERS[1]

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Abstract

The ability to retain and lock-in customers in the face of competition is a major concern for e-commerce businesses. If a firm is able to build a significant amount of switching cost and brand loyalty, then it can benefit from a long-term flow of profits and recover investments in customer acquisition. In this paper, we propose a method to measure the magnitude of switching costs for on-line service providers, which we apply to the on-line brokerage industry. We find a significant variation in calculated switching costs between brokers—on the factor of 2—suggesting that brokers have substantial influence over their switching costs.

Keywords: Electronic markets, measures, empirical research, marketing, financial sector

1. INTRODUCTION

Many emerging e-commerce companies, especially those focused on business to consumer (B2C) e-commerce, are in an aggressive phase of recruiting new customers in what analysts have called a "land grab." These firms devote a large amount of their resources to advertising and promotion, and increasingly to outright customer subsidies. For example, E*trade was offering $400 in free computer merchandise for new customers who signed up between January and March, 2000, and spent about $400 million in 1999 on selling and marketing, representing over 60% of their non-interest expenses and over 45% of net revenue. Customer acquisition costs, which are estimated to range from about $40 per customer for Amazon.com to over $400 for some on-line brokers (McVey 2000), are probably the largest contributor of cost to new B2C startups and represent a substantial portion of the financial losses these firms typically incur. Clearly, the expectation is that these early investments in customer acquisition will result in a long-term stream of profits from loyal customers to offset these costs.[2]

Essential to this strategy is that customers experience some form of "lock-in" or switching costs to prevent them from defecting to another provider. Switching costs come in a variety of forms ranging from explicit contractual provisions, actual effort involved in switching or learning to use a new provider, or psychological costs of switching from a familiar provider to one whose quality is unknown (Klemperer 1987; Schmalensee and Willig1986). By creating or exploiting switching costs, firms can soften price competition, build a "first mover" advantage, and earn supranormal profits on advertising or other investments (Beggs and Klemperer 1992; Farrell and Shapiro 1988; Klemperer 1987, 1989, 1995; Nilssen 1992; Schmalensee 1974, 1982; Schmalensee

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[2]An alternative explanation is that these costs are incurred not to acquire customers now, but to increase the rate of customer adoption in the future either because of the presence of network externalities or the creation of brand awareness. However, while these explanations can lead to a misestimation of the per-customer acquisition costs, these costs still need to be recovered through the retention of profitable customers.

and Willig1986). However, if switching costs are inherently low and firms are unable to lock-in customers, long-term profitability may be difficult to attain, especially in many B2C e-commerce environments with low entry barriers (outside of customer acquisition) and limited differentiation.

Despite the critical role of switching costs in e-commerce strategy, there is surprisingly little empirical evidence about the presence, magnitude, or impact of switching costs on customer behavior. This appears to be true more broadly—despite a robust theory literature, there are few if any systematic empirical analyses of the role of switching costs in competitive settings with the exception of work in credit cards and airlines (Handelsman and Munson 1989; Zephirin 1994).

In this paper, we make innovations on two fronts. First, we develop a model that allows the estimation of the differences in switching costs across providers utilizing web site traffic data.[3] The fundamental idea of our model is that if new customers to a market have the same preferences as existing customers in a market, we can estimate the extent of switching costs by comparing the rate of adoption of different service providers for new customers to the rate of switching faced by each provider. If these rates are the same across all providers, then switching costs are also similar across providers. In other words, if there were no switching costs, then each period a customer could make a new adoption decision, and if preferences between new and existing customers are the same, in aggregate customer adoption patterns for new and existing customers would be the same. If, however, customer defections have a different distribution across different providers than new customer adoption, this is indicative of variations in switching costs.

Second, we apply this model to estimate the switching costs for on-line retail brokers. Retail brokers provide individual investors with the ability to purchase and trade stocks, bonds, and other financial instruments; on-line brokers differ from their traditional counterparts by conducting the vast majority of their transactional activity using the Internet. This industry is an interesting candidate to study for a number of reasons. First, the market is large and significant—there were over 140 on-line retail brokers by the end of 1999 and they have thus far captured about $860 billion customer assets (Gomez 1999), representing about 15% of all brokerage assets and 30% of all stock trades (Saloman Smith Barney 2000). Second, this industry is known to have very aggressive customer acquisition tactics and requires large advertising expenditures. For example, E*trade spent over $154 million and Schwab spent $101 million on advertising in the first quarter of 2000 alone (McVey 2000). Third, there is reason to believe that switching costs have a substantial influence on customer behavior. Executing a stock trade is a potentially significant financial transaction and there is some complexity in learning to use the tools and interface of a new broker. This deters customers from switching brokers. In addition, switching brokers either requires that the customer convert their entire portfolio into cash (incurring significant trading costs) or transfer the assets individually, which requires a waiting period of up to six weeks for completion. Finally, the lifetime value of an active account is large (> $1,000) which implies that firms may be willing to make significant investments in customer retention.

To estimate our models, we utilize data from Media Metrix, a firm that tracks web site usage data for a panel of over 25,000 households. Our dataset includes all customers' activities for the top 11 brokers (covering over 95% of the market), where activity is defined as a web page visit in the first quarter, 1999, and the last quarter, 1999. This yields a dataset of 1,930 total customers who are tracked by Media Metrix in both datasets and have broker activities in at least one period, including 790 new customers (with 875 broker accounts) in Q4 and 549 customers who had no broker activities in Q4. While these data have a number of limitations for use in this study, the dataset is the one of the most comprehensive and accurate data sources available on customer web usage patterns.

Our analysis suggests that there is significant variation in switching cost between brokers—on the order of a factor of 2. This suggests that firms have substantial control over their switching cost and that managing this switching cost is a potentially important component of firm strategy.

The remainder of this paper is organized as follows. In section 2, we discuss the previous literature on switching costs and brand loyalty. The model is introduced in section 3. We present our analysis in section 4 followed by a summary and conclusion in section 5.

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[3]This model is applicable to any setting in which a customer's relationship with multiple service providers can be precisely observed. However, these data are typically difficult to obtain in the offline world because few datasets exist that can comprehensively capture customer interactions with multiple, competing businesses.

2. LITERATURE: BRAND LOYALTY AND SWITCHING COSTS

In many markets, consumers face non-negligible costs of switching between different brands of products or services. As classified by Klemperer (1987), there are at least three types of switching costs: transaction costs, learning costs, and artificial or contractual costs. Transaction costs are costs that occurred to start a new relationship with a provider and sometimes also include the costs necessary to terminate an existing relationship. Learning costs represents the effort required by the customer to reach the same level of comfort or facility with a new product as they had for an old product. Artificial switching costs are costs created by deliberate actions of firms and are very common in the marketplace: frequent flyer programs, repeat-purchase discounts, and "clickthrough" rewards are all examples. Switching costs have been theoretically shown to have positive effects over prices, profits, and entry deterrence, and have been linked to a variety of competitive phenomena such as price wars and deep discounts offered by firms to attract new customers (Beggs and Klemperer 1992; Farrell and Shapiro 1988; Klemperer 1987, 1989, 1995; Nilssen 1992; Schmalensee 1974; Schmalensee and Willig 1986).

The marketing literature identifies a specific manifestation of switching cost, termed "brand loyalty." Brand loyalty is usually defined as the minimum price differential needed before consumers who prefer one brand switch to some competing brand (Raju et al. 1990; Pessemier 1959). Brand loyalty may be due to real switching costs, decision biases (e.g., the "Status Quo Bias"), or uncertainty in the quality of other brands. Much of this extensive literature emphasizes the identification of loyal customers (Jacoby and Chestnut 1978) by individual behaviors (e.g., repeat purchase) or expressed preferences in surveys or focus groups. Our paper infers switching cost from aggregated individual behaviors.

3. MODEL

Our model is based on the conditional logit model (McFadden 1974a), which is commonly used in modeling the consumer choice among multiple products (Boskin 1974; McFadden 1974b; Schmidt and Strauss 1975a, 1975b). Consider a set of consumers who have preferences over a set of goods that are comprised of two parts: a systematic component related to the observable and unobservable characteristics of the good common across all consumers (ν), and a random component that is idiosyncratic to an individual customer and arises due to specific tastes or random error in selection (ε).

We further subdivide the common characteristics ν into a price index (r), a vector of non-price attributes (x), and a collection of unobservable attributes or firm-specific effects that can be represented by a parameter (γ). For a set of N consumers choosing among M firms, we write the utility of a particular consumer if she chooses firm j ($j \in [1,2,...M]$) as:

$$u_j = \nu_j + \varepsilon_j = \gamma_j + x_j\beta - \alpha r_j + \varepsilon_j \tag{1}$$

If we observe a customer choosing firm j, we can infer that this choice provides the consumer with the highest utility over the set of M firms. That is, the probability that a consumer will choose firm j is determined by the relative utility level:

$$p_j = prob.(u_j \geq u_k, \forall k) \tag{2}$$

As shown by McFadden (1974a), if the error term is independent and identically distributed with Weibull distribution, also known as "extreme value" distribution (that is, $prob.(\varepsilon_j \leq \varepsilon) = e^{-e^{-\varepsilon}}, \text{ where } -\infty < \varepsilon < \infty$), then we have a simple expression for the choice probabilities:

$$p_j = \frac{e^{\nu_j}}{\sum_{l=1}^{M} e^{\nu_j}} = \frac{e^{\gamma_j + x_j\beta - ar_j}}{\sum_{l=1}^{M} e^{\gamma_l + x_l\beta - ar_j}} \tag{3}$$

We now introduce switching costs in this model. Let s_k be the cost (disutility) a consumer must overcome when switching from firm k ($k \in [1,2,...$M]) to another firm. Note that we have implicitly assumed that the switching cost does not depend on the firm the customer switches to, but only on the firm from which she switches.[4]

[4]Based on this assumption, we only have to estimate M parameters rather than Mx(M-1) parameters if we assume switching cost depends both on where the customer switches from as well as where she switches to. As a result, this is a common assumption in literature.

Consider a two-period setting where some consumers with unit demand[5] choose a firm in period 1, while others do not. In period 2, some of the early adopters stay, some of the early adopters switch firms, and new customers enter the market that had not previously adopted. For a consumer who chose firm k in period 1, her utility from choosing to stay with firm k in period 2 is:

$$u_{k|k} = \nu_k + \varepsilon_k = \gamma_k + x_k\beta - ar_k + \varepsilon_k \tag{4}$$

where the notation $u_{a|b}$ denotes the utility a customer gets if she chooses firm *b* in period 1 and then switches to firm *a* in period 2.

However, if she decides to switch to, say, firm j, she incurs a switching cost s_k, and as a result, the utility of choosing j is:

$$u_{j|k} = \nu_j - s_k + \varepsilon_j = \gamma_j + x_j\beta - ar_j - s_k + \varepsilon_j \tag{5}$$

If the user is new in period 2, then there is no switching cost, so the utility of choosing any j is (where we denote "n" as representing new users):

$$u_{j|n} = \nu_j + \varepsilon_j = \gamma_j + x_j\beta - ar_j + \varepsilon_j \tag{6}$$

Again, we have implicitly assumed that the preferences for new customers over price and other attributes is the same for new customers as well as existing customers, except for switching costs and the customer-specific utility ε. However, customers who switch differ from new adopters in that they incur the disutility from switching. Given the utility expression derived in equations (4) and (5), the probability that a user from firm k will choose to stay with firm k is:

$$p_{k|k} = \frac{e^{\nu_k}}{e^{\nu_k} + \sum_{l \neq k} e^{\nu_k - s_k}} \tag{7}$$

And the "odds ratio" for staying with firm k is then:

$$\frac{p_{k|k}}{1 - p_{k|k}} = \frac{e^{\nu_k}}{\sum_{l \neq k} e^{\nu_l - s_k}} = \frac{e^{s_k} e^{\nu_k}}{\sum_{l \neq k} e^{\nu_l}} \tag{8}$$

Similarly the equivalent odds ratio for a new adopter choosing firm k is:

$$\frac{p_{k|n}}{1 - p_{k|n}} = \frac{e^{\nu_k}}{\sum_{l \neq k} e^{\nu_l}} \tag{9}$$

By dividing the two odds ratios, we get exact measure for firm k's level of switching cost.

$$\frac{\dfrac{p_{k|k}}{1 - p_{k|k}}}{\dfrac{p_{k|n}}{1 - p_{k|n}}} = e^{s_k} \tag{10}$$

A switching cost level of s_k is measured in the same terms in prices. The value $\frac{s_k}{\alpha}$ can be interpreted as how much a site would have to lower (quality-adjusted) prices to attract a customer from a site with equivalent characteristics. For our study, we only

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[5]Our model easily generalizes to consumers who purchase more than one product. If consumers purchase the same number of products across all firms or if total demand is not sensitive to firm characteristics, then this is already captured by the unit demand case. When this does not hold, a similar set of expressions for choice hold, but include quantity as a parameter (derivation available from authors).

have two periods of data and, therefore, cannot estimate the price elasticity parameter α when there are likely to be substantial firm-specific effects. In general, with more than two periods of data, we can compute α by estimating demand functions (Berry 1994; Besanko et al. 1998). When α doesn't vary across firms, which is a common assumption, we can get a proportional measure of switching cost that is directly comparable across brokers. Note that we have already controlled for all broker characteristics (other than switching costs) in the analysis.

We have derived this model under the assumption that each customer has a unit demand for brokerage services. Our analysis suggests that if we capture demand as frequency of visiting the site, we cannot reject the hypothesis that the demand is the same for all brokers when we examine the new adopters in the sample ($F_{10, 864} = 0.73$, not significant). Otherwise we would also have to account for differences in transaction volume across brokers (c.f. footnote 4).

4. DATA AND ANALYSIS

4.1 Data Sources

Our primary data for this study is drawn from a panel of "clickstream" data provided by Media Metrix. Media Metrix has a panel of more than 25,000 households that have an applet installed in their computers that tracks the user, time, and URL of every page request they make on the world wide web. They also collect demographic information from the users (gender, household income, age, education level, occupation, race, and others). We have two samples of these data, the first from January-March, 1999, and the second from October-December, 1999 (we refer to these as the Q1 and Q4 datasets respectively). We restrict our analysis to customers who appear in both datasets so that we can get proper estimates of the number of first period non-adopters. Using market research data (Salomon Smith Barney and Morgan Stanley Dean Witter) we identified the 11 largest retail brokers,[6] which account for over 95% of all on-line brokerage accounts, and extracted all page references to these sites. We use the number of days that a broker is accessed and total time spent in a quarter as a proxy for activity at the broker. To determine whether a customer is an account holder or not, we examine the individual URLs that each customer visited: if they accessed any pages that are restricted to account holders only during the period, we define the customer as an account holder. Our analysis is limited to account holders only; individuals who browse broker sites that do not have an account are excluded.

There are two key limitations of these data. First, while we can tell whether the customer is an account holder, we cannot determine their trading volume. Second, our data covers home usage but not work usage. Given that significant trading activity in many accounts occurs during the daytime when the financial markets are open, our visit frequencies may not be indicative of trading activity. However, to the extent that most users utilize these sites for both trading (during market hours) and research and financial management (in the off-hours), we are not likely to be missing the overall adoption decision.

4.2 Summary Statistics and Preliminary Analysis

Between our two datasets from Media Metrix, we have a total of 25,166 households, of which 12,420 households are tracked in both the Q1 and Q4 datasets (this includes both customers who use on-line brokers and customers who do not). Restricting our sample to only individuals that appear in both datasets,[7] we have 1,140 users with 1,374 accounts in Q1 and 790 new adopters in Q4 with 875 accounts. Figure 1 shows our customer counts in various customer categories and how they migrate in the sample between Q1 and Q4.

Table 1 summarizes market share in each period, as well as the share of new adopters for each broker we examine. The table shows that market shares are relatively stable with the exception of NBD (National Discount Brokers) who appear to be growing in share somewhat, although from a very small base. These market share numbers are consistent with share numbers obtained from other sources (Morgan Stanley Dean Witter 1999).

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[6]These brokers are Ameritrade, Datek, DLJDirect, E*Trade, Fidelity, Fleet (which owns QRonline and Suretrade), MSDW, Schwab, TDWaterhouse, Vanguard, and NDB.

[7]This is necessary to distinguish new adopters in Q4 from individuals who already had brokerage accounts that joined the Media Metrix panel during the year.

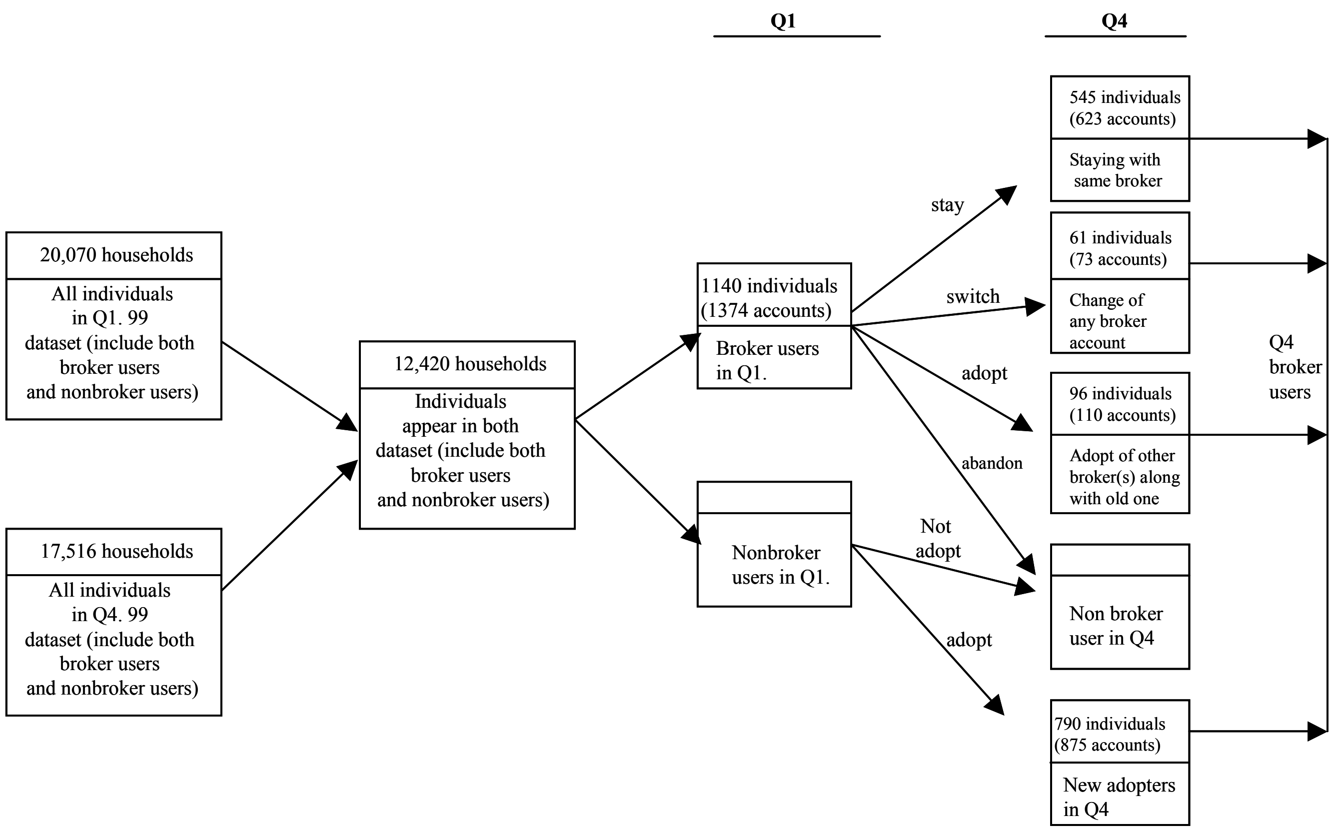

Figure 1. Data Flow Diagram

Table 1. Market Share by Broker for Existing and New Customers

BROKER	Q1 ACCOUNTS	Q1 MARKET SHARE	Q4 ACCOUNTS	Q4 MARKET SHARE	NEW ADOPTERS	MARKET SHARE OF NEW ADOPTERS
AMERITRADE	87	6.3%	108	6.5%	47	5.4%
DATEK	34	2.4%	60	3.6%	26	3.0%
DLJDIRECT	63	4.6%	66	4.0%	38	4.3%
ETRADE	328	23.9%	365	21.8%	217	24.8%
FIDELITY	253	18.4%	417	24.9%	233	26.6%
FLEET	33	2.4%	49	2.9%	24	2.7%
MSDW	24	1.8%	35	2.1%	19	2.2%
NDB	8	0.6%	25	1.5%	17	1.9%
SCHWAB	232	16.9%	267	16.0%	125	14.3%
TDWATERHOUSE	99	7.2%	119	7.1%	49	5.6%
VANGUARD	213	15.5%	162	9.7%	80	9.1%
TOTAL	1374	100%	1673	100%	875	100%

*New adopters refer to those who have no broker activity in Q1.

Table 2. Customer Movement Among Brokers

	A	*B*	*C*	*D*	*E*	*F*	*G*	*H*	*I*
BROKER	**Q1 ACCOUNTS**	**SWITC H OUT (NO.)**	**STAY (NO.)**	**ABANDON (NO.)**	**ADOPT (NO.)**	**SWITCH IN**	**Q4 ACCOUNTS**	**STAY RATE**	**SWITCHING RATE**
AMERITRADE	87	5	50	32	56	2	108	91%	9%
DATEK	34	2	20	12	34	6	60	91%	9%
DLJDIRECT	63	7	21	35	42	3	66	75%	25%
ETRADE	328	21	109	198	245	11	365	84%	16%
FIDELITY	253	7	143	103	257	17	417	95%	5%
FLEET	33	1	15	17	29	5	49	94%	6%
MSDW	24	1	6	17	26	3	35	86%	14%
SCHWAB	232	6	130	96	128	9	267	96%	4%
TDWATERHOUSE	99	3	56	40	57	6	119	95%	5%
VANGUARD	213	20	68	125	92	2	162	77%	23%
TOTAL (all 11 brokers)	1374	73	623	678	985	65	1673		

A=B+C+D
C+E+F=G
H=C/(B+C)
I=B/(B+C)

* We do not report the numbers for NDB due to the small number of observations.
******Note that Column E includes both brand new adopters who have no broker activity in Q1 as well as adopters who adopt a new account along with other accounts.

Table 3. Test Statistics for Demographics Variables (ANOVA Analysis) Based on All New Adopters

	χ^2 (DF)	P VALUE
Sex	12.72 (9)	0.18
Income	42.903 (36)	0.20
Occupation	54.837 (45)	0.15
Education	33.014 (27)	0.20
Race	27.579 (18)	0.07
Married	25.542 (18)	0.11

	F	P value
Age	$F_{9,\ 832} = 3.02$	0.0015 **

*We exclude users of NDB from the analysis due to the small number of observations.

In Table 2, we examine customer activity in more detail. This table shows there is a substantial amount of movement of customers with about 10.5% changing brokers. Even more importantly for the purposes of our analysis, there is substantial heterogeneity in brokers' abilities in retaining customers: Fidelity is able to retain 95% of their customers, while only 75% of customers at DLJDirect stay for both periods. For top three brokers, E*Trade's switching rate (16%) is over three times that of Fidelity (5%) and Schwab (4%). A test that switching rates are the same across brokers is clearly rejected ($\chi^2_{10} = 79.66$, $p < .0001$). Another interesting observation is that attrition appears to be a serious problem for some brokers (Column D in Table 3). This may be due to seasonal effects, or alternatively it could be a direct result of subsidized adoption without screening. These brokers may attract a significant number of customers who adopt solely because of the subsidy and then promptly drop out afterward.

4.3 Analysis and Discussion

Our summary analysis suggests substantial heterogeneity in switching rates, which suggests heterogeneity in switching costs. However, these simple statistics do not take into account the different levels of utility offered by different brokers. Using our model developed in section 3, we can calculate an estimate of switching costs. Our measured switching cost is the disutility perceived by a representative user of each broker regardless of what causes the switching cost. Because these numbers have a relative but not absolute interpretation absent a good estimate of price elasticity, we normalize the firm with the lowest switching cost (E*Trade) to 1.0.

The results of this calculation are shown in Figure 2. Overall, there is substantial heterogeneity in switching costs—Fleet, TDWaterhouse and Datek have the "stickiest" sites, with switching costs over two times that of E*trade. Among the major three brokers, it is about 1.8 times more difficult to induce a representative customer to switch out of Schwab than to induce a representative customer to switch out of E*trade.

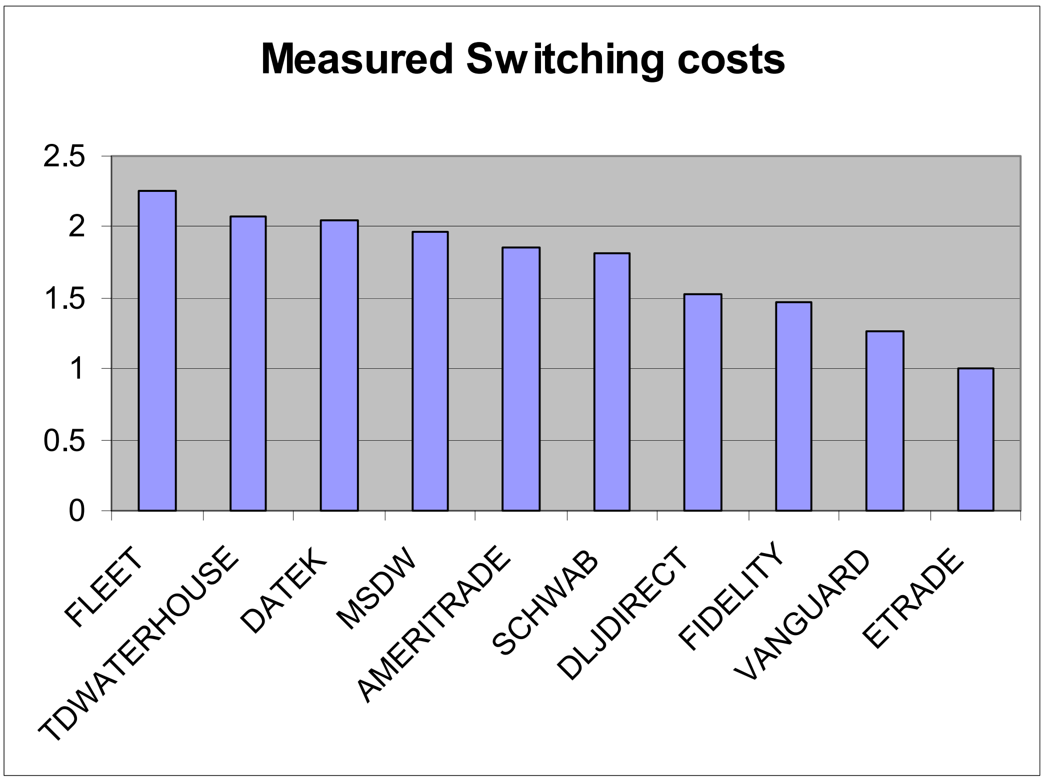

Figure 2. Switching Cost Estimates by Broker (with E*Trade Normalized to 1)

There are at least two plausible explanations for the asymmetric switching costs we observe. First, through investments in service, loyalty programs, or other retention activities, firms can influence the switching behaviors of their customers. Second, some types of customers may have different switching propensity and these customers may be differentially attracted to different brokers due to firm specific practices (e.g., advertising campaigns or user subsidies) or unobserved customer characteristics like price sensitivity. In this analysis they are observationally equivalent, although they have profoundly different strategic implications. If switching is due to firm rather than customer characteristics, a firm could improve their apparent switching costs by investing more in retention. Alternatively, if switching is an inherent customer characteristic, the firm should alter their approach to customer acquisition to target customer segments that are inherently more loyal.

With further analysis, we may be able to (partially) distinguish these effects. We can determine the effect of customer heterogeneity on switching behavior if (1) there is a link between some set of observable customer characteristics and switching behavior and (2) customers at different brokers differ in these characteristics.

To study the effects of customer heterogeneity, we can investigate the effects of demographic variables on broker choice. On average, firms do not appear to differ significantly on the distribution of any of the six demographic variables we show in Table 3 (sex, income, occupation, education, race, marital status). The only demographic variable with a substantial difference is customer age—users who choose Fidelity, TDWaterhouse, or Vanguard are, on average, older than users who choose E*Trade or Fleet online (owner of Suretrade and Quick&Reilly). However, a logistic regression that predicts switching as a function of all demographic variables shows no effect (Table 4, column 1). Although age appears to be significant when we examine age alone (Table 4, column 2), it has no predicting/explanatory power when we compare predicted decision and real switching decision. As a result, the explanatory power of age is too weak to be the major reason that causes the variation of switching costs among brokers. For instance, both E*Trade and Fleet attract younger people, but Fleet has a switching cost over twice that of E*Trade.

Table 4. The Relationship Between Switching Probability and Demographic and Behavioral Variables (Logistic Regression)

Dependent variable: switch = 1, non-switch = 0

	Demographic Model	**Demographic Model: Age Only**	**Use Frequency**
Variable	column 1	column 2	column 3
Intercept	1.899 ** (0.6736)	1.0842 ** (0.3862)	1.390 *** (0.2022)
sex[F-M]	0.137 (0.1811)		
Age	0.016 (0.0122)	0.0230 ** (0.0083)	
mktsize[1-9]	0.597 (0.5252)		
mktsize[3-9]	-0.185 (0.4126)		
mktsize[4-9]	0.040 (0.4001)		
mktsize[5-9]	-0.133 (0.2694)		
mktsize[6-9]	0.039 (0.2833)		
Race[1-4]	-0.125 (0.3149)		
Race[3-4]	0.094 (0.4322)		
married[1-4]	0.218 (0.2359)		
married[3-4]	-0.230 (0.3501)		
Educ[3-6]	0.421 (0.5802)		
Educ[4-6]	-0.390 (0.3183)		
Educ[5-6]	-0.236 (0.2731)		
occ[&-o]	0.593 (0.5001)		
occ[1-o]	-0.296 (0.2871)		
occ[2-o]	-0.541 (0.3068)		
occ[4-o]	0.332 (0.5467)		
occ[5-o]	0.110 (0.5035)		
inc[H-M]	0.043 (0.5492)		
inc[HM-M]	-0.404 (0.3017)		
inc[L-M]	-0.246 (0.6907)		
inc[LM-M]	0.450 (0.4844)		
Frequency			0.106 ** (0.0377)
Absdiff			0.050 (0.0347)
Absdiffratio			-0.073 (0.0495)
R^2 (U)	8.44 %	1.67 %	8.88 %
N	559	695	696

(standard errors in parenthesis)
*** - p<.001, ** - p<.01 * - p<.05
See the appendix for variable definitions

From our switching cost framework, we would expect users with high transaction frequencies to have higher incentives to switch since a one-time switching cost will be amortized over more transactions and, therefore, be lower relative to differences in utility between brokers. In addition, if customers with different transactions volumes "sort" themselves into different brokers, we might expect that customers whose volumes have changed would also be more likely to switch (another variant of customer heterogeneity). Our results (Table 4, column 3) on this analysis suggest that while overall volume makes customers more likely to switch, changes in volume have little effect. This corroborates the analysis on demographics that found little evidence that customer heterogeneity drives switching behavior (except in ways that would be predicted by our choice model).

It should be noted that the variables explored so far are only some of the variables that might indicate customer differences that drive behavior, so we cannot rule out all forms of customer heterogeneity conclusively. The current size of our sample limits us in directly testing whether firm strategy influences switching cost, but the absence of a customer heterogeneity effect does suggest that some other factor may be driving switching behavior differences across brokers.

5. CONCLUSION

Previous theoretical work has shown that the presence of switching costs, either generally or in specific firms, can have a substantial effect on profitability. However, the creation of switching costs requires substantial and deliberate investments by the firm in customer retention. By understanding the magnitude of these switching costs, it is then possible to understand tradeoffs between investments in loyalty and retention programs and other types of investments such as advertising (for building new customer acquisition rates) and service level improvements or price reductions which raise both the acquisition and retention rates simultaneously. Our analysis reveals that implied switching costs vary substantially across brokers, but that it does not appear to be explained by differences in customer characteristics. This suggests that factors under the firm's control may influence these switching costs. Using additional data, we hope to explore this conjecture directly by correlating firm characteristics and switching behavior as well as controlling other indirectly observable customer characteristics, such as price sensitivity, in future research.

The method and approach used by this paper is readily applicable to analyze other online markets or industries. The method proposed here is especially suitable for online businesses because we are able to observe all the products a customer considered and know for certain the options that were available at the time the customer made an adoption choice. Our goal is to develop a platform that enables the components of switching cost to be separated, measured, and correlated with firms' attempts to retain customers. Our initial results for the on-line brokerage industry suggest that this is a promising approach.

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Appendix
Variable Definitions

Variable description and code:

VARIABLE	**DESCRIPTION**	**CODE**
sex	Gender	F: female; M:male
mktsize	Market size- MSA	1 = 50,000–249,999; 3 = 250,000–499,999; 4 = 500,000–999,999; 5 = 1,000,000–2,499,999; 6 = 2,500,000 and over; 9 = Non-MSA.
race		1 = White, 3 = Oriental, 4 = Black and other
married	Marital Status	1 = married, 2 = widowed or divorced or separate, 4 = single
educ	Education	3 = Grade School, Some High School or Graduated High School; 4 = Some College; 5 = Graduated College; 6 = Post College Graduate
occ	Occupation	1 = Professional; 2 = Proprietors, Managers, Officials; 4 = Sales; 5 = Craftsmen, Foremen or operative; & = Retired, Unemployed; o = others.
inc	Income	L = under 25,000; LM = 25,000–44,999; M = 45,000–69,999; HM = 70,000–99,999; H = 100,000 and over
frequency	Visiting frequency (number of days visit)	
Absdiff	$\lvert Q4\ freq. - Q1freq. \rvert$	
Absdiffratio	$\frac{\lvert Q4\ freq. - Q1freq. \rvert}{Q1\ freq}$	