A Model of Consumer Switching Behavior on the Internet

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Abstract

This study develops a multivariate multinomial Logit-Markov framework and a statistical estimation procedure to evaluate consumer switching-behavior. The switching probabilities of a first-order Markov process are formulated as a function of explanatory variables that include the previous state as well as variables that capture specific market situations and the resulting heterogeneity of switching probabilities among consumers. This study extends methodologies widely used in choice models. In particular, it extends previous approaches that utilize generalized least-squares methods to estimate multi-brand switching behavior models with explanatory variables by proposing a more compelling Maximum Likelihood Estimation procedure.

An empirical study of the dynamics of consumer switching behavior across major portal Web sites on the Internet on the basis of online panel data is provided as an illustration of the model. This application highlights the potential managerial implications of the model in the context of E-commerce.

[Key Words: Multinomial Logit Models, Markov Process, Maximum Likelihood Estimation, Internet Browsing Behavior, Web-Site Choice Behavior, Web Panel Data Analysis, Market Structure Analysis.]

1. Introduction

The modeling of the relationship between brand switching patterns and explanatory variables is important from a number of marketing perspectives. For example, among its wide applications, switching pattern research can be used to evaluate and predict the market performance of packaged goods as a function of marketing mix and consumer demographic variables (e.g., Zufyden, 1984, 1986), for the study of market structures (e.g., Carpenter and Lehmann, 1985), in Conjoint analysis (e.g., Mahajan, Green and Goldberg, 1982), and for new product evaluation (e.g., Urban, Hauser and Roberts, 1990).

In the latter studies, a first-order Markov chain framework has been shown to provide a viable modeling approach. An appealing property of the first-order Markov model is its ability to characterize consumer behavior in multi-brand (or more generally multi-state) market situations and provide a way to describe competitive behavior. In addition, first-order Markov models can provide potentially useful diagnostic outputs describing consumer switching as well as brand loyalty measures. Furthermore, the latter models can provide useful predictive outputs that include short and long-term market share predictions as a function of explanatory variables. Moreover, as shown in this study, the model can be based on a tractable Multinomial Logit model framework whose parameters may be estimated by means of available statistical procedures. All of these features make it an attractive theoretical modeling approach that has relevance from a managerial perspective.

In the discussion that follows, we first provide an overview of related stochastic models developed in the brand choice literature. Along with this overview, we highlight the inherent limitations of the previous estimation techniques used to implement these models. Next, we formulate a multivariate multinomial Logit-Markov framework to study consumer switching behavior. We subsequently develop an alternative estimation approach based on a Maximum Likelihood Estimation (MLE) procedure. We then illustrate an empirical application of our model with a study of consumer switching behavior across portal Web sites on the Internet. We conclude by exploring both theoretical and practical implications of our study. In particular, we highlight some of the study's implications to the understanding of Web site switching behavior on the Internet as well as for enhancing the decision-making process of E-commerce managers. In addition, we summarize the study's contributions and limitations, as well as opportunities for future research.

2. Overview of Related Literature

The study of stochastic models of brand choice behavior has received considerable attention in the marketing literature. A major focus of early models, proposed in the 60's and 70's, dealt with alternative ways of characterizing the "order" of the brand purchase behavior process. This led to the examination of the potential effect of present purchase behavior on future purchase probabilities (i.e., "purchase event feedback"). Among the first types of models considered were 1) zero-order models (e.g., Frank, 1962; Bass, Jeuland and Wright, 1976; Kalwani and Morrison, 1977), 2) first-order Markov models (e.g., Harary and Lipstein, 1962; Ehrenberg, 1965; Herniter, 1971), and 3) infinite-order models (e.g., Kuehn, 1962; Carman, 1966; and Zufryden, 1978).

Aside from a few exceptions that considered the effect of a single marketing variable (e.g., Tesler, 1962; Lilien, 1974; and Horsky, 1976), early stochastic models generally did not consider the effect of explanatory variables, such as marketing mix and consumer segmentation variables, on brand choice probabilities. Consequently, despite their usefulness in describing the brand choice behavior process, their practical application and actionability was limited from a managerial perspective. With this major limitation in mind, subsequent models sought to enhance the managerial usefulness of prior models by relating brand choice probability to marketing mix variables.

In an early attempt to consider explanatory variables in stochastic brand choice models, Jones and Zufryden (1980) and Zufryden (1980) suggested using a binomial logit-based brand choice model formulation to examine the market performance of packaged goods. They included price and consumer demographic data as explanatory variables. However, a limitation of these early models is that they defined a market in terms of only two brand states (i.e., a brand of interest versus all other competing brands) and thus did not provide a complete competitive view of the market. Wagner and Taudes (1986) later proposed an extension of previous zero-order models by developing a multi-brand stochastic model framework where the mean purchase rate from a Poisson process is expressed as a function of marketing mix variables and time. Numerous recent studies have followed to further investigate the relationship between brand choice probability and explanatory variables using consumer panel data (e.g., Bucklin, Russell, and Srinivasan 1998; Chintagunta, Jain, and Vilcassim 1991; Cooper 1988; Jain, Vilcassim, and Chintagunta 1994; Kalwani, Meyer, and Morrison 1994; Kamakura and Russell 1989; Kamakura and Srivastava 1984; Russell and Kamakura 1994).

A stream of research that relates most closely to the developments in the present study has sought to incorporate explanatory variables within first-order Markov brand choice processes. Zufryden (1981) developed a logit-based Markov model approach that relates explanatory variables to transition probabilities in a two-brand market. The study was later extended to the multi-brand case by proposing a multinomial-logit-based model in Zufryden (1986). Other marketing studies have focused on the relationship between brand switching patterns and explanatory variables in

various marketing contexts. For example, several studies have relied on brand switching to examine market competition and define market structures (e.g., Carpenter and Lehman, 1985; Kalwani and Morrison, 1977). Givon and Horsky (1990) developed a two-state first-order Markov model that incorporates advertising and pricing effects. Mahajan, Green, and Goldberg (1982) have shown that multi-brand switching models can be used to measure cross-price demand relationships in Conjoint Analysis studies. Urban, Hauser, and Roberts (1990) utilize a Markov process to model custom flows across states as a function of marketing variables in the analysis of the launch of new products.

A review of the estimation procedures used in the research reviewed in the preceding paragraphs reveals some limitations and logical inconsistencies. Carpenter and Lehmann (1985), do not specifically define the "last brand choice" as an independent variable in their formulation but rather use a coding scheme based on pair-wise brand similarities. Subsequently, a restricted generalized least squares (GLS) technique is proposed that draws on the results of Nakanishi and Cooper (1982) to estimate model parameters. However, as noted in Zufryden (1986), the estimation procedure proposed by Carpenter and Lehmann does not enforce the logical consistency of the underlying model (e.g., the sum of the conditional probabilities across each row of a first-order Markov switching matrix must be equal to 1). In contrast, Zufryden (1986) proposes an estimation procedure that is based on a restricted weighted least squares procedure and enforces the logical consistency of the Markov model. Consequently, in addition to yielding probabilities that are properly constrained, between 0 and 1, the resulting conditional transition probabilities of the estimated first-order Markov model appropriately sum to unity for each row of the transition matrix. Nevertheless, this procedure also suffers from drawbacks. It is best suited for the incorporation of categorical explanatory variables (e.g., demographics) and is difficult to apply to continuous variables (e.g., price). Furthermore, it requires a large amount of data to permit model estimation and avoid the tendency for sparse observations within observational cells.

Given the limitations of previous estimation techniques, this study proposes an MLE technique. This approach can be shown to provide a more attractive estimation procedure as it easily permits the consideration of both continuous and categorical explanatory variables in first-order Markov switching models. In addition, MLE avoids the potential problem of sparseness of data within cells, and leads to parameter estimates with appealing statistical properties.

3. Development of Switching Behavior Model

We now develop a first-order Markov switching behavior model whose transition probabilities are functions of explanatory variables. It should be noted that this model provides a general framework that can be used to describe the transition probabilities in various contexts, from a given state (e.g., brand, or Web site) to another. However, to facilitate the empirical illustration that will be discussed later, which applies to switching behavior across portal sites on the Web, we define our model within the latter context.

We assume that there are *J* Web sites (states) that a consumer can switch to at his/her i^{th} visit. These *J* alternatives are mutually exclusive and collectively exhaustive. Using the notation of Zufryden (1986) and following the logistic formulation described in Diebold, Lee and Weinback (1994), Filardo (1994), and Gray (1996), we define the $J \times J$ matrix of transition probabilities for a first-order Markov process as¹:

$$P_{s}^{i}(j \mid k) = \frac{e^{\mathbf{b}_{j}X(k) + \mathbf{l}_{j}v_{s} + \mathbf{e}_{j}}}{1 + \sum_{l=1}^{J-1} e^{\mathbf{b}_{l}X(k) + \mathbf{l}_{l}v_{s}}} \quad \text{for } j=1,2,3,\dots,J-1, \; ; k=1,2,\dots,J,$$
(1)

where, we define a the *transition probabilities* $P_s^i(j | k)$ as the probability that a consumer facing situation *s*, will switch to the site *j* at the *i*th visit given that his/her previous visit was to site *k*. In addition, we define the following variables and parameters:

- $v_s = (v_{sl}, v_{s2,...}, v_{sM})$ is a vector of *M* explanatory variables, corresponding to a particular situation *s* (e.g., a particular setting of user-specific variables such as demographics, user behavior, marketing mix at a given choice occasion, etc.), with *s*=1,2,...,*S*.
- $x = (1, x_1, x_2,..., x_{J-1})$ is a previous state (i.e., last site visited) specification vector consisting of binary variables with $x_k = 1$ if a consumer was formerly in state k (e.g., if Web site k was chosen at the previous visit occasion), and 0 otherwise, for sites k = 1, 2,..., J.
- X(k) = Particular setting of vector x.
- $\boldsymbol{b}_{j} = (\boldsymbol{b}_{j0}, \boldsymbol{b}_{j1,...}, \boldsymbol{b}_{jJ-1})$ is a vector of parameters corresponding to x.

¹ (1) can be obtained directly from the standard multinomial logit form:

 $p_j = exp(b_i x_i)/S_i exp(b_i x_i)$, for j = 1, 2, ..., J by setting vector b_J to 0 (zero vector) as a normalization.

 $I_{i} = (I_{il}, I_{i2,...}, I_{iM})$ is a vector of parameters corresponding to the situational variables v_{s} .

and $e_i = a$ random error term.

Note that each individual is assumed to have the same transition probability <u>given</u> that s/he faces the same explanatory variables. However, each individual will face different settings of the explanatory variables because s/he faces different situations, including different Internet use patterns, marketing mix, and possesses different demographics. Thus, modeling individual differences in the explanatory variables s/he faces captures some level of heterogeneity among individuals.

To enforce logical consistency, we now define conditional probabilities $P_s^i(j = J / k)$ corresponding to the last state j=J as:

$$P_{s}^{i}(j = J \mid k) = 1 - \int_{j=1}^{J-1} P_{s}^{i}(j \mid k) = \frac{1}{1 + \int_{l=1}^{J-1} e^{b_{l}X(k) + I_{l}v_{s}}}.$$
(2)

Thus, the above model specification is logically consistent as it satisfies the condition that the resulting switching matrix is stochastic (i.e., that the sum of conditional transition probabilities equals one over each row, or l = 1

 $P_s^i(j \mid k) = \prod_{j=1}^{i} P_s^i(j \mid k) + P_s^i(J \mid k) = 1 \text{ over each row}, \text{ and since (2) is a multinomial logit form, all the}$

conditional probabilities are properly range-constrained between 0 and 1.

Now, assuming that the sum of the error term $e_j = 0$ and e_j follows the *standard extreme distribution*, (e.g., j=1

see Guadagni and Little, 1983) we obtain the following generalized multinomial logit model of the switching behavior as a function of explanatory variables, that includes the previous state:

$$\ln\left[\frac{P_s^i(j \mid k)}{P_s^i(J \mid k)}\right] = \boldsymbol{b}_j X(k) + \boldsymbol{l}_j v_s + \boldsymbol{e}_j.$$
(3)

4. Estimation of the Switching Behavior Model

We now propose an MLE procedure to estimate the parameters of the first-order Markov model developed above, based on the matrix of conditional transition probabilities. MLE procedures have commonly been applied to multinomial logit models in the brand choice modeling literature (e.g., Bucklin and Gupta 1993; Chintagunta 1993; Guadagni and Little 1983,1998; Gupta 1988; McFadden 1981).

We now assume that observations are independent of each other and that a given observation depends on the particular situation *s* we are considering. Thus, the likelihood of observing the sample data is found by taking the product of the probabilities at every site visit. Since we consider the odds ratio of $P_s^i(j/k)$ to $P_s^i(J/k)$ in (3), the likelihood function is given by the following product:

$$L = \sum_{i=1}^{N} \sum_{s=1}^{S} \sum_{k=1}^{K} \sum_{j=1}^{K-1} \frac{P_s^i(j \mid k)}{P_s^i(J \mid k)}.$$
(4)

Now, based on the relationship in (3), (4) becomes:

$$L = \sum_{\substack{i=1 \ s=1 \ k=1 \ j=1}}^{N \ S \ K \ J-1} \left(e^{\mathbf{b}_{j}X(k) + \mathbf{l}_{j}\mathbf{n}_{s} + \mathbf{e}_{j}} \right),$$
(5)

Then, taking the logarithm of both sides of (5), leads to the following log likelihood:

Ln(L) = N S K J-1

$$\boldsymbol{b}_{j}X(k) + \boldsymbol{l}_{j}v_{s} + \boldsymbol{e}_{j}$$
.

The $D_{j}A_{k}(k) + I_{j}v_{j} + C_{j}$ resulting log likelihood function (6) has a linear form, in terms of parameters, and can be used to readily estimate the first-order Markov model by maximizing Ln(L) by appropriate choice of the parameter vectors, \boldsymbol{b}_{j} and \boldsymbol{l}_{j} .

(6)

5. An Empirical Illustration

5.1. Background for Empirical Illustration

The recent grown of the Internet medium has led to numerous new business opportunities. Among these, search engine sites (i.e., Yahoo!, Excite, Infoseek, Lycos), virtual communities (e.g., AOL, Geocities), ISP's (Internet Service Providers), Internet browser companies (Microsoft and Microsoft Network, Netscape), and online shopping companies (e.g., Amazon.com) have become relatively important players on the Internet.

It has been suggested that Internet giants are seeking to become *portal* web sites². Portals are sites that provide general Internet capabilities and serve as a gateway to additional information (Hanson, 2000). Thus, increased competition is expected among giants on the Internet (e.g., see "The battle of the portals", in Business Week, 1998). It has been suggested that a key to winning this battle is for a site to develop *stickiness*. Stickiness is Web jargon for the ability of a Web site to induce "surfers" to come back to use the site's services.

As suggested by Shapiro and Varian (1999) and Business Week (1998), Internet giants are currently spending large amounts of money to keep old customers satisfied and generate new online customers. New visitors can be drawn from two sources: "Current Internet Users" mainly visiting other competing sites, and "Non-Internet Users" who have never used the Internet before.

As of yet, no study has investigated the dynamics of competition among main portals. Thus, one objective of this study is to apply the proposed model to explore the dynamics of consumer switching behavior, and stickiness, among major portal sites on the Internet. Through the analysis of switching behavior, it is expected that managers of portal sites may potentially determine the relative market strength of their companies, in terms of consumer visits to their sites, as well as potentially measure the impact of their marketing activities or segmentation strategy on the switching probabilities that will determine their future market shares.

5.2. Description of Empirical Data

Commercially available online Web panel data now provide a powerful source of consumer information, especially to study consumer switching behavior on the Internet. In this study we used a set of online panel data provided by a leading Web measurement research firm. The data is based on observations of panel members recruited by using a random digit dialing method and weighted to represent the Internet population. The data set consists of more than 800,000 Web browsing activities of about 50,000 online panel members and covers more than 1,000 different Web sites. Since this data set is based on an online "panel," it does not suffer from the common data limitation of log file analysis in identifying unique visitors.³ Thus, we were able to unambiguously distinguish multiple visits by individual Web users from single visits by multiple Web users.

The estimation of the switching model is based on calibration data (covering a time span of four weeks, from 2/11/98 - 3/10/98). The validation of the model is based on holdout data (covering a span of three weeks, from 3/11/98 to 4/1/98). The model calibration period consisted of a total of 488,000 browsing events made by 4,500 different individuals panel members from a nation wide U.S. sample. In turn, the holdout data consisted of 350,000 browsing events made by 2,800 different Web surfers.

5.3. Application to Portal Switching Behavior on the Internet

To illustrate the application of the switching model, we investigated major portal sites including search engines (i.e., Yahoo!, Excite, and Infoseek, etc.), main browsing companies (Microsoft, Netscape), and ISP or virtual communities (e.g., AOL, Geocities, Microsoft Networks). The focus on major portals is justified in view of the large portions of total traffic on the Internet they generate as well as the fierce nature of the competition between them in the quest of becoming a leader of the E-commerce world. In addition, the investigation of the comparative market structure among the main portals is expected to be of interest to managers as well as researchers.

In our empirical illustration, we considered five mutually exclusive and collectively exhaustive site *states*. These states include Yahoo!, AOL, Netscape, and other main portal sites (i.e., Excite, Microsoft, MSN, Geocities, and Infoseek which were classified within an "Other Portals" category). These portal sites were selected in view of their relative importance on the Internet⁴. In addition, other Web sites not included in the portal categories were grouped into a "non-portal site" category.

² A reason why Internet companies are seeking to be portals is suggested in an argument based on "Increasing Return to Scale of Information Goods" by Shapiro and Varian (1999). Since the marginal cost for producing an additional unit is very low, they suggest that most Internet companies who succeed in drawing numerous Web users to their sites are easily tempted to expand their business services.

³ See Drèze and Zufryden, 1998, for a review of the problems associated with tracking individuals using log file data.

⁴ According to a report from Forrester Research (2000a, 2000b), Yahoo! AOL, and MSN alone currently enjoy 15% of all Internet traffic and 45% of the advertising spend. Thus, although the portal sites investigated here comprise less than 20% of total traffic on the Internet, they earn more than 60% of total online advertising expenditures. In addition, these sites represent highly competitive E-companies, vying for a successful position among all E-commerce sites.

To operationalize our model, we first defined explanatory variables to reflect the last site visited (prior state) as follows:

- $X_1 = 1$ if a consumer's previous state was Yahoo!,
 - =0 otherwise.
- X₂ =1 if a consumer's previous state was AOL, =0 otherwise.
- $X_3 = 1$ if a consumer's previous state was Netscape,
 - =0 otherwise.
- X₄ =1 if a consumer's previous state was one of the "Other Portals", =0 otherwise.

In addition, we considered the following situational variables:

- $X_5 = 1$ if a consumer visits a site during the evening (6pm-midnight),
- =0 otherwise.
- $X_6 = 1$ if a consumer visits a site on a day during the first half of the week (Mon through Wed), =0 otherwise.
- $X_7 =$ a continuous variable representing how long a consumer stayed at the previous Web site.
- $X_8 = 1$ if a consumer is a heavy user (at least 11 visits in a month),
 - =0 oherwise.⁵
- $X_9 = 1$ if a consumer is male,
 - =0 otherwise.

5.4. Estimation Results

The switching model described in (6) was estimated using the proposed MLE method and implemented by using the CATMOD procedure of SAS. The results of the estimation are summarized in Table 1. One should note that all the variables investigated here are statistically significant (p < 0.05).

Table 2 provides a summary of the estimation results for each explanatory variable as well as the relative magnitudes of each parameter and their levels of statistical significance. The estimation results in Table 2 show that 32 out of a total of 40 parameters are statistically significant at the a=0.05 level; 27 out of a total of 40 parameters are significant at the a=0.01 level. In particular, the coefficients along the diagonal of the transition matrix, corresponding to variables X₁ through X₅ tend to be the most statistically significant. This implies that the switching probability to a particular site is significantly affected by a consumer's previous state. This empirical finding supports "*path-dependence*," that consumer browsing behavior follow a *first-order* Markov process as opposed to a *zero-order* (memory-less) process. This finding is consistent with previous studies (i.e., Zufryden 1984, 1986). Thus, we conclude that the former site variables, which represent the site visited at the previous visit occasion, are useful in predicting what site the consumer will visit next.

5.5 Interpretation of Model Parameters

The magnitude of model parameters reflects the relative importance in the contribution of particular explanatory variables to the switching probability. It is recalled that this study uses the logarithm value of the *odds ratio* of the conditional switching probabilities (a portal web site vs. a non-portal web site) to formulate the relationship with the explanatory variables. Thus, for an indicator variable such as X_1 (previous state was Yahoo!) with values 0 and 1, by taking e^b , we obtain the change in the ratio of $P_s^i(j/k)$ to $P_s^i(j/k)$ controlling for the other covariates. For example in Table 2, we have b_{1i} =4.4168. This yields e^{b11} =82.8. Therefore, controlling for the other covariates, the ratio of the conditional probability of visiting Yahoo! over the probability of visiting a non-portal web site is 82.8 times greater for those whose previous visit was to Yahoo! than for those who previously visited a non-portal web site. To translate this increase in probability ratio to an actual transition probability, we can go back to equation (1) and plug-in the estimated values of all the b_{1i} parameters. Table 3 illustrates such an exercise for a scenario where we assumed that all other

⁵ The criterion to determine "heavy vs. light user group" was based on the total number of prior visits (switches). The number 11, used as a usage classification criterion, was based on the mean value that was calculated from the frequency distribution observed in the calibration data.

covariates were equal to 0 (i.e., $P[j | k] = \frac{e^{b_{oj} + b_{1j}X_k}}{1 + e^{b_{ol} + b_{1l}X_k}}$). As one can see, the 82.8 fold increase in the ratio of the

probability of going to Yahoo! over the probability of going to a non-portal web site translates in a change in conditional probability from 0.028 to 0.650. In other words, the probability of visiting Yahoo! after visiting another web site is 2.8% while the probability of revisiting Yahoo! if the last web site visit was to Yahoo! is 65%. Whether the last site visited is Yahoo! rather than a non-portal web site also affects the probability of visiting the other portals. Thus, the probability of visiting AOL decreases from 2% to 0.8%; the probability of visiting Netscape increases from 1.6% to 1.9%; and the probability of visiting another portal decreases from 9.3% to 8.3%.

This interpretation can be applied to the other dummy variables in this study such as "previous state was AOL, Netscape or Other Portals," "Log on time," "Log on day," and "Heavy user." For instance, the coefficients for "Log on time" show that log on in the evening, rather than during other times of the day, increases the probability of visiting Yahoo!, and decreases the probability of visiting Other Portals. It is also noted that heavy users are less likely to use portals than light users (parameters b_{81} , b_{82} , b_{83} , and b_{84} all have negative signs). Finally, in contrast to males, the female segment has a greater propensity to use AOL and Other Portals, and a lower propensity to visit Netscape.

For a continuous variable such as "Total time spent at the previous site," we can use the transformation $100(e^{b}-1)$, which gives the percentage increase in the expected ratio of conditional switching probability for each one-unit increase in the variable. For example, consider the effect of how long a consumer stayed at the previous website. For Yahoo!, $b_{7l=}$ -0.0318 and consequently, $100*(e^{-0.0318}-1) = -3.13$. According to this result, each additional 1 minute increase in time spent at the previous site is associated with a 3.13 % decrease in the expected switching probability to the Yahoo! site during the next visit, holding other covariates constant.

Note that the Yahoo! site has greater consumer retention power (b_{11} =4.4168) than AOL (b_{22} =4.3711). Consumers who visit Yahoo! come from AOL and Netscape sites as well as other main portal sites. Particularly, other main portal sites (b_{41} = 1.4172), such as "Excite," "Infoseek," "Microsoft," and so on, appear to provide the most significant source of switching to Yahoo!.

Similarly to the results of Zufryden (1986), we find the constant terms all negative in sign. These constant terms reflect the contributions to each site's switching probability from consumers whose last visit was made to a regular web site as opposed to a portal. In sum, the previous illustrations highlight how model parameters may provide potentially useful diagnostic information about the market structure for main portal sites as well as for competitive strategy in a dynamic market.

5.6. Model Validation

To provide additional evidence of the descriptive and predictive goodness of fit of the switching model, we examined the switching model results specific to two explanatory variables: gender and visit frequency. Actual switching matrices were developed based on a segmentation of consumers in one of four groups: Heavy user & Male, Heavy user & Female, Light user & Male, and Light user & Female. Based on these segments, we contrasted the estimated switching probabilities we derived from our model with the actual values observed from our data. The results corresponding to our five states are summarized in Table 4. These results show that the coincidence between actual and estimated switching probabilities is very good. The log likelihood ratio indicates the model is statistically significant (p-value = 0.00000). The Chi-square test of estimated and actual switching probabilities for each segment also suggests that the estimated probabilities and the actual probabilities are not statistically different, implying a good overall model fit.

For purposes of predictive model validation, we compared the estimated switching probabilities obtained from the calibration data (2/11/98 - 3/10/98, 4 weeks) with the actual switching probabilities observed in the holdout data. The holdout sample consisted of switching behaviors observed during the 3-week period of 3/10 through 4/1/97.

By updating the initial portal site market shares observed during the calibration period with the estimated Markov switching matrix (e.g., see Zufryden 1984, 1986), we predicted portal site shares for the holdout period. Table 5 provides market share predictions, as well as estimated steady state shares, from our predictive test. Here, it is noted that the model produces reasonably accurate future-market share forecasts. Overall, the results show average absolute errors of 12.5% to 39.1% from the actual values.

The steady-state probabilities provide us with interesting insights about the role played by the various portals with respect to alternative market segments. For example, note how the share of non-portal sites changes depending on whether one is a light or a heavy user. Whereas light users rely on portals for 60% of their visits; heavy users rely on portals for only 20% of their visits. This indicates that heavy users either use the Internet for a different purpose than light users, or perhaps that they are more knowledgeable about where things are online and, consequently, do not need to rely on portals as much as light users. They might have developed a library of bookmarks, or know the URL of the sites they want to visit without relying as much on portals to consolidate the information for them.

One can also use the steady-state probabilities to better understand the positioning of the three portals studied. Our results suggest that Yahoo! dominates AOL in every segment except the light-female segment. Similarly, Netscape dominates or equals AOL on all but the light-female segment. Yahoo! seems to be appealing to all user groups, while AOL appeals to light-females users, and Netscape to light-male users.

6. Conclusion

This study proposes a multivariate Web-site choice model based on a multinomial logit-Markov framework for analyzing individual switching behavior. The switching behavior model is expressed as a function of explanatory variables that includes the site that was previously visited as well as Internet use behavior and demographic variables. The model also captures individual heterogeneity in switching probabilities across consumers by expressing switching probabilities as a function of possible situations the consumers may face. Based on a MLE estimation technique, an application of the model framework was illustrated in an analysis of consumer switching behavior across major Web portal sites on the Internet.

From a methodological perspective, this study extends approaches used in choice models. In particular, this study extends research by Carpenter and Lehmann (1985) and Zufryden (1986) that utilize GLS-based methods to estimate multi-brand Markovian stochastic choice models. More specifically, this study describes the direct application of a MLE procedure for estimating switching behavior on the Internet on the basis of online panel data. Thus, the study highlights the importance of "path-dependence" in evaluating browsing behavior on the Internet.

From a practical perspective the results of the model provide E-commerce managers with potentially useful insights for understanding web site switching and loyalty behavior. Existing Internet companies have sought to maintain their current positions or expand through mergers and/or acquisitions of new Internet companies. As pointed out in, *Net Gain* (Hagel and Armstrong 1997), the final winner on the Internet will depend on which company has the most accurate information about Internet users. Insights from the switching model can potentially help managers enhance their understanding of their current or potential market positioning on the Internet. Thus, the model provides useful information about the determinants of Web site choice behavior and loyalty formation. This information has managerial relevance for the analysis of market structure and market dynamics and the development of effective promotion strategies on the Internet.

Based on the switching probability matrix, managers can measure the relative market strength of their sites and their competitors by evaluating the magnitudes of the switching probabilities. That is, given the initial market share, if the ratio of the probability of switching to Yahoo! from AOL to the probability of switching to AOL from Yahoo! is greater than 1, we can say that more customers are switching from AOL to Yahoo! than are switching from Yahoo! to AOL. Thus, as Yahoo! is drawing more customers from AOL than AOL is from Yahoo!, in the long run, AOL is expected to lose market share to Yahoo!

In addition, the diagonal elements of the switching matrix may be defined as "site loyalty" or "stickiness." For example, the empirical investigation in this study shows that overall, Yahoo! has higher loyalty than AOL in each of the four segments that were analyzed.

Parameters of the switching model can also provide insights about the structure of competition within an online market - particularly for main Internet players like portals. In particular, managers can evaluate the impact of any changes in the individual-level switching probability with respect to changes in the explanatory variables on the market shares over time of specified market segments. Thus, managers can evaluate their current consumer franchise and potentially redefine market segments so as to enhance their market shares. Furthermore, the model provides managers with potential guidelines to define and evaluate their target market segments, to assess the competitive market structure among competing Web sites, and to develop more effective marketing strategies leading to increases in long-run market shares.

Despite the potential contributions that have been described above, certain limitations of our study should be noted. First, it investigates conditional switching behavior. That is, we do not attempt to predict when an Internet user will be active. Rather, we predict what site (or site category) will be visited given that the user is active. Thus, based on the occurrence of a given visit, we provide a conditional probability that a particular web site will be selected given the setting of the situational variables. Hence, a natural extension of this model would be to develop composite models that study the visit frequency and conditional switching behavior within a comprehensive model structure (e.g., Zufryden, 1984).

The only aspects of the previous visits that we take into account are which site was visited and the duration of the visit. However, there is clearly more information obtainable from the data gathered during each visit. Portals such as Yahoo! or AOL or very heterogeneous in their content and site visitors can use them for many different purposes. What visitors do on the site should tell us something about their likelihood of revisit or switching. For example, a user who visits Yahoo! to check stock quotes or play games is probably more likely to return to Yahoo! that a user who visits Yahoo! to search for information. Indeed, this second user is likely to find a link on Yahoo! that will send him/her to

another web site where the information is located - thereby creating an immediate switch to another site. Hence, an understanding of *within* visit behavior might contribute to the explanation of switching patterns.

In our study, we capture consumer heterogeneity in a classical way by considering user characteristics and visit history to capture differences across consumers. However, one could potentially use hierarchical Baysian methods to model consumer heterogeneity (e.g., Allenby Arora, and Ginter, 1998; Arora, Allenby, and Ginter, 1998; and Chang et al, 1999)

Finally, although this study suggested a flexible general model framework, that can incorporate marketing mix variables, given limitations in our data, an empirical evaluation of the latter's effect was not undertaken here. Hopefully, as more comprehensive online data, including information about marketing mix variables becomes more readily available, the proposed model can be refined so as to include these.

Nevertheless, despite its limitations, this study provides a potentially useful and mathematically tractable framework for analyzing switching behavior. In particular, this study has illustrated how the proposed model may be used to provide valuable insights and a better understanding of how consumers choose portal Web sites. Consequently, it is expected that future model refinements should provide further insights about consumer behavior as well as aid managers in more effectively evaluating and planning their marketing efforts.

References

- Allenby, Greg M., Neeral Arora, and James L. Ginter (1998), "On the Heterogeneity of Demand," *Journal of Marketing Research*, Vol. 35, August, pp. 384-389.
- Arora, Neeraj, Greg M. Allenby, and James L. Ginter (1998), "A Hierarchical Bayes Model of Primary and Secondary Demand," *Marketing Science*, Vol. 17, No. 1, pp. 29-44.
- Bass, Frank M., Abel P. Jeuland, and Gordon P. Wright (1976), "Equilibrium Stochastic Choice and Market Penetration Theories: Derivation and Comparisons," *Management Science*, Vol. 22, (June), pp. 1051-1063.
- Bucklin, R. E. and S. Gupta (1993), "Brand Choice, Purchase Incidence, and Segmentation: An Integrated Approach," *Journal of Marketing Research*, Vol. 29, pp. 201-215.
- Bucklin, Randolph E., Gary J. Russell, and V. Srinivasan (1998), "A Relationship Between Market Share Elasticities and Brand Switching Probabilities," *Journal of Marketing Research*, Vol. 35, February, pp. 99-113.
- BusinessWeek (1998), "The Battle of the Portals," Special Report, September 7th Issue [http://www.businessweek.com/search.htm]
- Carman, J. M. (1966), "Brand Switching and Linear Learning Models," *Journal of Advertising Research*, Vol. 6, (June), pp. 23-31.
- Carpenter, Gregory S. and Donald R. Lehmann (1985), "A Model of Marketing Mix, Brand Switching, and Competition," *Journal of Marketing Research*, 22 (August), pp. 318-29.
- Chang, Kwangpil, S. Siddarth, and Charles Weinberg (1998), "The Impact of Heterogeneity in Purchase Timing and Price Responsiveness on Estimates of Sticker Shock Effects," *Marketing Science*, Vol. 18, No. 2, 178-192.
- Chintagunta, Pradeep K. (1993), "Investigating Purchase Incidence, Brand Choice and Purchase Quantity Decisions of Households," *Marketing Science*, Vol. 12, pp. 184-208.
- Chintagunta, Pradeep K., Dipak C. Jain, and Naufel J. Vilcassim (1991), "Investigating Heterogeneity in Brand Preferences in Logit Models of Panel Data," *Journal of Marketing Research*, Vol. 28, November, pp. 417-28.
- Cooper, Lee G. (1988), "Competitive Maps: The Structure Underlying Asymmetric Cross Elasticities," *Management Science*, Vol. 34, June, pp. 707-723.
- Drèze, X, and F. Zufryden (1998), "Is Internet Advertising Ready for Prime Time?," *Journal of Advertising Research*, May/June 1998, Vol 38, No. 3, pp. 7-18.
- Dieblold, F.X., J.H. Lee, and G.CF. Weinback, 1994, "Regime switching with time-varying transition probabilities," in Hargreaves, C., ed. *Time Series Analysis and Coiontegration*, Oxford Press.
- Ehrenberg, A. S. C. (1965), "An Appraisal of Markov Brand Switching Models," *Journal of Marketing Research*, Vol. 2, pp. 347-363.
- Filardo, A. J., 1994, "Business-Cycle Phases and their Transitional Dynamics," *Journal of Business and Economic Statistics*, 12, 3, pp. 299-308.
- Forrester Research (2000a), "The Portal Race Is Over The race for online marketing dollars is just beginning," January 28, Cambridge, MA. [http://www.forrester.nl/ER/Press/Release/0,1769,234,FF.html]
- Forrester Research (2000b), "Research Reports of Fourth Quarter and 1999 Results," February 3, Cambridge, MA. [http://www.forrester.nl/ER/Press/Release/0.1769.241,FF.html

Frank, Ronald E. (1962) "Brand Choice as a Probability Process," Journal of Business, Vol. 35, (January), pp. 43-56.

- Givon, Moshe and Dan Horsky (1990) "Untangling the effects of Purchase Reinforcement and Advertising Carryover," *Marketing Science*, Vol. 9, No. 2, (Spring), pp. 171-197
- Gray, S.F., 1996, "Modeling the Conditional Distribution of Interest Rates as a Regime-Switching Process," *Journal of Financial Economics*, 42, pp. 27-62.
- Guadagni, P. M. and John D. C. Little (1983), "A Logit Model of Brand Choice Calibrated on Scanner Data," *Marketing Science*, Vol. 2, pp. 203-238.
- Guadagni, P. M. and John D. C. Little (1998), "When and What to Buy: A Nested Logit Model of Coffee Purchase," *Journal of Forecasting*, Vol. 17, (June/July), pp. 303-326.
- Gupta, Sunil (1988), "Impact of Sales Promotions on When, What, and How Much to Buy," *Journal Marketing Research*, Vol 25, pp. 342-355.
- Hagel, John and Arthur G. Armstrong (1997), "Net Gain: Expanding Markets Through Virtual Communities," Harvard Business School Press.
- Harary F. and B. Lipstein (1962), "The Dynamics of Brand Loyalty: A Markovian Approach," *Operations Research*, Vol. 10, pp. 19-40.
- Hanson, Ward, (2000), "Principles of Internet Marketing," South-Western Colledge Publishing.
- Herniter, Jerome, (1971), "A Probabilistic Market Model of Purchase Timing and Brand Selection," *Management Science*, Vol. 18, No. 4 (December).
- Horsky, Dan (1976), "An Empirical Analysis of the Optimal Advertising Policy," *Management Science*, Vol. 23, (June), pp. 1037-1049.
- Jain, Dipak C., Naufel Vilcassim, and Pradeep K. Chintagunta (1994), "A Random-Coefficient Logit Brand-Choice Model Applied to Panel Data," *Journal of Business and Economic Statistics*, Vol. 12, July, pp. 317-328.
- Jones, J. Morgan and Fred S. Zufryden (1980), "Adding Explanatory Variables to a Consumer Purchase Behavior Model – An Exploratory Study," *Journal of Marketing Research*, Vol. 17 (August), pp. 323-334.
- Kalwani, Manohar U. and Donald G. Morrison (1977), "A Parsimonious Description of the Hendry System," *Management Science*, Vol. 23, pp. 467-477.
- Kalwani, Manohar, Robert Meyer, and Donald Morrison (1994), "Benchmarks for Discrete Choice Models," *Journal of Marketing Research*, Vol. 31, February, pp. 65-75.
- Kamakura, Wagner A. and Gary J. Russell (1989), "A Probabilistic Choice Model for Market Segmentation and Elasticity Structure," *Journal of Marketing Research*, Vol.26, November, pp. 379-391.
- Kamakura, Wagner A. and Rajendra K. Srivastava (1984), "Predicting Choice Shares Under Conditions of Brand Independence," *Journal of Marketing Research*, Vol. 21, November, pp. 420-434.
- Kuehn, Alfred A. (1962), "Consumer Brand Choice A Learning Process?" *Journal of Advertising* Research, Vol. 2, (December), pp. 10-17.
- Lilien, Gary (1974), "An Application of a Modified Linear Learning Model of Buyer Behavior," *Journal of Marketing Research*, Vol. 11 (August), pp. 279-285.
- Mahajan, Vijay, Paul S. Green, and Stephen M. Goldberg (1982), "A Conjoint Model for Measuring Self and Cross Price/Demand Relationships," *Journal of Marketing Research*, Vol. 19 (August), pp. 334-342.
- McFadden, D. (1981), "Econometric Models of Probabilities Choice," in Manski, C. F. and McFadden, D. (eds), Structural Analysis of Discrete Date with Econometric Applications, Cambridge, MA: MIT Press.
- Nakanishi, Masao and Lee G. Cooper (1982), "Simplified Estimation Procedures for MCI Models" *Management Science*, Vol. 1 (Summer), pp. 314-322.

- Russell, Gary J. and Wagner A. Kamakura (1994), "Understanding Brand Comparison with Micro and Macro Scanner Data," *Journal of Marketing Research*, Vol. 31, May, pp. 289-203.
- Shapiro, Carl and Hal R. Varian (1999), "Information Rules A Strategic Guide to the Network Economy," Harvard Business School Press, MA.
- Tesler, L. G. (1962), "The Demand of Branded Goods as Estimated from Consumer Panel Data," *Review of Economics and Statistics*, Vol. 53, No. 1, pp. 27-44.
- Urban, Glen L., John R Hauser, and John H. Roberts (1990), "Prelaunch Forcasting of New Automobiles," *Management Science*, Vol. 36, No. 4, pp. 401-421.
- Wagner, Udo, and Alfred Taudes (1986), "A Multivariate Polya Model of Brand Choice and Purchase Incidence," *Marketing Science*, Vol. 5, No. 3, (Summer), pp. 217-244.
- Zufryden, Fred S. (1978), "An Empirical Evaluation of a Composite Heterogeneous Model of Brand Choice and Purchase Timing," *Management Science*, Vol. 24, pp. 761-773.
- Zufryden, Fred (1980), "A Multivariate Stochastic Model of Brand Choice and Market Behavior," *Research in Marketing*, Vol. 3, J. Sheth, ed. Greenwich, CT: JAI Press, Inc., pp. 237-303.
- Zufryden, Fred, S. (1981), "A Logit-Markovian Model of Consumer Purchase Behavior based on Explanatory Variables," *Decision Science*, Vol. 12 (October), pp. 645-660.
- Zufryden, Fred S. (1984), "A General Model for Assessing New Product Marketing Decisions and Market Performance," *The Institute of Management Science Studies in the Management Sciences*, 18, pp. 63-83.
- Zufryden, Fred (1986), "Multibrand Transition Probabilities as a Function of Explanatory Variables: Estimation by a Least-Squares-Based Approach," *Journal of Marketing Research*, Vol. 23 (May), pp. 177-183.

Sou	rce	DF	Chi-Square	Prob*	
	Intercept		4	1086.25	0.0000
X1	Former Yahoo!	4	6055.61	0.0000	
X2	Former AOL	4	3219.61	0.0000	
X3	Former Netscape	4	3975.69	0.0000	
X4	Former Other Portals	4	0196.61	0.0000	
X5	Log on Time (6pm-midnight)	4	21.71	0.0002	
X6	Log on Day (Mon-Wed)	4	13.18	0.0104	
X7	Total Time Spent	4	369.69	0.0000	
X8	Heavy User	4	210.76	0.0000	
X9	Male		4	25.33	0.0000
Likelihoo	d Ratio	2336	4121.03	0.0000	

*Bold type values denote significance at the 0.01 level. Italicized values indicate significance at the 0.05 level.

				-
	Response Function 1	Response Function 2	Response Function 3	Response Function 4
	In[P(Yahoo! Xk) / P(non-portals Xk)]	In[P(AOL Xk) / P(non-portals Xk)]	In[P(Netscape Xk) / P(non-portals Xk)]	In[P(Other portals Xk) / P(non-portals Xk)]
Parameter	Yahoo Site	AOL Site	Netscape Site	Other Portal Sites
Intercept	-3.4149	-3.7585	-3.9804	-2.2092
	(0.1910)	(0.1953)	(0.1960)	(0.1060)
Former Yahoo	4.4168	0.3489	1.4677	1.1563
	(0.0570)	(0.2570)	(0.1371)	(0.1276)
Former AOL	0.4294	4.3711	0.0575	1.3149
	(0.2495)	(0.0775)	(0.3086)	(0.1438)
Formor Notocono	1 9929	0.3210	4 4601	1 4770
i onner Netscape	(0.1106)	(0.3213	4.4001	(0.1207)
	(0.1196)	(0.3224)	(0.0710)	(0.1297)
Former Other Portals	1.4172	1.6113	1.5658	4.8122
	(0.1092)	(0.1285)	(0.1173)	(0.0478)
Log on Time	0.0867	-0.0258	-0.0631	-0.1909
(6pm-midnight)	(0.0526)	(0.0730)	(0.0631)	(0.0463)
Log on Day	0.0597	0.1052	0.1732	0.0862
(Mon- Wed)	(0.0521)	(0.0698)	(0.0610)	(0.0443)
Total Time Spont	0.0218	0.0006	0.1157	0.0170
Total Time Spent	-0.0318	0.0900	0.1157	0.0170
	(0.0079)	(0.0083)	(0.0077)	(0.0064)
Heavy User	-0.4134	-0.6824	-0.5414	-1.3667
,	(0.1825)	(0.1796)	(0.1830)	(0.0945)
	(0.1525)	(0.1700)	(0.1000)	(0.0010)
Male	0.0439	-0.2927	0.1071	-0.0865
	(0.0528)	(0.0693)	(0.0625)	(0.0447)

* Bold type values denote significance at the 0.01 level. Italicized values indicate significance at the 0.05 level. The numbers in parentheses are standard errors of the estimates.

MLE estimates*

Site	P[site non – portal]	P[site Yahoo!]
Yahoo!	0.028	0.650
AOL	0.020	0.008
Netscape	0.016	0.019
Other Portal	0.093	0.083
Non-Portal	0.833	0.239

 Table 3: Sample switching probabilities

 Table 4: Actual vs. Estimated Switching Probability Matrices

Actual Switching Probability Matrix*											
Heavy & Male						Light&Male					
State**:	1	2	3	4	5	State:	1	2	3	4	5
1	0.6253	0.0034	0.0229	0.0256	0.3228	1	0.8108	0.0000	0.0000	0.0811	0.1081
2	0.0107	0.5027	0.0071	0.0463	0.4332	2	0.0000	0.4375	0.0000	0.1250	0.4375
3	0.0548	0.0053	0.4984	0.0443	0.3973	3	0.0000	0.0000	0.7778	0.0278	0.1945
4	0.0188	0.0136	0.0188	0.7425	0.2063	4	0.0070	0.0099	0.0042	0.9042	0.0747
5	0.0205	0.0100	0.0176	0.0213	0.9306	5	0.0238	0.0381	0.0333	0.1095	0.7952
		He	avy & Fem	ale		Light & Female					
State:	1	2	3	4	5	State:	1	2	3	4	5
1	0.5728	0.0118	0.0321	0.0300	0.3534	1	0.7000	0.0000	0.0000	0.3000	0.0000
2	0.0186	0.5422	0.0118	0.0422	0.3852	2	0.0000	0.4348	0.0000	0.0652	0.5000
3	0.0647	0.0090	0.5108	0.0504	0.3651	3	0.0909	0.0000	0.7273	0.0909	0.0909
4	0.0237	0.0131	0.0187	0.7059	0.2385	4	0.0080	0.0186	0.0053	0.8963	0.0718
5	0.0208	0.0146	0.0132	0.0298	0.9216	5	0.0154	0.1154	0.0154	0.0615	0.7923

Expected Switching Probability Matrix*											
Heavy & Male						Light&Male					
State:	1	2	3	4	5	State:	1	2	3	4	5
1	0.6120	0.0056	0.0266	0.0272	0.3286	1	0.6435	0.0092	0.0349	0.0773	0.2351
2	0.0154	0.4692	0.0101	0.0458	0.4594	2	0.0129	0.6120	0.0106	0.1034	0.2611
3	0.0573	0.0055	0.5184	0.0425	0.3763	3	0.0528	0.0079	0.5975	0.1058	0.2360
4	0.0212	0.0126	0.0186	0.7219	0.2257	4	0.0098	0.0090	0.0107	0.8996	0.0709
5	0.0210	0.0107	0.0165	0.0241	0.9278	5	0.0278	0.0221	0.0273	0.0862	0.8365
		He	avy & Fem	ale		Light & Female					
State:	1	2	3	4	5	State:	1	2	3	4	5
1	0.6014	0.0078	0.0246	0.0299	0.3365	1	0.6305	0.0127	0.0322	0.0846	0.2400
2	0.0126	0.5455	0.0078	0.0419	0.3922	2	0.0101	0.6791	0.0078	0.0903	0.2127
3	0.0578	0.0079	0.4914	0.0478	0.3952	3	0.0534	0.0113	0.5677	0.1193	0.2483
4	0.0193	0.0162	0.0159	0.7343	0.2142	4	0.0088	0.0116	0.0091	0.9042	0.0664
5	0.0201	0.0145	0.0148	0.0257	0.9249	5	0.0264	0.0299	0.0244	0.0915	0.8279

* Summary of Chi-Square Tests for Each Cell

		Chi-Sq V	df	P-Value
Cell1	Heavy& Male	1.000000	16	1.0000
Cell2	Heavy & Female	1.000000	16	1.0000
Cell3	Light & Male	1.000000	16	1.0000
Cell4	Light & Female	0.999995	16	1.0000

** State: 1=Yahoo!, 2=AOL, 3=Netscape, 4=Other Portals, 5=non-portal sites.

Table 5: Evaluation of Future Share Predictions for Holdout Sample

		Heavy & Male Segment				Light & Male Segment	
Site	Actual	Estimated	Steady-State	Site	Actual	Estimated	Steady-State
	Share	Share	Share		Share	Share	Share
Yahoo!	0.0629	0.0539	0.0542	Yahoo!	0.0357	0.0405	0.0520
AOL	0.0169	0.0195	0.0192	AOL	0.0549	0.0292	0.0358
Netscape	0.0325	0.0343	0.0343	Netscape	0.0220	0.0374	0.0450
Other Portals	0.0735	0.0906	0.0838	Other Portals	0.4753	0.6212	0.4675
Non-Portals	0.8143	0.8016	0.8085	Non-Portals	0.4121	0.2718	0.3998
Mean Absolute		12.05%		Mean Absolute		39.01%	
% Error				% Error			
		Heavy & Female Segment				Light & Female Segmer	nt
Site	Actual	Estimated	Steady-State	Site	Actual	Estimated	Steady-State
	Share	Share	Share		Share	Share	Share
Yahoo!	0.0661	0.0496	0.0499	Yahoo!	0.0287	0.0347	0.0450
AOL	0.0203	0.0304	0.0301	AOL	0.0654	0.0270	0.0555
Netscape	0.0253	0.0291	0.0290	Netscape	0.0253	0.0193	0.0357
Other Portals	0.1052	0.0987	0.0928	Other Portals	0.5911	0.6100	0.4918
Non-Portals	0.7832	0.7922	0.7982	Non-Portals	0.2895	0.3089	0.3720
Mean Absolute		19.43%		Mean Absolute		22.72%	
% Error				% Error			