CONSIDERATION, CHOICE AND CLASSIFYING LOYALTY

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Abstract

The authors present an approach to classify a brand's buyers into groups with varying degrees of loyalty along a continuum from "hard-core loyal" to "hard-core switcher." A classification scheme is developed based on the joint use of stated consideration set and brand switching data. The resulting loyalty taxonomy yields five mutually exclusive segments: Hard-Core Loyal (HCL), Soft Loyal (SL), Soft Switcher (SS), Hard Switcher (HS), and Hard-Core Switcher (HCS). The five classifications from the proposed taxonomy generalize the "loyal" versus "potential switcher" segments derived from previous analyses of brand switching data. In an empirical application to the automobile industry, the authors show that the current switching data-based models substantially overstate the number of the hard-core loyals (buyers who repurchase with probability one) versus the taxonomy's classification, which is based on both consideration and purchase data. These overestimates can mask the relative health or sickness of brands within the product category. The authors also illustrate how the proposed taxonomy can aid managers in understanding markets and addressing and targeting buyers with varying degrees of loyalty.

Key Words: Consideration Sets, Switching Matrix, Brand Loyalty, Automobiles

Introduction

Customer retention has been a mainstay concept in marketing for many years and is one of the pillars of customer equity programs (e.g. Blattberg et al. 2001, Reichheld et al. 1996, Rust et al. 2000). Retention (or repeat purchase) also measures brand loyalty in a behavioral sense (Keller 1998, Aaker 1996, Jacoby and Chestnut 1978) and has been used to optimize marketing budget allocations (Blattberg and Deighton 1996). Yet, retention or repeat purchase *per se* need not be synonymous with strong brand preference (Dall'Olmo Riley et al. 1997). Some customers who are retained may have almost switched to a competing brand; other customers seemingly lost to competitors may have almost made a repeat purchase. Assessing brand health with repeat purchase data, while challenging for frequently purchased products, is an even more daunting task for consumer durables, where there is often only one purchase observation. For example, a finding that an automobile brand enjoys more or less "hard-core loyalty" than is in fact the case could easily lead to misdirected marketing resources (e.g., monies wasted on customers who would repurchase in any event).

The objective of this paper is to present a parsimonious new approach to classifying brand loyalty that overcomes some of the limitations of relying solely upon brand switching and repeat purchase data. In our approach, we incorporate data on repeat purchase as well as stated consideration. This permits us to provide an assessment of how traditional brand switching models recover the proportion of hard-core loyal customers.

Our research makes two contributions. One is substantive, the other is methodological. First, we find that the current benchmark loyalty models based on switching data, Colombo-Morrison (1989)– hereafter CM –and Grover-Srinivasan (1987)– hereafter GS–, give badly upwardly biased estimates of true hard-core loyalty. In addition the results from CM and GS give misleading indications of the "health" of the brand, e.g. the recently discontinued automobile brand names, Plymouth and Oldsmobile. Second, almost all switching data are collected in some form of quota sampling so that "small" brands have big enough sample sizes. Thus, the sample switching matrix is a biased estimate of the true switching matrix. We show how to correct this bias. Further we show that the results from the unadjusted switching matrix yield managerial implications that differ strongly from those obtained using the correctly adjusted switching matrix.

The reader should be also aware that there is no new or even improved model in this research. Rather, a new framework, applied to a data set on consumer durables, is used to gain considerable insight on existing models that use brand switching data.

How Loyal are the "Loyal" Customers

One challenge is that the ability to uncover whether seemingly loyal buyers are "hard-core" (i.e., repeat purchase with probability one) or "soft" (i.e. repeat purchase with probability less than one) depends on the nature and extent of the customer information available. In a frequently purchased product category such as yogurt, for example, observing a customer buy the same brand 10 consecutive times in six months should indicate high loyalty and correspondingly high future retention probabilities. While there are a number of obvious caveats (e.g., purchases need to be observed under different price and promotion conditions), the point is that long strings of purchase observations can yield good inferences about loyalty. On the other hand, among infrequently purchased consumer durables such as automobiles, observing a buyer purchase the same brand twice in six years would provide a much weaker inference regarding loyalty. Accordingly, assessing the extent of customer loyalty with observed purchase data alone is likely to be more difficult when there are few observations per buyer and/or longer time intervals between purchases as in most durable goods or infrequently purchased services datasets.

To take and example from the automobile data used in this study, in 1997 approximately 39% of buyers who traded in either a Nissan or Jeep bought a new Nissan or Jeep, respectively. A purely retention-based analysis would suggest that these two makes have a similar level of loyalty. Yet, 63% of those seemingly "loyal" to Nissan stated that they considered buying other makes, but only 43% of those who repeat purchased a Jeep consider switching. This example highlights the inherent limitations of repeat purchase measures alone for assessing loyalty in consumer durables. Moreover, unlike consumer packaged goods, historical transaction or panel-type data are usually not available for consumer durables or services. Thus, in order to assess loyalty, survey methods are required just to obtain brand switching as well as repeat purchase information. Fortunately for the case of durable goods, consumers can typically recall the previous brands of most big-ticket items they have purchased (e.g., the make of the last car they owned, the name of the hotel where they stayed during their last family vacation or the brand of their dishwasher or computer). Using repeat purchase and switching dyads investigators can construct switching matrices and apply a wide array of techniques to study brand loyalty. However, these techniques will suffer from the limitations just identified: they fail to take into account the underlying extent of brand loyalty. Given that survey methods are already employed, we argue below, that researchers should take one additional step and collect data on the stated consideration set as well.

Existing Approaches to Identify Loyal Customers with Switching Data

One naïve interpretation of a switching matrix asserts that *loyal* customers are in the diagonal and *switchers* are in the off diagonal cells. This effectively assumes that consumers who repeat purchase are brand loyal and consumers who switch are not. It cannot tease out the different degrees of brand loyalty either among those consumers who repeat purchase or among those who switch.

Stochastic models offer a richer interpretation of brand-switching matrices and do attempt to identify different degrees of brand loyalty among repeat purchase customers (Grover and Srinivasan, 1987; Colombo and Morrison 1989; Jain, Bass and Chen, 1990; Cooper and Inoue, 1996). Two stochastic methods that explicitly provide estimates for the extent of brand loyalty are the approaches proposed by Colombo and Morrison (1989) and Grover and Srinivasan (1987).[1] These models uncover a latent market

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[1] Technically, Grover and Srinivasan (1987) used panel data. But they developed a matrix of joint probabilities based on the cross-classification of brands purchased on two successive occasions (specifically the first two purchases made by households in their sample). Consequently, their modeling approach is compatible with the analysis of survey-based switching data for consumer durables.

structure by segmenting the market into loyal and switching segments (see the Appendix). The primary difference between the CM and the GS models is the number of switching segments. CM assumes homogeneity across switchers (i.e. only one switching segment); GS accounts for heterogeneity across, but not within, switching segments.[2] A common finding from the application of these models was that consumers who repeat purchase (the diagonals of the switching matrix) are not equally loyal. Some repeat purchases come from "hard-core loyal" (HCL) customers who are assumed to repeat purchase with probability 1.0 (i.e., do not consider no other brands). The *remaining* repeat purchases come from one or more switching segments whose members are assumed to repeat buy with probability less than 1.0. In other words, they also considered buying other brands but did not switch. We will call this second group of repeat buying customers *soft loyals* (SL).

While HCL and SL buyers share the same choice outcomes, they differ in their attitude or commitment towards the brands. This is, in general, unobserved by the researcher applying the CM or GS models. This raises the concern that it is problematic to distinguish HCL from SL customers based on single repeat purchase data alone. *A priori* it is not possible to know the extent to which the proportion of HCL customers is accurately recovered or overestimated by stochastic models applied to brand switching matrices (Grover and Srinivasan 1987, p. 152). Moreover, because the various latent segments must sum to 100 percent of the market, an error in determining the size of the hard-core loyal segment will also affect the size of other segments.

An Alternative Approach to Identifying Hard and Soft Loyal Customers

To address this concern, we propose that users or survey-based switching data for consumer durables consider an alternative approach to assessing the extent of the hard-core and soft loyalty to their brand. Recall that an HCL customer may be defined as one who repeat purchases without having *considered* any

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[2] In their appendix, Grover and Srinivasan (1987) discuss the estimation of a model with heterogeneity within switching segments. However, that model is not identifiable with switching data. It requires multiple observations per buyer. Panel data is not generally available for most durable products or infrequently purchased services.

other brands. One way of capturing this information is to use the consideration stage of the buyer's choice process. In this stage, consumers filter the alternatives so that the reduced set contains only those alternatives from which the final choice is to be made (Shocker et. al. 1991, Roberts and Lattin 1997, Siddarth et al. 1995). By combining consideration sets with the repeat purchase information, it becomes possible to differentiate those buyers who intended only to repeat purchase (i.e., they only considered the last brand purchased) from those who may have had some interest in switching (i.e., they considered other brands in addition to the brand last purchased). Thus, HCL customers as well as the SL customers can be identified more accurately. In addition, studying consideration and choice data enables us to distinguish whether switchers reconsider the brand they bought last (i.e., they are *potential* switchers) or not (i.e., they are *sure* switchers). Finally, combining the attitudinal (i.e., consideration) and behavioral (i.e., choice) data allows us to differentiate those *sure* switchers who only consider one brand, and therefore will buy it with probability 1.0, from those *sure* switchers who consider multiple brands.

Survey methods can provide information about the consumer brand choice decisions on the last two purchase occasions as well as the consideration set pertaining to the last purchase. With this information, managers and researchers can deterministically, as opposed to probabilistically, estimate the size of the HCL segment.

An empirical study conducted by Lapersonne et al. (1995) indicates the extent to which hard-core loyalty may be found in stated consideration data. For the French automobile industry, they report that about 22 percent of car buyers considered only one brand and roughly 17 percent considered only the brand of their previous car. We note that the gap between 22 and 17 indicates the existence of another interesting segment of buyers. We call these group "hard-core switchers" because they are buyers that switch to a particular brand with probability 1.0. While Lapersonne et al. did not compare their findings with brand-switching data models, we note that neither of the stochastic modeling approaches discussed above explicitly accommodates the hard-core switcher behavior. Therefore, it seems promising that a combination of repeat purchase data and consideration data might permit us to better identify hard-core loyal, soft loyal, and different types of switching consumers.

To make operational our two-level (consideration and choice) approach, we develop an *a priori* market segmentation scheme that takes into account both the consideration and choice stages of the consumer's shopping process. The proposed taxonomy consists of five mutually exclusive segments each representing a different degree of brand loyalty. In the proposed taxonomy, consumer loyalty, or lack thereof, underlies not only repeat purchase, but also repeat consideration. We apply our framework to survey data for the U.S. automobile industry. For benchmark comparisons, we estimate the Colombo-Morrison (1989) and Grover-Srinivasan (1987) models using the same data.[3] We find that they overstate the proportion of hard-core loyal customers by one-half to two-thirds versus our proposed approach. We attribute the discrepancy to the fact that both models allow *every switcher* to *consider all brands*. This stands in contrast to the consideration set literature, which has shown that consumers choose from a reduced set of alternatives. This set may include one or more brands and may or may not include the previously purchased brand.

Before proceeding, we briefly note what we are *not* doing. First, are not providing a universal definition or measure of brand loyalty, or a universal segmentation scheme. There are nearly as many definitions of loyalty as researchers (Jacoby and Chestnut 1978) and the 'best' segmentation scheme is obviously situation specific.

Second, we are also not modeling brand choice as a two-stage process (e.g., Roberts and Lattin 1991, Andrews and Srinivasan 1995, Siddarth, Bucklin and Morrison 1995, and Bronnenberg and Vanhonacker 1996). Even though these models account for the consideration stage, they are not concerned with the estimation of hard-core loyalty. Their principal goal is to improve brand choice prediction. Moreover, in

[3] We do not replicate switching matrix based models that do not specifically estimate a loyal segment for each brand (e.g., Jain, Bass and Chen 1990).

the case of durables such as automobiles, these two-stage models are not practical. In durable products, both consumer lifestyles (income, age, marital status, etc.) and market characteristics (number of brands, product characteristics, prices, etc.) can change substantially from one purchase occasion to the next. Thus, the consideration set across purchases may be substantially different. Reliably determining a consideration set based on consumers' past purchases is therefore not possible in such instances. In this paper, we propose an approach for analyzing brand switching (*not* brand choice) data that divides the market into groups of loyal and switcher customers based on consideration and choice data and that is appropriate for consumer durables and infrequently purchased services.

Third, even though we cannot estimate the full NBD-Dirichlet model with two purchases from each buyer, we can under certain assumptions estimate the Dirichlet mixing distribution on buyers' multinomial probability vectors. However, the Dirichlet does not allow for discrete mass points where buyers always purchase a particular brand with probability 1.0. These excluded Dirichlet mass points are the essence of the CM and GS models. Likewise, these mass points capture the buyers in our sample who explicitly considered only the brand they purchased. Yes, the Dirichlet may fit our data reasonably well, but that is not relevant to our task. Our main objective is to see how well the CM and GS implicitly estimated hard-core loyal buyers (i.e., the size of the discrete probability mass points in the mixing distribution) compared with the explicit, self identified hard-core loyal buyers in our data. In this research accurately estimating extremely loyal buyers is more important than merely fitting the observed switching matrix.

The paper is structured as follows. In section two we introduce a loyalty taxonomy framework that incorporates both consideration and purchase information. In section three we present an empirical application of the loyalty taxonomy to the automobile industry and compare the results to those from the stochastic brand switching models. In section four we discuss additional insights obtained from our classification framework. We conclude with a summary and limitations.

Framework

Our proposed loyalty taxonomy is an *a priori* market segmentation approach based on a combination of consideration and choice data. It is constructed by combining two pieces of information: 1) the brands considered by a consumer during her last purchase and 2) her brand choice decisions on the last two purchases. The segmentation approach consists of three steps. The first step classifies consumers based on their repeat consideration behavior. The second uses the consideration set size and content as a segmentation criterion. The final step uses choice data to further divide the market into a final set of five groups of loyal and switcher customers.

Step 1: This first step uses information on whether a consumer reconsiders the brand she has last purchased. Based on this 'consideration loyalty,' consumers are classified into one of two groups: Loyal customers are those who include the brand they purchased last in their consideration set and Disloyal customers are those who do not reconsider it.

Step 2: Loyalty is not a dichotomous variable as in our first step (i.e., loyal or disloyal), but a continuum that depends on the consumer's brand commitment level (e.g., Bloemer and Kasper 1995). In our second step, we approximate the consumer's brand commitment level by taking into account (a) the consideration set size and (b) the consideration set content. Using consideration set size, we differentiate consumers with the highest level of commitment (i.e., consideration set of size one, which implies a probability of purchasing the considered brand equal to one) from those who show lower levels of commitment (i.e., consideration set of size greater than one, which implies a probability of purchase for any considered brand less than one).[4] We propose this binary classification instead of one using

[4] It could be argued that, from the market structure point of view, studying which alternatives are considered simultaneously provides interesting insights regarding brand competition. Those brands that tend to be included in the same consideration set present a higher level of competition. Nevertheless, from the 'consideration loyalty' point of view there is no need to look at such detailed level information. To reveal whether seemingly loyal buyers are "hard-core or soft" loyal, only an assessment of repeat consideration in conjunction with a measurement of brand commitment is required.

consideration set size because we can only be certain of a decrease in the purchase probability for a considered brand when we compare consideration sets of size one with sets greater than one. We are *not* suggesting that as customers consider more brands their commitment with all the considered brands decreases. This claim cannot be made by only knowing consideration set membership.[5] Combining the information about consideration set size with the information about consideration set content, we further divide the two step 1 segments into four segments.

Consumers who reconsider the last brand purchased (i.e., *loyal* consumers in our first step) are further divided into *Hard-core Loyal (HCL)* and *Potential Switchers (PS).* The first group consists of those individuals who *only* consider and therefore buy the brand last purchased.[6] These HCL consumers present the highest level of commitment and loyalty possible. *Potential Switchers* are those who consider not only the last brand purchased but also other brands. Therefore, a *PS* can either repeat the brand last purchased or switch to one of the other considered brands. It is important to distinguish between this definition of *PS* and the one used by previous loyalty models (e.g., Colombo and Morrison 1989). In our taxonomy, the fact that a consumer shops around for different brands (i.e., consideration size greater than one) is a necessary but not sufficient condition to become a *PS*. To be a *PS*, a consumer needs to *reconsider* her previous choice. When she does not reconsider the brand last purchased (i.e. *disloyal*), she switches with probability equal to one. Hence, she is a *sure switcher* as opposed to a potential one.

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[5] Suppose that a consumer is considering buying only brand A, CS = {A}. In this case, she will buy brand A with probability equal to one, Pr(A) = 1. Suppose now that the same consumer is also considering brand B, CS = {A, B}. In this case, both brands have a positive probability of being chosen. For example, without loss of generality, we can assume that Pr(A) = .8 and Pr(B) = .2. Hence, Pr(A) < 1. We can safely say that her commitment to brand A decreases as we go from {A} to {A, B}. Now, suppose that in addition to brands A and B she also considers brand C, CS = {A, B, C}. In this case, we *cannot* say with certainty that the probability of buying brand A decreases with respect to that of {A, B}. It might well be the case that Pr(A) stays constant and that the positive probability of buying brand C is originated only at the expenses of a lower probability of buying brand B. Using the same example as above, Pr(A) = .8, Pr(B) = .1 and Pr(C) = .1. Therefore, we can *only* be certain of a decrease in the probability of buying brand A when we compare consideration sets of size one with sets of size two or more.

[6] As some authors (e.g., Grover and Srinivasan 1987) have discussed in earlier research, the HCL segment could be further divided into *n* different segments, one for each of the *n* brands included in the analysis.

We also apply the same consideration set size and content criterion to those customers who *do not* reconsider the last brand purchased (i.e., *disloyal* customers in our first step). By doing so, *disloyals* are divided in two segments: *Hard-core Switchers (HCS)* and *Hard Switchers (HS).* Individuals who only consider one brand—different from the last brand purchased—are called *HCS.* Those who consider more than one brand but who do not reconsider the brand last purchased are labeled *HS*.

From a behavioral loyalty perspective, this additional segmentation of the disloyal customers into *HS* and *HCS* might seem unnecessary since both types of consumers are sure switchers. On the other hand, HS and *HCS* consumers have different types of switching behaviors that could yield different implications for strategy. For example, while it might be worthwhile to try to retain a *HS* because they at least show a willingness to consider multiple brands, it might be too expensive to try to retain a *HCS*. Moreover, as we discuss below, ignoring that these two segments differ in the probability of buying a new brand is one source of possible misspecification of the CM and GS brand-switching models.

Thus, the four resulting, mutually exclusive segments from step 2 are: Hard-Core Loyal, Potential Switchers, Hard Switchers and Hard-Core Switchers. They differ on repeat *consideration* behavior and on the size of their consideration set.

Step 3: The final step incorporates information about the choice outcome. In our taxonomy, the Potential Switcher *(PS)* segment is the only one affected by the addition of the choice data. Using choice, the *PS* segment is divided into *soft loyal (SL)* and *soft switchers (SS)*. After evaluating all considered brands, soft loyals end up repurchasing the last brand. Soft switchers are those consumers who reconsider the previous brand but end up switching. Note that for the *HCL* and *HCS* segments there is only brand considered. Thus, there is no uncertainty regarding the choice outcome (conditional on a purchase having been made). Consumers in the HS segment consider multiple brands but do not reconsider the last brand purchased. Consequently, knowing which brand they ultimately select does not alter the loyalty implications for the focal brand.

To summarize, in the loyalty taxonomy for a given brand, every previous buyer of that brand is assigned to one and only one of five mutually exclusive segments: (1) *hard-core loyal*, (2) *soft loyal*, (3) *soft switcher*, (4) *hard switcher*, and (5) *hard-core switcher* (see Figure 1).

Empirical Application

We illustrate the loyalty taxonomy using data on the U.S. automobile market. Data are from the 1997 J. D. Power and Associates' Early Buyer Survey (EBS '97). This dataset consists of 45,006 responses to a questionnaire that J.D. Power and Associates (JDPA) annually sends to customers who have bought a new car early in the model year. In this survey, buyers are asked to state what cars (i.e., makes and models) they seriously considered while shopping for a new car. We use this information as customers' revealed consideration sets. The survey also contains information about the trade-in (i.e., last brand purchased) and the new car (i.e., brand choice).

We apply the taxonomy framework at the *make* level (e.g., Chevrolet, Toyota, Honda). For example, if a consumer considered two different car models that were both of the same make (e.g. Honda Civic and Honda Accord), her consideration set size would be defined as equal to one. We have two reasons for this approach. First, there are approximately 43 makes in the US market, but there are hundreds of different models – more than 400 in the EBS'97 database. Second, because consumers' interpurchase time in the automobile industry is long (approximately six years for new cars in our data), and because, in general, consumer lifestyles change over this period, car manufacturers tend to implement umbrella brand policies (i.e., one make, multiple models). Due to this umbrella brand strategy, consumers who are switchers at the model level might be loyal at the make level. To capture the umbrella brand effect, we apply the taxonomy to the make level in the automobile market.

The EBS'97 survey truncates the revealed consideration set to a maximum of five self-reported vehicles. The truncation does not affect the loyalty taxonomy because the consideration set size criterion is a binary indicator corresponding to a set size of one or greater than one.[7] Table 1 gives the distribution of consideration set sizes based on the number of *makes* considered.

We restrict our analysis to the 14 major makes available in the U.S. These account for more than 80 percent of market sales (see Table 2). The final sample consists of 20,162 respondents. It is about half of the original sample size because of a quota-sampling scheme used by JDPA. The company samples respondents to ensure that each brand, specifically small brands, has enough respondents (i.e., survey share given by the columns of the switching matrix) so that statistically significant results can be obtained. The quota-sampling implies that small share brands have more survey share than their market share and vice versa for large share brands. Though the 14 major brands account for more than 80% of the market, their survey share is only about 50%. In retaining only those observations for consumers who traded-in or purchased one of the 14 major brands, the sample size shrinks disproportionately.

Using a Quota-Sampled Switching Matrix: Warning!

An important consequence of the quota-sampling scheme is that the probability of randomly choosing a consumer who bought brand j from the EBS '97 sample is equal to brand's j **survey share** and not to brand j's **market share**. In other words, the marginal probability of buying a new brand j, i.e. P(new j), is biased. This means that using the raw (original) switching data will lead to *meaningless* conclusions. Fortunately, because JDPA selects the survey subjects based on the new car bought and not on the traded-in vehicle, the rows of the switching matrix (i.e., the traded-in car shares) are free of the quota-sampling problem. Therefore, the column conditional probability, i.e. P(old i | new j), is unbiased. In order to obtain the unbiased probability of buying a new car j given old car i, we rescale the original data by

[7] It might be argued that for some customers, the brand last purchased might have been the sixth or higher order considered brand. If that were the case, the truncated consideration set will omit the last purchased brand. The result will be an overestimation of the HS segment and an underestimation of the SS one. Yet, this will have *no implications* for the HCL or the SL segments. Moreover, the proportion of consumers in the EBS'97 database who considered five brands is very small, i.e. 1.83%. Hence, the proportion of individuals who might have been forced (some of them probably considered exactly five brands) to truncate their consideration set given that they also consider the brand last purchased as the sixth or higher order brand is very small.

applying Bayes theorem. Specifically, to estimate the unbiased probability of buying a new *j* given that an old *i* was traded in, we apply Bayes theorem on the unbiased conditional probability P(old *i* | new *j*), weighted by the actual (unbiased) brand *j* market share:

$$\mathrm{P(new\ j \mid old\ i)} = \frac{\mathrm{P(\ old\ i \mid new\ j)} \times \mathrm{P(\ new\ j)}}{\sum_{q=1}^{N} \mathrm{P(\ old\ i \mid new\ q)} \times \mathrm{P(new\ q)}} \quad \textit{for all i and j, and for q=1,..., N} \tag{5}$$

where P(old *i* | new *j*) is given by the column of conditional probabilities obtained from the *original switching matrix* and P(new *j*) is the *actual market share* for brand *j*. The rescaled switching matrix is given in the Web Appendix. The foregoing discussion highlights the need for investigators to consider sample selection issues when analyzing brand switching data. Indeed, as we will point out subsequently, analyses of the not rescaled switching data yielded quite different representations of the market.

Estimation

We apply the loyalty taxonomy framework to the *rescaled* EBS ’97 data. Table 5 reports the full set of results. Our attention focuses first on the findings pertaining to the estimated sizes of the hard-core loyal segments for each brand and a comparison of these with the CM and GS models. We will return to a more general discussion of Table 5 shortly.

To obtain estimates for the CM and GS model parameters, we also used the *rescaled* EBS ’97 data and followed the specific procedures described by the authors in their original papers. The CM model was estimated with maximum likelihood, using the function described in the appendix of CM (equation A1) for the parameter space $\theta = \{\alpha_i, \pi_i\}$ (see the Appendix for definition and model). Table 3 reports the results of this estimation. To estimate the GS model, we followed the two-step approach described by the authors. First, we estimated an unconstrained model varying the number of switching segments and holding the number of brand loyal segments at 14, one for each car make or brand. By comparing the goodness-of-fit, as defined by the adjusted R^2 in GS equation 24, we determined the optimal number of switching segments. The best solution was four switching segments. Second, we constrained the model by setting to zero any choice probabilities estimated to be less than .01 in the four switching segments. Several starting solutions were used to maximize chances of the iterative maximum likelihood procedure ending with global optimal parameter estimates. The parameter vector $\theta = \{V_i, W_k, \pi_i\}$ (see Appendix) that maximized the GS likelihood function is also shown in Table 3.

Estimates of Hard-Core Loyal Customers

We now assess how well the traditional brand switching models, as represented by CM and GS, recover the proportion of HCL customers. We compare the estimates of the HCL segment size because it is the segment with a common definition across the three approaches. As noted above, an error in the estimation of one segment size affects the estimation of others due to the summation to one constraint.

The loyalty taxonomy and CM model specify the HCL segment size *as a proportion of brand i's current users* who are completely loyal and will buy brand *i* with probability one. On the other hand, the GS model estimates the HCL segment size *as the proportion of consumers in the total market* who are loyal to brand *i*. Therefore, we rescale the GS HCL results so as to make them comparable with the HCL results from the other two models.[8] Of course, while both CM and GS models produce the HCL segment sizes probabilistically, the loyalty taxonomy does so deterministically.

A comparison shows that both CM and GS estimate the size of the HCL segment to be larger than the figures derived from the loyalty taxonomy (see Table 4). On average, CM estimates the HCL segment sizes to be 67% larger than the taxonomy approach. For GS, the average difference is 48%. Though the

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[8] The sizes of the *n* loyal segments in GS model are defined with respect to the total market sales and not conditional on the number of consumers trading in a particular car. Therefore, after estimating the GS model, we rescaled the sizes of these *n* loyal segments to make it comparable with the HCL segment sizes obtained with the CM model and the taxonomy framework. We used the following transformation rule:

$\alpha_i = \dfrac{\widehat{V}_i \times Total\ Sample\ Size}{Total\ trade\ in\ Brand\ i}$ where $\widehat{V}_i$ GS estimated proportion of buyers in the *total* market who are loyal to brand *i*

CM parameters deviate from the taxonomy by a higher percentage, we note that estimates for CM do have a higher correlation with the taxonomy's HCL results than the GS estimates (r=.92 versus r=.78).

The differences stem from the inherent limitations of repeat purchase data to discriminate among switching behaviors. Specifically, the CM and GS models have two important limitations. First, without consideration information, they cannot discriminate between those switchers who reconsider the last purchased brand (i.e. potential switchers) and those who do not reconsider it (i.e. sure switchers).[9] Second, these models cannot discriminate between those switchers who only consider one brand and those who consider multiple brands. Hence, another limiting assumption is that none of the switchers will switch to a new brand with probability equal to one. These two limitations lead to estimated average repeat purchase probabilities for switchers (π_i or π_{ik} for CM and GS respectively) that are too high. This 'higher-than-true' probability for switches implies, in turn, that the total number of switcher customers (i.e., no HCL) should be smaller than the 'true' number of switchers. This leads to switching segment sizes that are too small. Given the sum constraint for segment sizes, estimating switching segments that are too small goes hand in hand with HCL segments that are too large.

Given that all repeat purchasers are either hard-core loyals or soft loyals in our framework, it is straightforward to examine the implications of HCL estimation for SL estimation. To do so, we calculate the proportion of SL customers implied by the CM and GS models as the proportion of repeat purchase customers who are not HCL. Thus, the SL segment size equals the repeat purchase rate minus the HCL segment size. The CM and GS models imply that almost all repeat purchase customers are HCL customers (see Tables 4). The ratio of HCL to SL customers is roughly 1:1 for the taxonomy approach but about 7:1 for the GS model and about 10:1 for the CM model. By combining consideration and choice information, the loyalty taxonomy is able to distinguish between potential versus sure switchers

[9] Even though CM and GS differ in the number of switching segments, both models allow every switcher to consider all brands in the product class.

and reveal switchers who only consider buying one brand. Thus, the heterogeneity across switchers is better captured by the taxonomy than by the CM or GS models.

Improved identification of hard-core loyal customers has important implications for marketing budget allocations and profitability. A simple example illustrates the cost of estimating too many HCL customers. In the new car market, consumer rebates of $1,000 and up are commonly offered. Assuming that HCL customers need no incentive, we can calculate the overspending on HCL customers. Combining trade-in information with the estimated proportions of HCL customers from the EBS'97, CM and GS would overstate the number of HCL customers by an average of 217 and 116, respectively. These results are calculated based on our sample, which is less than 0.02% of the U.S. market. For the total market, the implied overspending on rebates for HCL customers would be approximately $46 to $86 million.

In previous research, scholars have shown that brands with larger market shares are more likely to attract more loyalty (as measured by repeat-purchase rates) than brands with smaller market shares, a phenomenon called "double jeopardy" (Ehrenberg et. al. 1990, Fader and Schmittlein 1993, McPhee 1963). We examined whether the double jeopardy phenomenon holds also for hard-core loyalty. The correlation between market shares and the taxonomy HCL estimates is .85. This correlation is higher than the correlation of market shares and HCL estimates from both CM and GS (r=.70 and r=.45 respectively). Therefore, at least for this dataset, market share is a better predictor of hard-core loyalty when it is based on consideration and choice information than when it is defined using switching matrix data alone.

Using the Framework for Market Analysis

We now return to a discussion of Table 5, which reports the complete loyalty taxonomy results. We interpret some of the findings here, with an eye towards how they may be used for market analysis.

Based on the 1997 data and taxonomy application, Ford is the strongest umbrella brand in the U.S. automotive market. It has the highest repeat purchase rate (64%) and the highest proportion of HCL buyers (39%). The taxonomy reveals that Ford's strength is also grounded in the attitudes of those customers who trade-in a Ford but buy a different brand. About 40% percent of Ford's switchers still reconsider buying a Ford as evidenced by the proportion of soft switchers to total switchers (14.2% divided by 36.4%).

Recently, and subsequent to the collection of these data in 1997, the manufacturers of Plymouth and Oldsmobile have announced decisions to phase out these brands. Our findings indicate that Chrysler and General Motors are correct in recognizing the weakness of the Plymouth and Oldsmobile brands. Both brands have the lowest proportion of hard-core loyals (8% and 15% respectively) as well as low repeat purchase rates (20% and 29% respectively). We also note that applying the loyalty taxonomy to the raw, unadjusted switching data led to very different results. Using the *unadjusted* quota-sampled data, Oldsmobile is the second strongest brand as ranked by the size of the HCL segment. With those data, the HCL segment size of Oldsmobile was determined to be 30%, twice the size obtained from the rescaled data. This highlights our earlier warning about using directly the quota-sampled data.

Analyzing the taxonomy results also provides insights for Buick. While Buick's repeat purchase rate (41%) is slightly below the average (42%), it has the highest ratio of HCL customers to the total number who repurchase Buick. Given that loyal customers may be willing to pay more than other customers, Buick managers may be able to increase profits by targeting their HCL customers with premium prices.[10]

The loyalty taxonomy also shows that the Japanese brands (Honda, Nissan, and Toyota) have greater soft loyal segment sizes than the domestic brands – i.e., they do better than the domestics in retaining those customers who reconsider the brand last purchased as well as other brands. These Japanese brands, however, do not perform better than domestic brands when examining the total proportion of retained customers (i.e. HCL plus SL).

[10] Even though this might sound like a harvesting strategy, which could be dangerous, our empirical results illustrate that HCL consumers paid, on average, the highest prices (please see Table 8).

Another interesting finding in Table 5 is that Nissan's proportion of HCL customers is second to last (15%). The only brand that has a lower proportion of HCL customers than Nissan is Plymouth—a now discontinued brand. Moreover, the other discontinued brand, Oldsmobile, has a proportion of HCL customers that is slightly higher than Nissan's. In spite of this low level of HCL customers, the taxonomy reveals that Nissan is in a better position than both Plymouth and Oldsmobile. Nissan is the fourth best brand in the industry in retaining customers who consider other brands in addition to the brand last purchased. This result reflects Nissan's ability to achieve a repeat purchase rate (39%) only slightly below the industry average (42%) even though it is one of the brands with a low HCL proportion.

Interestingly, the CM and GS models tell a very different story about Nissan (Table 3). Both models estimate Nissan's HCL segment size (35.6% and 33.1%) to be close to the industry average (37.5% and 33.2%). Moreover, Table 4 reports that the sizes of the SL segment indirectly estimated by the CM and GS models (2.9% and 5.4%) are both below the industry average (4.1% and 8.4% respectively). The loyalty taxonomy shows that the strength of Nissan comes from its SL buyers but both stochastic models indicate that Nissan's strength comes from a high proportion of HCL customers.

Figure 2 shows a chart of the HCL vs. SL segment sizes for each brand obtained from the loyalty taxonomy. Each brand is located in one of the four quadrants depending on whether the estimated size of the HCL and SL customers are above or below the industry median. The two discontinued brands, Plymouth and Oldsmobile, are located in the lower right quadrant along with Chrysler, Mercury, and Pontiac. (Interestingly, speculation has also recently surfaced in the business press regarding the long-term prospects for the Mercury brand.) In the lower left quadrant, labeled "opportunity", are Nissan and GMC. Though they have a low proportion of HCL customers, they retain a large proportion of those consumers who considered other brands. The upper-left quadrant arguably contains the strongest brands in the market. Brands "at risk" are included in the top-right quadrant. These brands have a large proportion of HCL buyers but a small proportion of SL customers.

Figure 2 could also be constructed based on the CM and GS results. If this were done, we would observe several changes. For example, Pontiac moves to the "opportunity" cell while GMC becomes "at risk". The GS results would also classify Plymouth in the "opportunity" cell, though the CM results do not.

The practical value of the above described results—or any additional insights that could be obtained from Table 5—are directly related to the addressability and targetability of these five loyalty segments. As numerous researchers have pointed out (e.g., Blattberg et al. 1978), the managerial relevance of a segmentation procedure is related to its ability to partition the consumer population into relatively homogeneous groups that differ substantially in purchase behavior. We find that the loyalty taxonomy segments differ in their demographic and shopping behavior characteristics (see Table 6). For instance, the application of the loyalty taxonomy to the EBS'97 dataset shows that HCL consumers are, on average, the oldest in the market for new cars, pay the highest prices, visit the smallest number of dealers, and are the most satisfied with the car they traded in.

Table 6 also reveals that whether the traded-in car was bought new or used partially explains the differences between loyals and switchers in their interpurchase time. On average, repeat buyers (i.e. HCL and SL) change their car two years earlier than switchers (i.e. SS, HS and HCS). Another difference between those who repeat purchase and those who switch is that the former have a higher level of satisfaction and drive, on average, newer cars (i.e. the car traded in was bought new and was driven for fewer years).

Managers may be able to customize their marketing efforts and optimize marketing budget allocations by taking advantage of the differences in the demographic and shopping behavior characteristics exhibited in Table 8. For example, managers might optimize direct mail by knowing that loyal customers change their cars more frequently than do switchers. Also, given that a higher proportion of switchers test driv`e the car bought, managers can design events such as "The no boundaries experienced 2002"[11] organized by Ford Motor Company to encourage consumers to buy a new Ford Explorer. In sum, the loyalty taxonomy characterizes the market as five mutually exclusive segments that are addressable (i.e., they are identifiable) and can be targeted separately (i.e., have different needs and preferences).

Conclusions, Limitations and Future Research

In this paper we present an *a priori* market segmentation suitable for use with consumer durables that incorporates both the consideration and choice stages of the consumer's shopping process. The proposed taxonomy consists of five mutually exclusive segments, each representing a different degree of brand loyalty: *Hard-Core Loyal, Soft Loyal, Soft Switcher, Soft Disloyal and Hard-Core Disloyal.* In the proposed taxonomy, consumer loyalty, or lack thereof, underlies not only purchase behavior, but also consideration. By combining a behavioral response (i.e., purchase) with the psychological process that precedes it (i.e., consideration), we propose that researchers and managers can achieve a better understanding of consumers' loyalty and switching behaviors for infrequently purchased products or services.

We compare and analyze the value added by the proposed two-level approach over and above approaches based on switching data alone. Specifically, we compare our approach to the models proposed by Colombo and Morrison (1989) and Grover and Srinivasan (1987). Because these models are based only upon brand switching and repeat purchase data, potentially important elements of the heterogeneity in switching behavior are not represented. The resulting specification of these models (e.g., allowing all potential switchers to have a positive probability of repeat purchase) leads to an overstatement of the size of a brand's hard-core loyal segment. This, in turn, produces an understatement

[11] "The no boundaries experienced 2002" was a promotional campaign organized by Ford Motor Company in which consumers were invited by mail to a central location, like the Rose Bowl in Los Angeles, where they could test-drive a Ford SUV or a Ford Mustang and get additional information about pricing, financing etc.

of the size of soft loyal segments (buyers who repeat purchase but have also considered one or more other brands). In particular, the two stochastic switching models produce estimates of the hard-core loyal segments that are, on average, approximately one-half to two-thirds larger than the number of buyers assigned to this segment using our proposed loyalty taxonomy framework.

These differences have important implications for the assessment of brand strength and for the allocation of marketing resources in customer retention activities. Because brand loyalty is a basic construct in any customer equity or customer relationship management program, the overestimation of HCL customers might lead to overreactions and poor marketing budget allocations. Information on the different degrees of brand loyalty across consumer segments allows managers to prioritize resources to strengthen relationships with more valuable customers. Our two-level loyalty measure provides a better criterion to optimize the marketing budget allocation by balancing what is spent on customer acquisition with what is spent on retention. The empirical findings also show a high degree of homogeneity within and heterogeneity across the five loyalty segments with respect to their demographic characteristics and shopping behaviors. Thus, managers can contact customers or groups of customers individually—addressability—and identify their preferences or purchase behaviors with the purpose of customizing marketing offerings—targetability (Chen, Narasimhan, and Zhang 2001; Blattberg and Deighton 1996).

Our goal in this paper has been to put forth the notion that the *combination* of straightforward consideration and choice information can lead to an improved assessment of brand loyalty and segmentation when compared to some popular existing approaches based on choice data alone. As such, it is obviously far from the last word on this important subject. The proposed taxonomy has a variety of limitations that should be noted by researchers and managers. For example, it is a market status reporting approach, not a market response approach – a characteristic shared with the benchmark models. In other words, it does not offer any link between why a particular customer belongs to a specific segment and the marketing actions run by different companies. Because it is not a “model” per se, we are unable to offer objective measures of fit and predictive validity. To extend the present framework, further research that incorporates covariates to capture causality in the loyalty behavior would be needed. Thus, the value of the approach lies in the understanding it provides to managers, not in whether or not it provides the best possible statistical representation of buyer consideration and choice behavior.

Because transaction data provides information about choice but not consideration, the required data to construct the taxonomy cannot be taken from a switching matrix or from panel data. Our approach requires a survey, which can imply additional data collection costs.[12] Surveys also suffer from the drawback that, unlike transaction data, they are not automatically updated with every consumer purchase.

Our taxonomy assumes that the stated consideration set is the true consideration set. However, it is possible that some respondents will not write down all the different makes considered. Due to structure of our classification scheme, relaxing this assumption to allow the stated or observed consideration set to be different form the true consideration set (i.e., O=T+E), will imply a larger overestimation of the HCL segment.

An additional limitation is that the loyalty taxonomy as it is described in this paper is not dynamic. Although it is applied to the case where the consumer choice decision is observed over two consecutive occasions, the consumer's consideration set is known only for the second occasion. Cases where the number of purchase occasions, T, is greater than two imply an increase in the complexity of the analysis. The number of different possible consideration and choice patterns increases by at least 5 with each additional *t*. In this paper we use T=2 not only to keep the framework parsimonious, but also because most loyalty models, and specifically the ones we use as a benchmark here—CM and GS—are based only

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[12] It might be argued that with click stream data the consideration set can be drawn from the consumer searching activity. However, this type of information will only provide information about the brands searched through the web. It will not take into account the searching activity in which consumers might be simultaneously engaged in brick and mortar retail stores. Moreover, whereas the stated consideration set is a statement about the brands that a consumer seriously considered buying, a clickstream pattern might not truly reflect consumer's intention to buy but just random information searching.

on repeat purchase data (i.e., T=2). Furthermore, for product categories with long interpurchase cycles (e.g., automobiles), T>2 may span large changes in consumers' lifestyle and product supply.

Another avenue of inquiry we have not pursued is to extend the stochastic models to incorporate the stated consideration set data. This could involve respecifying the models in equations 1 to 4 to explicitly account for the stated consideration information. Because of the differences we found between the taxonomy approach and the stochastic models, we believe this may be a promising topic for future research.

Despite its various limitations, we note that our proposed two-level brand loyalty classification gathers most of the desirable measurement criteria listed by the 1999 MSI workshop on Brand Equity Metrics (Ailawadi et al. 2002). Besides being unique and objective, it is easy to measure, has diagnostic value, and is intuitive. It is a loyalty classification that allows managers to better identify which customers to focus on and which to ignore or give less attention. As such, we hope that its application should lead to more productive allocations of scarce marketing resources.

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Appendix

Synopsis of Colombo-Morrison (1989) model

Colombo-Morrison model assumes that there are two classes of buyers, *Hard-Core Loyal* (who consider no other brands and automatically repurchase) and *Potential Switchers* (who *consider all N brands* and choose brand *i* with probability π_i, $i = 1, \ldots$ N, where N is the total number of brands). With these assumptions the model defines the probability of repeat purchase, p_{ii}, and the probability of switching, p_{ij}, as:

$$p_{ii} = \alpha_i + (1-\alpha_i)\pi_i \qquad\qquad p_{ij} = (1-\alpha_i)\pi_j$$

where α_i is the proportion of brand *i* current users who are hard-core loyal customers and π_i is the proportion of potential switchers who will next buy brand *i*.

Synopsis of Grover and Srinivasan (1987) model

GS assumes that there are *n brand loyal segments* (each formed by only those consumers who repurchase the brand they last purchased with probability equal or '*very close'* to one) and *m switching segments* (each formed by consumers who *consider all N brands* and choose brand *i* with probability π_{ik}, $i = 1, \ldots$ N, and $k = 1, \ldots$ M, where N is the total number of brands and M is the total number of switching segments). With these assumptions the model has the following form:

$$p_{ii} = V_i + \sum_{k=1}^{m} W_k \pi_{ik} \pi_{ik} \qquad\qquad p_{ij} = \sum_{k=1}^{m} W_k \pi_{ik} \pi_{jk}$$

where V_i denotes the proportion of consumers in the total market who are loyal to brand *i*, W_k denotes the proportion of consumers belonging to switching segment *k*, and π_{ik} denotes the probability of choosing brand *i* given that a consumer belongs to switching segment *k*.

Table 1

Summary Statistics for Consideration Set Size

Set size	Frequency	Percentage	Cumulative Frequency
1	17441	38.75	17441
2	15479	34.39	32920
3	7939	17.64	40859
4	3325	7.39	44184
5	822	1.83	45006
Mean Consideration Set Size = 1.99 Std. Dev. = 1.01			

Table 2

Unit Sales and Market Share by Make

MAKE	Units Sold (year 1998) *	Share
Ford Division	3,288,544	25.3%
Chevrolet	2,418,510	18.6%
Dodge	1,442,777	11.1%
Toyota Division	1,204,765	9.3%
Honda Division	899,208	6.9%
Nissan Division	560,808	4.3%
Pontiac	536,469	4.1%
Jeep	459,294	3.5%
GMC	450,783	3.5%
Mercury	410,186	3.2%
Buick	398,156	3.1%
Oldsmobile	329,742	2.5%
Chrysler Division	307,841	2.4%
Plymouth	296,641	2.3%
14 major makes' total sales	13,003,724	83.4% of Total Market Sales
Total Market Sales	15,596,546	

* Total car and light truck units sold
Source: Automotive News Data Center

Table 3

Results for the Switching Matrix Models *

	Colombo and Morrison Model	
MAKE	α_i	π_i
Buick	0.40	0.02
Chevrolet	0.45	0.18
Chrysler	0.31	0.03
Dodge	0.39	0.14
Ford	0.54	0.21
GMC	0.38	0.04
Honda	0.48	0.07
Jeep	0.36	0.05
Mercury	0.34	0.03
Nissan	0.36	0.05
Olds	0.27	0.02
Plymouth	0.18	0.03
Pontiac	0.26	0.05
Toyota	0.52	0.09

α_i: the proportion of brand *i*'s current users who are completely loyal and will automatically repurchase brand *i*.

π_i: the proportion of potential switchers who will next buy brand *i*

Grover and Srinivasan Model					
	Brand loyal weight (V)	Switching Segments			
		1	2	3	4
		Weights W (total = .64)			
		0.06	0.03	0.17	0.39
MAKE		within-segment market shares			
Buick	0.02	—[a]	—	0.08	0.02
Chevrolet	0.07	0.03	0.00	0.35	0.13
Chrysler	0.01	0.02	0.14	0.03	0.02
Dodge	0.02	—	0.50	0.10	0.10
Ford	0.10	—	—	0.00	0.40
GMC	0.01	—	—	0.08	0.02
Honda	0.03	0.28	—	0.04	0.04
Jeep	0.01	0.06	0.06	0.03	0.03
Mercury	0.01	—	—	—	0.06
Nissan	0.02	0.19	0.04	0.02	0.04
Olds	0.01	0.01	—	0.09	0.02
Plymouth	0.00	0.01	0.26	0.02	0.03
Pontiac	0.01	—	—	0.13	0.04
Toyota	0.03	0.40	—	0.04	0.06
Total	0.36	1.00	1.00	1.00	1.00

[a] Probabilities constrained to zero for model identification

* In the interest of space, standard errors are not reported because virtually all of the estimates are significant at the 0.01 level.

Table 4

Estimating Hard-Core and Soft Loyal Segment Sizes [a]

MAKE	Percentage of Hard-Core Loyal Consumers			Percentage of Soft Loyal Consumers		
	Grover-Srinivasan	Colombo-Morrison	Consideration Set	Grover-Srinivasan	Colombo-Morrison	Consideration Set
Buick	38.69	39.73	25.76	2.30	1.27	15.23
Chevrolet	40.39	45.15	32.87	14.62	9.87	22.14
Chrysler	29.00	30.66	17.52	3.68	2.02	15.16
Dodge	31.48	39.30	27.35	16.38	8.56	20.51
Ford	38.88	54.14	38.81	24.82	9.55	24.88
GMC	37.03	38.47	20.10	3.91	2.46	20.83
Honda	42.82	47.70	25.74	8.40	3.52	25.48
Jeep	35.67	36.01	22.31	3.28	2.94	16.64
Mercury	32.96	34.27	18.92	3.36	2.05	17.40
Nissan	33.14	35.62	14.58	5.39	2.91	23.94
Olds	25.31	26.97	14.87	3.32	1.66	13.75
Plymouth	12.38	17.75	8.28	7.92	2.56	12.02
Pontiac	24.15	26.48	16.47	5.82	3.49	13.50
Toyota	42.94	52.49	30.20	13.82	4.27	26.56
Average	33.20	37.48	22.41	8.36	4.08	19.15

[a] Cells represent the proportion of consumers classified as either Hard-Core or Soft Loyal by each model.

Table 5

Results from Applying the Loyalty Taxonomy

	CONSIDERATION SET SEGMENTS[a,b]					Repeat Purchase
MAKE	HCL	SL	SS	HS	HCS	
Buick	25.8%	15.2%	14.6%	25.1%	19.3%	41.0%
Chevrolet	32.9%	22.1%	16.3%	14.3%	14.4%	55.0%
Chrysler	17.5%	15.2%	11.1%	35.9%	20.4%	32.7%
Dodge	27.3%	20.5%	15.7%	19.6%	16.8%	47.9%
Ford	38.8%	24.9%	14.2%	11.4%	10.7%	63.7%
GMC	20.1%	20.8%	17.3%	20.8%	21.0%	40.9%
Honda	25.7%	25.5%	12.5%	22.6%	13.7%	51.2%
Jeep	22.3%	16.6%	11.0%	31.2%	18.8%	38.9%
Mercury	18.9%	17.4%	11.4%	26.4%	25.9%	36.3%
Nissan	14.6%	23.9%	12.0%	29.5%	20.0%	38.5%
Oldsmobile	14.9%	13.8%	14.8%	34.0%	22.6%	28.6%
Plymouth	8.3%	12.0%	15.1%	40.2%	24.4%	20.3%
Pontiac	16.5%	13.5%	14.2%	36.0%	19.8%	30.0%
Toyota	30.2%	26.6%	15.1%	16.3%	11.8%	56.8%
Average	22.4%	19.2%	14.0%	26.0%	18.5%	41.6%
Std. Dev	8.2%	4.9%	2.0%	8.9%	4.5%	12.1%

[a] Cells represent the row conditional probabilities, i.e. the probability that a consumer who buys brand i in will a member of the loyalty segment j. For instance, cell (1,1) implies that 28% of the consumers who buy a Buick are hard-core loyal customers of that brand.

[b] Segments names: HCL = Hard-Core Loyal, SL = Soft Loyal, SS = Soft Switcher, HS = Hard Switcher, and HCS = Hard-Core Switcher

Table 6

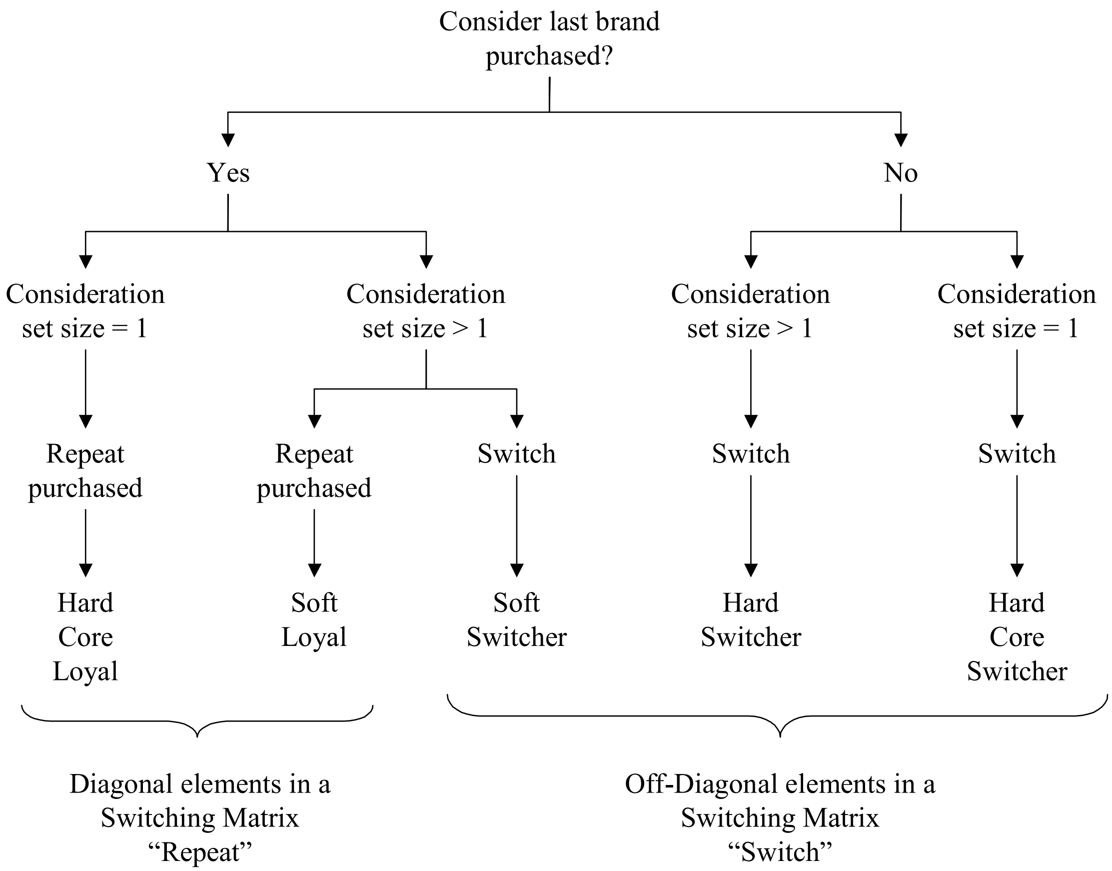
Demographics and Purchase Behavior by Segment

	Segments				
Analysis at the Make Level	HCL	SL	SS	HS	HCS
Variables	Mean	Mean	Mean	Mean	Mean
Old model year	91.90[a]	91.58[b]	90.57[c]	90.01[d]	90.09[e]
Shopped used	0.11[a]	0.21[b]	0.27[c]	0.29[d]	0.18[e]
Price	22,654[a]	22,485[b]	21,879[c]	21,449[d]	21,734[e]
Rebate value	1,240[a]	1,185[b]	1,180[b]	1,232[c]	1,269[d]
Age	49.56[a]	45.72[b]	44.41[c]	42.23[d]	45.12[e]
Dealers shopped	2.31[a]	4.70[b]	5.97[c]	6.36[d]	3.47[e]
Schooling	4.45[a]	4.70[b]	4.63[c]	4.69[d]	4.42[e]
Hispanic	0.04[a]	0.06[b]	0.05[c]	0.05[d]	0.06[e]
Children	0.77[a]	0.85[b]	0.85[c]	0.93[d]	0.88[e]
Income	8.75[a]	9.07[b]	8.84[c]	9.01[d]	8.55[e]
Consideration set size	1.00[a]	2.42[b]	2.70[c]	2.53[d]	1.00[a]
	%	%	%	%	%
Replaced car was acquired new	83.07[a]	78.23[b]	70.29[c]	63.91[d]	64.39[d]
Replaced car was acquired used	16.93[a]	21.77[b]	29.71[c]	36.09[d]	35.61[d]
Very Satisfied	79.74[a]	70.98[b]	70.24[b]	52.83[c]	58.1[d]
Somewhat Satisfied	15.65	21.12	23.45	30.37	27.28
Somewhat Dissatisfied	2.92	4.47	4.72	9.57	8.45
Very Dissatisfied	1.69	3.44	1.6	7.24	6.17
Do not shopped online	93.15[a]	88.35[b]	85.96[c]	82.54[d]	89.31[b]
Shopped online	6.85	11.65	14.04	17.46	10.69
Test Drive = Yes	70.9	76.48	82.21	83.71	80.1
Test Drive = No	29.1	23.52	17.79	16.29	19.9
2nd Test Drive = Yes	49.45	64.3	69.32	71.76	59.71
2nd Test Drive = No	50.55	35.7	30.68	28.24	40.29
White	94.68	92.57	93.79	92.75	93.02
Black / African-American	2.63[a]	3.09[a]	2.63[a]	2.87[a]	2.63[a]
Asian	1.4[a]	2.14[a]	1.97[a]	2.59[a]	2.63[a]
Other	1.28[a]	2.2[a]	1.61[a]	1.79[a]	1.72[a]
Married	73.95	73.73	74.05	69.77	71.31
Single	11.22	13.48	14.36	17.84	14.81
Widowed/Divorced/Separated	14.83[a]	12.79[a]	11.59[a]	12.38[a]	13.88[a]
Number of people in the segment	5214	4356	3152	4353	3087

Differently lettered superscripts across segments means and proportions denote differences that are significant at the .05 level; segments means and proportions with like superscripts are not significantly different from each other.

Figure 1

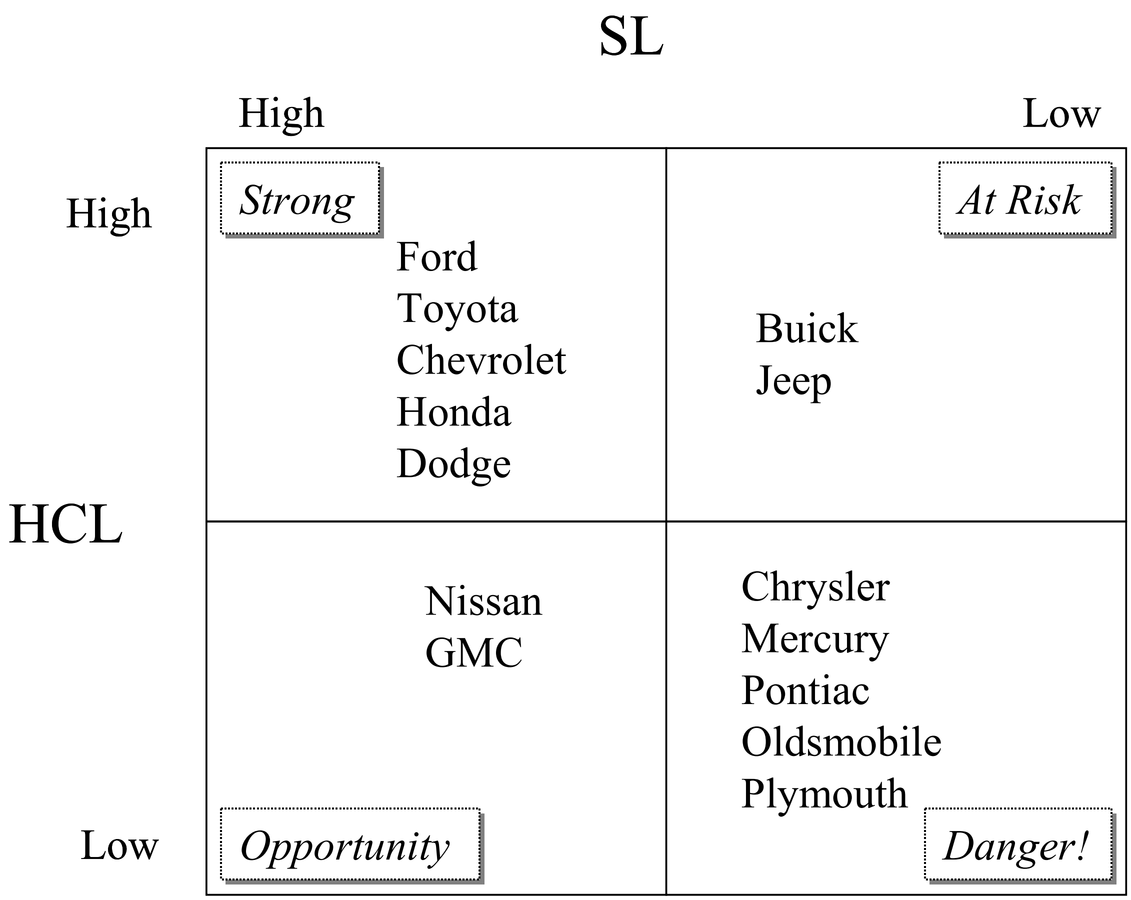
Loyalty Taxonomy



- Hard-core Loyal (HCL): Buyers who only consider and therefore buy brand *i*, which is the same brand last purchased. Individuals in this segment will buy brand *i* with probability equal to one. Define the probability of purchasing brand *i* as π_i. Then, Pr(choice = *i*) = $\pi_i = 1$.
- Soft Loyal (SL): Buyers who have 2 or more brands in their consideration set among which brand *i*, the last purchased brand, is included and whose final choice is to repurchase brand *i*. Individuals in this segment will buy brand *i* with probability π_i such that $0 < \pi_i < 1$.
- Soft Switchers (SS): Buyers who have 2 or more brands in their consideration set among which brand *i*, the last purchased brand, is included and whose final choice is different from brand *i*. Individuals in this segment will buy brand *j* with probability π_j for *j* = any brand included in the consideration set such that $0 < \pi_j < 1$.
- Hard Switchers (HS): Buyers who have 2 or more brands in their consideration set but do not reconsider brand *i*, the last purchased brand. Individuals in this segment will buy brand *j* with probability π_j for *j* = any brand included in the consideration set such that $0 < \pi_j < 1$. Moreover, $\pi_i = 0$.
- Hard-core Switchers (HCS): Buyers who only consider and therefore buy brand *j*, which is different from the brand last purchased. Individuals in this segment will buy brand *j* with probability equal to one, $\pi_j = 1$. Moreover, $\pi_i = 0$.

Figure 2

Hard-Core vs. Soft Loyal Brand Classifications



APPENDIX

(for the web)

Table

Re-scaled Switching Matrix

	PURCHASED MAKE														Total
REPLACED MAKE	BUICK	CHEVROLET	CHRYSLER	DODGE	FORD	GMC	HONDA	JEEP	MERCURY	NISSAN	OLDS	PLYMOUTH	PONTIAC	TOYOTA	
BUICK	389	151	26	38	107	18	23	9	21	15	49	16	53	32	948
	41.0%	*15.9%*	*2.8%*	*4.0%*	*11.3%*	*1.9%*	*2.5%*	*1.0%*	*2.2%*	*1.6%*	*5.2%*	*1.7%*	*5.6%*	*3.3%*	*100%*
CHEVROLET	37	2054	30	307	462	170	85	98	34	63	59	46	145	144	3733
	1.0%	*55.0%*	*0.8%*	*8.2%*	*12.4%*	*4.6%*	*2.3%*	*2.6%*	*0.9%*	*1.7%*	*1.6%*	*1.2%*	*3.9%*	*3.9%*	*100%*
CHRYSLER	17	49	152	63	45	5	16	11	8	15	10	26	16	32	466
	3.5%	*10.6%*	*32.7%*	*13.6%*	*9.6%*	*1.1%*	*3.5%*	*2.3%*	*1.8%*	*3.2%*	*2.2%*	*5.5%*	*3.5%*	*6.8%*	*100%*
DODGE	15	160	55	754	196	25	55	60	27	31	11	79	39	69	1576
	1.0%	*10.1%*	*3.5%*	*47.9%*	*12.5%*	*1.6%*	*3.5%*	*3.8%*	*1.7%*	*2.0%*	*0.7%*	*5.0%*	*2.5%*	*4.3%*	*100%*
FORD	21	351	56	429	3188	81	153	113	157	104	24	71	81	175	5005
	0.4%	*7.0%*	*1.1%*	*8.6%*	*63.7%*	*1.6%*	*3.1%*	*2.3%*	*3.1%*	*2.1%*	*0.5%*	*1.4%*	*1.6%*	*3.5%*	*100%*
GMC	6	122	5	66	73	254	11	11	4	4	13	1	25	25	621
	1.0%	*19.7%*	*0.8%*	*10.7%*	*11.7%*	*40.9%*	*1.8%*	*1.8%*	*0.6%*	*0.6%*	*2.0%*	*0.2%*	*4.0%*	*4.1%*	*100%*
HONDA	6	112	15	53	107	12	668	46	10	67	6	13	20	169	1304
	0.4%	*8.6%*	*1.2%*	*4.1%*	*8.2%*	*0.9%*	*51.2%*	*3.5%*	*0.8%*	*5.2%*	*0.5%*	*1.0%*	*1.6%*	*12.9%*	*100%*
JEEP	4	58	12	56	63	14	18	200	6	16	4	7	11	45	514
	0.7%	*11.2%*	*2.3%*	*10.9%*	*12.2%*	*2.8%*	*3.5%*	*38.9%*	*1.3%*	*3.1%*	*0.8%*	*1.3%*	*2.2%*	*8.8%*	*100%*
MERCURY	14	83	17	50	229	5	26	4	295	18	11	13	19	28	814
	1.8%	*10.2%*	*2.0%*	*6.2%*	*28.2%*	*0.6%*	*3.2%*	*0.4%*	*36.3%*	*2.2%*	*1.4%*	*1.6%*	*2.3%*	*3.5%*	*100%*
NISSAN	3	75	11	71	117	19	84	47	13	380	8	10	14	134	986
	0.3%	*7.6%*	*1.2%*	*7.2%*	*11.9%*	*1.9%*	*8.5%*	*4.8%*	*1.3%*	*38.5%*	*0.8%*	*1.1%*	*1.4%*	*13.6%*	*100%*
OLDS	59	166	20	56	115	33	36	15	19	26	267	17	53	48	932
	6.3%	*17.8%*	*2.2%*	*6.0%*	*12.4%*	*3.6%*	*3.9%*	*1.6%*	*2.1%*	*2.8%*	*28.6%*	*1.8%*	*5.7%*	*5.2%*	*100%*
PLYMOUTH	6	63	39	127	101	11	20	16	10	25	7	119	13	30	586
	1.0%	*10.7%*	*6.7%*	*21.6%*	*17.2%*	*1.9%*	*3.4%*	*2.8%*	*1.7%*	*4.2%*	*1.2%*	*20.3%*	*2.2%*	*5.0%*	*100%*
PONTIAC	33	207	23	99	132	36	53	38	13	31	33	28	325	34	1085
	3.0%	*19.1%*	*2.1%*	*9.1%*	*12.2%*	*3.3%*	*4.9%*	*3.5%*	*1.2%*	*2.9%*	*3.0%*	*2.5%*	*30.0%*	*3.1%*	*100%*
TOYOTA	9	98	14	66	165	15	145	44	18	75	9	13	16	903	1592
	0.5%	*6.2%*	*0.9%*	*4.2%*	*10.4%*	*0.9%*	*9.1%*	*2.7%*	*1.2%*	*4.7%*	*0.6%*	*0.8%*	*1.0%*	*56.8%*	*100%*
Total	617	3750	477	2237	5099	699	1394	712	636	870	511	460	832	1868	20162
	3.1%	*18.6%*	*2.4%*	*11.1%*	*25.3%*	*3.5%*	*6.9%*	*3.5%*	*3.2%*	*4.3%*	*2.5%*	*2.3%*	*4.1%*	*9.3%*	*100%*

For each make, the first cell represents the total number of consumer buying a row brand on the first purchase occasion and column brand on the second purchase occasion. The second cell represents the row conditional proportions, i.e. of those who traded-in brand *i* what percentage bought brand *j* on the next occasion.