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AN INVESTIGATION OF THE IMPACT OF PROMOTIONS
ON ACROSS-SUBMARKET COMPETITION*

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ABSTRACT

There is a recent trend among manufacturers of consumer package goods such as Proctor & Gamble to eliminate sales promotions and replace them with every-day low prices on their products. The objective of this study is to investigate *whether* and *how* such a significant change in promotional strategy would affect the competitive patterns in a market. Specifically, what would be the impact of such a move on competition between different brands in a market? Would the competitive structure change significantly as a result? How would this affect specific brands? We propose a methodology based on a dogit model of brand switching to evaluate and test the impact of promotions on competitive structure and to identify the nature of the impact. Our findings reveal that some sales promotions (e.g., displays and price cuts) have a significant impact in shaping competitive patterns characterizing submarkets for crackers. The magnitude of this impact decreases with increased product differentiation and increased intensity of the promotional activities in the market. Our findings help managers determine how the elimination of certain sales promotions may re-shape competitive patterns before making such a move. The knowledge of which submarket boundaries are stable and which boundaries can be affected by promotions also help managers decide which product alternatives to promote (or not to promote) so as to maximize short-term revenues.

1 Introduction

There is a recent trend among manufacturers of consumer package goods to reduce or eliminate short-term promotions such as coupons, price promotions and features and to offer everyday low prices on their products. Proctor & Gamble, for example, has been the leader in such a move (Doyle 1992; Economist 1992) and they have also called upon other manufacturers to follow suit. Many manufacturers have followed the leader's move while others are evaluating their own position and strategy in the market before making the decision (Marketing News 1997). Various arguments have been put forth in support of such a move, chief among them being that such a move will reduce sales expenditures and would benefit consumers, retailers, and manufacturers alike. Given that most consumers have been trained over the years to expect promotions when making purchases of most packaged goods (Fader and McAlister 1990), this campaign of P&G, if successful, could significantly alter consumer purchase behavior. Therefore, it is critical for managers to understand the consequences of such a significant change in promotional strategy. Specifically, managers would like to know whether such a move could fundamentally shift the patterns of competition in a market. That is, how individual brands, especially their own brands, would be affected? This knowledge is crucial in making a choice between retaining or eliminating short-term promotions. Answers to such questions clearly depend on understanding the role short-term promotions play in shaping the competitive structure of the market.

Traditional competitive market structure studies, which defines groups of product alternatives (submarkets) where "within-group" competition is much stronger than "across-group" competition (Urban, Johnson, and Hauser 1984), view the structure as reflecting consumer preference for product attributes. For example in the soft drinks market, the conventional wisdom is that the submarkets are organized in terms of form (regular vs. diet) based on consumers' underlying preferences. Traditionally, analyses of market structure do not explicitly account for the effects of promotions or other manufacturers' actions (Day, Shocker, and Srivastava 1979; Srivastava, Leone, and Shocker 1984). Yet, promotion is an ongoing feature in many markets and can significantly impact the underlying structure. That is, the promotion-induced competitive patterns may overlay the preference-based structure characterizing the market. In order to understand the impact of eliminating

promotions in a market, a manager needs to identify both components of the “observed structure” -- the more stable, longer-term component based on consumers’ preference for product attributes and the promotion-induced component that overlays it.

There is evidence in extant literature that short-term promotions can influence competitive patterns significantly. Blattberg and Wisniewski (1989) considered product alternatives with similar attributes, for instance, different brands of stick margarine, light chunk tuna in oil, etc., and showed the existence of asymmetric price effects on competition due to different price tiers (store brands versus national brands) *within* submarkets. However, as Blattberg and Neslin (1990, p. 226) point out, in the case of a promotion for a stick margarine brand, “stick and tub margarine do compete” and thus promotional impact *across* submarkets could be significant enough to warrant an examination¹. In a related context, Kannan, Wright, and Worobetz (1991), studying the competitiveness of ground coffee submarkets over time, reported that the competitiveness of private-label brands in the coffee submarket changed significantly over time and the changes were highly correlated with incidence of short-term promotions. Such changes could be attributed to promotion-induced competitive patterns overlaying the longer-term preference-based structure.

It is important to separate the effects of promotions on *within-submarket* versus *across-submarket* switching. First, certain promotions may have a significant effect on within-submarket switching but the impact may not go beyond market boundaries to affect across-submarket switching. Second, very different managerial implications can be derived depending on which types of switching are impacted by promotions. If promotions only affect within-submarket switching, managers of brands in a submarket would only have to monitor promotional activities of competitors within the same submarket. However, if promotions could affect across-submarket switching, the scope of competition could expand beyond a brand’s own submarket. A few years ago, Coca-Cola Company aired a commercial that urged consumers of Regular Pepsi to switch to Diet Coke (Business Week 1989). Such a promotional activity is designed to help the brand appeal to a broader spectrum of consumers, and thus, cut across the traditional boundary of regular versus diet soft drinks. Whether

this type of promotion will be effective is going to depend on its ability to affect across-submarket switching.

Our primary objective is to fulfill the above information needs of a manager by seeking answers to three questions. First, is the identified competitive structure impacted by sales promotions? Second, if so, what is the nature of this promotion-induced impact? Third, what is the longer-term preference-based structure? The answers to these questions will provide clear implications for how a manufacturer's brand will be affected if specific promotions are eliminated, and thus, the manufacturer can decide whether it should make such a move. The proposed methodology provides a way to tease out the promotion-induced structure from the longer-term preference-based structure. It uses brand-switching measures derived from scanner data to define market structures and consists of two steps. In the first step, we model, at the individual level, consumers' brand switches conditional on their previous purchases as a function of marketing mix and product attribute variables. We use a logit formulation to capture the dynamic effect of previous purchase on current purchase (first-order effects) while avoiding the independence of irrelevant alternatives (IIA) problem. The calibrated model of brand switching reveals the differential effects of various marketing mix and product attribute variables on both within- and across-submarket switching. In the second step, we use the estimates from the brand switching model to predict the aggregate conditional switching patterns under different scenarios with and without the effects of promotional variables and statistically test whether across-submarket brand switching patterns have changed significantly. This provides the basis for examining the changes in competitive structures under the different scenarios and to understand the effect of promotions in shaping competitive structure.

In the next section, we describe the two-step methodology to evaluate and identify the impact of promotions in shaping competitive structure. In Sections 3 and 4, we discuss the application of our methodology to the cracker market and ground coffee market, respectively. In Section 5, we present implications of the results and suggest directions for future research.

¹ Nested logit models can be used to examine promotional impact across submarkets, *given* a priori specification of the structure. However, since the structure is pre-specified, one cannot use the model to examine the impact of promotion on the structure.

2 The Methodology

2.1 Modeling Brand Switching

In order to understand how promotions affect consumer brand switching and thereby impact the competitive structure, we estimate a dogit model of brand switching. The “dogit” formulation (Gaudry and Dagenais 1979) provides the flexibility to model the underlying competitive market structure without having to specify a structure *a priori*. There are four sets of parameters in our dogit model. The first set are the *product attribute* parameters that capture the switching between product alternatives based on the same product attributes such as brand name, form, etc. Then, the set of *marketing mix* parameters indicate the effects of marketing mix on both within- and across-submarket switching. Most important of all, we have the set of “*captivity*” parameters that represent the relative strengths of the alternatives in retaining customers regardless of marketing mix and promotion activities. Finally, the set of alternative *constants* provide the intrinsic preference for the different product alternatives that is not attributable to the marketing mix and product attribute variables.

In the dogit model, or the “logit captivity” model as it is more popularly called (Swait and Ben-Akiva 1985, 1987), the captivity parameter of an alternative alters a consumer’s probability of purchasing an alternative as dictated by the more commonly used logit formulation. This property of the captivity parameters in the dogit model helps alleviate the independence of irrelevant alternatives (IIA) problem of the logit model.

For expository purposes, we start our model development with a logit formulation. In a logit model, the probability of consumer n buying alternative j on occasion t , given that alternative i was bought on the last purchase occasion (assuming that alternative $j \in C_n$, the choice set of consumer n), is given by (McFadden 1974):

$$P_{ijt}^n = \frac{e^{V_{ijt}^n}}{\sum_{k \in C_n} e^{V_{ikt}^n}}, \quad (1)$$

where V_{ijt}^n is the deterministic component of the utility of alternative j as perceived by consumer n relative to his/her previous purchase of alternative i . In a dogit model, a portion of the above

probability will depend on the attractive power of alternative j relative to the attractive power of other alternatives and the rest will depend on the relative utilities of the alternatives as specified by the logit model. Formally, the probability that consumer n will purchase alternative j on occasion t , given that he/she bought alternative i on the previous occasion, is:

$$P_{ijt}^n = \frac{\theta_j}{\left(1 + \sum_l \theta_l\right)} + \frac{1}{\left(1 + \sum_l \theta_l\right)} \frac{e^{V_{ijt}^n}}{\sum_{l \in C_n} e^{V_{ilt}^n}}, \quad (2)$$

where θ_j is the ‘‘captivity’’ parameter associated with alternative j , ($\theta_j \geq 0$). It is easy to see that the relative probabilities of switching from alternative i to any two alternatives j and k , given by:

$$\frac{P_{ijt}^n}{P_{ikt}^n} = \frac{e^{V_{ijt}^n} + \theta_j \sum_l e^{V_{ilt}^n}}{e^{V_{ikt}^n} + \theta_k \sum_l e^{V_{ilt}^n}}, \quad (3)$$

are dependent on the attributes of all alternatives, thereby avoiding the IIA problem. However, depending on the values of the θ s, the dogit specification is flexible enough to allow the relative probabilities of some pairs of alternatives to be consistent with the IIA axiom while allowing the other pairs to be influenced by the captivity parameters². Thus, the dogit model (unlike logit) is a fully competitive model flexible enough to accommodate different competitive structures.

The deterministic component of utility, V_{ijt}^n , in equation (1) depends on the product attributes and marketing programs of alternatives i and j . Following Carpenter and Lehmann (1985), we express V_{ijt}^n as a function of (1) marketing mix variables such as price, newspaper feature, display, coupon, etc., and (2) product attribute variables such as brand name and other salient attributes. Specifically,

$$V_{ijt}^n = \mu_j + \sum_{q \in Q} \alpha_q X_{ijtq} + \sum_{r \in R} \beta_r Y_{ijr}. \quad (4)$$

In equation (4), μ_j are the alternative constants, and α_q and β_r are the marketing mix and product attribute parameters, respectively. Q is a set of marketing mix variables and R is a set of product

² The relative probabilities $\frac{P_{ijt}^n}{P_{ikt}^n}$ are consistent with the IIA axiom only if $\theta_j = \theta_k = 0$ or $\frac{\theta_j}{\theta_k} = \frac{e^{V_{ijt}^n}}{e^{V_{ikt}^n}}$ (see Gaudry and Dagenais 1979, p.106).

attribute variables, while i and j indicates the product alternative purchased on occasions $t-1$ and t , respectively. X_{ijtq} s are specified as deviations of the value of the marketing mix variable q of alternative j on purchase occasion t from that of alternative i on purchase occasion $t-1$. For example, on the price dimension which is a continuous variable, $PRICE_{i,t-1}$ serves as the reference price for the choice to be made on occasion t and the X_{ijtq} s are specified as $PRICE_{i,t-1} - PRICE_{j,t}$ if there is a gain with respect to the reference price (0 otherwise) and as $PRICE_{j,t} - PRICE_{i,t-1}$ if there is a loss with respect to the reference price (0 otherwise). On the display dimension, the X_{ijtq} s are a series of dummy variables X_{ijtq1} , X_{ijtq2} , etc., indicating the combination of the presence and absence of display activities for alternatives i and j on purchase occasions $t-1$ and t , respectively. For example, X_{ijtqg} (capturing a gain) takes on a value 1 if alternative i was not on display on purchase occasion $t-1$ and alternative j was on display on occasion t , 0 otherwise. Similarly X_{ijtql} (capturing a loss) takes on a value 1 if alternative i was on display on occasion $t-1$ and alternative j was not on display on occasion t , and so on. Y_{ijr} is a 0-1 variable indicating the value of alternative i relative to alternative j on product attribute variable r . For example, if alternatives i and j have the same brand name, Y_{ij} for the product attribute “brand name” takes on a value of 1, and a value of 0 otherwise.

Our model also captures the interactions between alternatives through X_{ijtq} s, which capture the *relative* gains (losses) on the corresponding marketing mix dimensions when switching from alternative i to alternative j , and through Y_{ijr} s, which specify the degree of similarity between alternatives i and j . These first-order effects capture the dependency of the odds ratio on the last purchased alternative over and above those provided by the “captivity” parameters in the dogit specification. The dogit model is estimated using standard maximum likelihood procedures in Gauss (c.f., Siddarth, Bucklin, and Morrison 1995). In the estimation, we allow the marketing mix parameters to be different for each alternative or group of alternatives to fully capture the competitive dynamics in the market.

2.2 *Competitive Structure and Impact of Promotions*

The parameter estimates from the dogit model of brand switching per se are not sufficient to describe all the important dimensions of the competitive structure characterizing the market. While

the significance of a product attribute variable in the dogit model indicates the existence of potential submarkets defined on the basis of that attribute, the model does not identify the specific submarket(s) contributing to the significance. For example, the significance of the “brand name” attribute in the coffee market may indicate that there could be submarkets defined on any brand names. It is not possible to identify the specific brand name(s) that contribute to this significance. Also, it is not uncommon to find multiple product attribute variables being significant at the same time (see Carpenter and Lehmann 1985). This may indicate that there could be a “Folgers” submarket, a “decaffeinated coffee” submarket, a “ground coffee” submarket, etc., which renders the task of identifying the specific submarkets even more difficult. Similar arguments can be extended to the case of the significance of a marketing mix variable. It is not easy to identify whether the marketing mix variable influences switching to the same extent across all alternatives or whether this influence is restricted to only a few specific alternatives. In addition, the dogit model of brand switching does not account for the market shares of the individual alternatives in estimating the significance of the attributes/marketing mix on switching. That is, all we know from the model is that there is significant switching across alternatives sharing a particular attribute(s). We *do not* know whether this switching is significantly greater than what the market shares would predict, which is one of the main criteria in identifying competitive market structures (see, for example, Urban, Johnson, and Hauser 1984; Grover and Srinivasan 1987).

To resolve the above problems, our approach involves two steps. First, we use the switching model as a forecasting tool to predict changes in aggregate switching shares under different scenarios when certain promotional variables such as display, price cut, etc. are no longer offered. Second, we analyze the predicted switching data using conventional market structure methods to identify any structural changes under the different scenarios³. To fully characterize the effect of a promotional variable, say display, on competitive structure, we conduct the following sequential analyses:

1. We perform an analysis of the original brand switching data, without removing any promotional effects, to identify the submarkets comprising the market using conventional market structure identification and testing procedures (see Appendix A for the specific procedures we use).

³ The use of the switching model as a forecasting tool is consistent with the many studies found in extant literature. For example, Guadagni and Little (1983) use their brand choice model to estimate the impact of promotional changes (changes in regular price, promotional price cuts, etc.) on the aggregate market shares and to estimate elasticities.

2. Based on the estimates from equations (2) and (4), we eliminate or partial out the effect of the promotional variable (display in our example) from the model and predict the aggregate brand switching matrix under the new scenario (i.e., when the effect of display is removed).
3. We test whether switching *across* submarkets, identified in Step 1, is significantly different under the new scenario as compared to the across-submarket switching in the original data using the Kullback, Kupperman, and Ku procedure (see Appendix B).
4. If the aggregate brand switching matrix, and thus, the competitive patterns are altered, we analyze the predicted brand switching matrix under the new scenario using market structure methods to identify the changes in the competitive structure.

The above procedures provide complete information on the effect of a promotional variable in shaping the competitive structure.

3 Analysis of the Cracker Market

3.1 Data, Product Alternatives, and Variables

We illustrate the proposed two-step methodology with an application to the cracker market. A subset of the IRI scanner panel data that we used covered the purchases of crackers of 1595 households for 104 weeks during 1984 and 1985 in the Williamsport, Pennsylvania market. The data set covering 104 weeks was divided into three subsamples. The first sample, covering Weeks 1 through 36 (Period 1, with 7148 product switches), was used as the model calibration sample. The second sample, covering Weeks 37 through 70 (Period 2, with 8015 product switches), and the third sample, covering Weeks 71 through 104 (Period 3, with 7197 product switches), were used as validation samples. To determine the scope of products to be included in this study, preliminary interviews were conducted with a group of 20 consumers to identify different usage situations of crackers, their salient product attributes, and the substitute products used in different usage situations. Since there was considerable overlap in substitutable cracker products used in different usage situations, the product-market was defined to be consisting of soda crackers, saltines, and flavor snack crackers. From this set, we selected for analysis the eighteen largest market share (based on the number of purchases) product alternatives (brand-sizes) each of which had at least 1% market share. Together, these eighteen brand-sizes account for about 50% of all purchases of soda, saltine, and flavor snack crackers in the market during the 104 weeks.

Period 1 brand switching data with 7148 switches among the 18 product alternatives was chosen as the calibration sample. The marketing mix variables, X_{ijtq} , are specified as follows: *regular price* is expressed as the deviation from the reference price to capture the effects of gains and losses on the price dimension. All other marketing mix variables -- *feature*, *store coupon*, *in-store display* and *price cut*⁴ -- are expressed using a series of dummy variables indicating the combination of the presence and absence of each of these promotional activities for alternatives i and j on occasions t and $t-1$ ⁵. The product attribute variables considered in the model are *brand name*, *low-salt*, *cheese/peanut-butter flavor*, *wheat-grain* and *package size*.

3.2 Calibration of the Brand Switching Model

Table 1 provides the results of the brand switching model for Period 1⁶. The coefficients of all the product attribute variables have positive signs with low-salt, cheese and brand name having relatively large values. That is, switching is more likely among alternatives that share these attributes than among alternatives that do not. Therefore, we could expect submarket groupings of alternatives on the basis of these attributes although the results do not indicate what these specific groupings are (except for the low-salt alternatives). Two sets of price coefficients, which are significantly different, were estimated – one for the saltines, Nabisco Ritz and Keebler Townhouse crackers and the other for the rest of the alternatives (specialty crackers).⁷ The coefficients for gain on the price dimension are positive as expected, because if alternative j has a price on occasion t lower than the price of alternative i on occasion $t-1$, there is a higher probability that a consumer will switch from alternative i to alternative j . On the other hand, if alternative j 's price on occasion t is higher than alternative i 's price on occasion $t-1$, then the probability of switching is affected negatively (significantly negative coefficients for loss on the price dimension). Two groups of coefficients for the promotional variables were estimated – the groupings were different across the variables. Coefficients for the first

⁴ Promotional price cut is a new variable that we added to the IRI cracker data set to represent whether there is a short-term (usually 2-3 weeks) price reduction offered on a product by a store during a particular week. The promotional price cut variable takes on a value of 1 if there is a short-term price reduction and a value of 0 otherwise.

⁵ In our analysis, the 1-1 combination and the 0-0 combination were also made distinct by adding another dummy variable for each marketing mix variable. However, since there were no significant differences in their effects, they were combined into one state.

⁶ Store coupon is dropped from the final model because only 8 of the 18 products ever offered store coupon and the overall availability of store coupon across products and stores is less than 1% of the time during the model calibration period.

set of variables capturing gains (PRCUT(1)G, DISPLAY(1)G, and FEATURE(1)G) are all positive as expected (leading to higher probabilities of switching), and the coefficients for the first set of variables capturing losses (PRCUT(1)L, DISPLAY(1)L, and FEATURE(1)L) are all negative (leading to lower probabilities of switching). (The second set of promotional coefficients was insignificant). While in the case of price cut and feature, the magnitude of gain and loss parameter estimates are very close, in the case of display the gain parameter estimate is much larger in magnitude as compared to the loss parameters. As in the case of the product attribute variables, the results of marketing mix variables do not reveal the specific submarket groupings. Ten (out of eighteen) captivity parameters are significant indicating that many alternatives exert varying degrees of pull on consumers. However, their magnitudes are quite low (the largest estimate is 0.094). The alternative-specific constants, $\hat{\mu}_j$ are large for Kraft Cheese Handi-Snack, Nabisco Better Cheddar, and Private-Label Peanut Butter, indicating higher intrinsic preference for those alternatives.

One of the implicit assumptions of the model of brand switching is that consumer purchase process is first-order. The test of significance for the explanatory variables, especially the product attribute variables, can also serve as a test of the first-order purchase process assumption. The above significant results of the product attribute and marketing mix variables clearly suggest that consumers' previous purchases have a significant influence on their current purchases. We have also compared the dogit model with our specification to alternate specifications – a logit model with marketing mix specified only for the current occasion (standard specification), a logit model with marketing mix specified as reference effects (switching specification), and a dogit model with standard specification. As shown in Table 1, the dogit model with switching specification outperforms the other models in Adjusted U^2 s and BIC values.

3.3 Competitive Structure Results

To identify the submarkets, cluster analysis was applied to two alternate inter-brand substitutability measures (see Appendix A) derived from Period 1's brand switching matrix. Ten alternate market structure candidates were identified out of which five were overlapping structures.

⁷ First, we estimated different marketing mix parameters for each of the product alternatives. Then, we combined the

These initial candidate submarkets were then subjected to confirmatory procedures of Urban, Johnson, and Hauser (UJH 1984) and Kalwani and Morrison (K-M 1977). Figure 1 provides the identified submarkets resulted from a series of confirmatory tests. This market structure has the highest aggregate UJH-statistics, and provides significant UJH statistics and acceptable K-M statistics for each submarket⁸.

Five distinct submarkets emerge from the analysis. Submarket 1 consists of only Nabisco brands including the saltine, Ritz crackers, Better Cheddar, and wheat-grain products. Submarket 2 consists of Private-Label Saltine, Kraft Cheese Handi-Snack and Private-Label Peanut Butter cracker. There are no easily identifiable attributes common among these alternatives. Submarket 3 is the low-salt category with Nabisco and a private-label brand. Submarket 4 consists of saltines: Private-Label Saltine Special and American Saltine. Submarket 5 consists of Keebler products along with American Cheez-It. The composition of the submarkets, by and large, conform to the results of the model of brand switching which indicated the possibility of groupings as per brand name, low-salt, and wheat-grain attributes. However, the cheese/peanut-butter grouping, though expected, did not materialize.

3.4 Testing the Impact of Promotions

Recall that all promotional variables in the brand switching model are significant in affecting switching across *product alternatives*. In order to test the impact of these variables on the *submarkets* identified in the previous step, we recast the original brand switching matrix at the submarket level. Thus, we construct a 5-by-5 switching matrix where the diagonal entries represent repeat purchases within the submarkets and the off-diagonal entries represent switching between submarkets. We test the impact of the promotional variables by systematically partialling out the effect of each variable, one at a time, and then two at a time, and so on (see Appendix B). We predict the submarket level

parameters for groups of alternatives which have insignificant within-group differences in parameters.

⁸The UJH z -statistics for the five submarkets in Figure 1 are highly significant (with p -values ranging from < 0.001 to < 0.0001). Thus, in all submarkets the actual within-submarket switching levels are much greater than what is predicted by the overall market shares. The aggregate z -statistic is also significant. The K-M goodness-of-fit χ^2 statistic has reasonable values (given the degree-of-freedom of one) for all submarkets except for Submarket 1. The K-M procedure is quite sensitive to departures from equilibrium conditions in the market and this seems to be the reason for the unusually high χ^2 value. On further analysis of the switching patterns of the alternatives in Submarket 1, we find that there is a significant one-way (unreciprocated) switching from Nabisco Premium Saltine to the Keebler crackers (indicated by the arrow in Figure 1). A candidate submarket consisting of these Nabisco and Keebler crackers was, however, rejected by the UJH confirmatory procedure.

switching matrix under each of the above scenarios and then compare it with the original matrix using the Kullback-Kupperman-Ku test of homogeneity.

The results indicate that removing the effects of display ($\hat{I} = 29.12$, p -value = 0.0854) and price cut, to some extent, ($\hat{I} = 27.37$, p -value = 0.1252) reveal a significantly different switching pattern from the original pattern. Partialling out both display and price cut intensifies this effect ($\hat{I} = 34.34$, p -value = 0.0239). Newspaper feature, although significant in the brand switching model (indicating an influence on within-submarket switching), does not affect across-submarket switching significantly. Next, we perform the market structure analysis on the brand switching matrix, predicted after removing the effects of both display and price cut, to identify the variables' impact on the submarket composition.

Figure 2 presents the final results of the extensive market structure analysis on the predicted data. The criteria of highest aggregate UJH z -statistics with significant statistics for each submarket resulted in the confirmation of six submarkets⁹. Submarket 1 is a specialty, flavor saltine category with Keebler Club and Nabisco Ritz products. Submarket 2 consists of Nabisco wheat-grain products: Wheatworth, Triscuit, and Wheat-Thin. Submarket 3, the low-salt category, remains the same as before. Submarket 4 is the cheese/peanut-butter category and Submarket 5 is the saltine category with the exception of Keebler Townhouse, which has a significant one-way switching to Submarket 1. Finally, Submarket 6 is a singleton with Nabisco Premium Saltine.

3.5 Discussion

A comparison of the submarket compositions in Figure 1 (with promotional effects) and those in Figure 2 (after removing promotional effects) shows that there are significant changes in the competitive patterns among the alternatives. Whereas some of the submarket groupings in Figure 1 could not be explained on the basis of product attributes alone, it is clear that after removing the promotional effects, the submarket groupings can be more easily explained on the basis of product attributes. For examples, Submarket 1 in Figure 2 is a specialty, flavor soda cracker submarket

⁹ The UJH z -statistics for all submarkets are significant (p -values < 0.0001). The K-M χ^2 values indicate good fit in Submarket 4, and reasonable fits in other submarkets. Nabisco Premium Saltine (in Submarket 6) has a significant one-way

consisting of products which are very similar to each other -- specialty saltine, flavor, and premium priced; and Submarket 2 consists of wheat-grained products, and so forth. On the basis of these results we can conjecture that the cracker market is generally form-primary, grouped on the basis of product attributes such as saltine, specialty/flavor, cheese/peanut-butter, low-salt, and wheat-grain. This structure seems to be distorted due to promotions such as display and price cut which change the attribute-based competitive patterns. However, the question of whether there is really an attribute-based structure needs to be validated.

Further comparison of the two submarket compositions in Figures 1 and 2 reveals that the cheese/peanut-butter submarket is affected the most by promotional effects. Two of its four brands are in different submarkets when promotional effects are present. The saltine submarket and the Nabisco submarket are affected to a lesser degree. However, not all product attribute groupings are affected by promotions. For example, Submarket 3 consisting of low-salt saltines remain competitive to the same extent even with promotional effects. These results are consistent with estimates from the brand switching model (Table 1) showing the low-salt attribute as the second strongest product attribute variable following brand name. This indicates that while promotion can be used to significantly change certain competitive patterns based on attribute (such as cheese/peanut-butter flavor) and brand name (e.g., Nabisco), other patterns (such as the one based on the low-salt attribute) may remain unaffected. It is possible that cheese/peanut-butter alternatives are attracting consumers of other product alternatives through promotions thereby altering switching patterns. On the other hand, consumers of low-salt saltines could be health-conscious consumers who may not want to switch to other alternatives even if they were on promotion. Overall, these results provide support to our hypothesis that the impact of short-term promotions on shaping competitive structure could depend on the extent of product differentiation. We will provide further support to this hypothesis from analysis of the ground coffee market.

3.6 Validation

switching to Private Label Saltine Special. However adding Nabisco Premium Saltine to Submarket 5 significantly lowers the fit for that submarket and thus it remains a singleton in the optimal scheme.

Internal Validity. We conduct further analyses to assess the internal validity of our findings and answer the question: do promotions, such as display and price-cuts, and price-tiers help shape the competitive patterns in the market? We want to check whether the submarket groupings in Figure 1 (especially Submarkets 2, 4, and 5 which cannot be easily explained by product attributes) can be explained by the effects of promotions and price-tiers. First, we examine the frequency and pattern of promotions (display, price cut) and prices for each alternative in a submarket. Second, we identify “heavy usage” consumers for the alternatives in a submarket. That is, more than 50%, 60%, 70%, or 80% of these consumers’ total purchases of crackers are made up of alternatives from the corresponding submarket. The complements of the above consumers who purchase these alternatives at least once are called the “light usage” consumers. Tests are then performed to determine whether the heavy usage consumers are different from the light usage consumers in terms of response to promotions and prices in their purchases (Table 2).

The three alternatives in Submarket 2 (in Figure 1 with promotional effects) are among the top four highly promoted alternatives in the market. They are on display 24%, 14%, and 13% of the store-time, respectively. An examination of the patterns of display over time for these alternatives indicates that 89% of the time at least one of these three alternatives have been on display. As shown in Table 2, “heavy usage” consumers of these three alternatives in Submarket 2 also have significantly more of their purchases associated with display and lower net prices paid. These results seem to indicate that these three alternatives of Submarket 2 appeal to “display-prone” consumers. These consumers may greatly value convenience, and thus, rely on display to simplify their purchase decisions (Blattberg and Neslin 1990, p. 71-72). This could, in part, explain the significantly larger gain parameter for DISPLAYG as compared to the loss parameter for DISPLAYL in the brand switching model.

We also note that the prices paid for Submarket 4 alternatives (American Saltine and Private-Label Saltine Special) are much lower than the prices paid for similar product alternatives (Keebler Saltine, Keebler Townhouse, and Keebler Club) in Submarket 5. In fact, American Saltine and Private-Label Saltine Special have the lowest average price paid among brand name and private-label crackers, respectively. It is thus possible that the saltine market is further partitioned by price-tiers

(c.f., Blattberg and Wisniewski 1989). In summary, results of these internal validations provide further support for our hypothesis that promotions and price-tiers play a significant role in shaping the competitive patterns.

External Validity. To examine the issue of whether there is a stable, long-term underlying structure in the market, we repeated the analyses on Period 2 and Period 3 data.¹⁰ Both periods essentially provided similar results, supporting the existence of a basic form-primary structure in the cracker market. The results of the validation analysis also provide clear support to the usefulness of our two-step methodology in separating out the effects of promotions on within-submarket versus across-submarket switching. The fact that a variable is significant in the model of brand switching does not mean that it affects across-submarket switching. Some variables such as display and price cut do, while others such as feature do not affect across-submarket switching. This separation of the effects of promotions on within-submarket versus across-submarket switching is important because very different managerial implications can be derived depending on which effect of promotions is observed.

4 Analysis of the Ground Coffee Market

We have shown in our analysis of the cracker market that certain submarket boundaries are affected by promotions while others are not. This impact of promotions may depend on the extent of product differentiation and the intensity and/or patterns of promotions. In this section, we apply our methodology to the SAMI ground coffee data to provide a more stringent test of this hypothesis. The ground coffee market is an ideal candidate for this test because (1) this is a market where brands are known to be well differentiated on the basis of form and type (Grover and Dillon 1985; Kannan and Wright 1991), and (2) it is a fairly common practice in the coffee market that each brand promotes all types of coffee at the same time. That is, we expect promotional activities, given our hypothesis, to have minimal, if any, effect on *across-submarket* switching. We considered 24 product alternatives. The marketing mix variables include *price paid*, *price cut*, and *feature*. The product attribute

¹⁰ Detailed results are available from the authors upon request.

variables include *brand name*, *package size*, *type* (regular, drip, or electric perk) and *form* (caffeinated versus decaffeinated).

The results of the brand switching model are presented in Table 3. Among the product attribute variables, the “type” variable has the maximum impact on switching, followed, in order, by package size, brand name, and form. Thus, one could expect submarket groupings based on types of ground coffee. This is confirmed in Figure 3, which provides the final submarket results from the market structure analyses¹¹. The submarket groupings are purely on the basis of form (caffeinated and decaffeinated groups) and within each form, by type: regular, drip, and electric perk. The results of the brand switching model indicate that price cut (loss) and feature (gain and loss) along with regular price are significant. However, the results of the test of homogeneity indicate that none of the promotional variables impact switching at the submarket level, although most of them are significant in the model of brand switching. The results suggest that promotions affect within-submarket rather than across-submarket switching in the coffee market as we have expected.

The coffee results also complement the cracker results in confirming that our methodology has substantial validity in identifying the impact of promotions at the submarket level. While the model of brand switching confirmed the significance of promotional variables in influencing switching among product alternatives, the test of homogeneity correctly attributed this influence to within-submarket switching rather than across-submarket switching. This lack of promotional impact across submarkets could be a reason why extant market structure studies, whether considering marketing mix effects or ignoring those effects, have consistently reported structures based on form and type.

5 Managerial Implications and Conclusions

We started out with three important managerial questions. First, is the competitive structure impacted by sales promotions? Second, if so, what is the nature of this impact? Third, what is the longer-term preference structure? Our methodology provides clear answers to all the above questions. We observe that promotions are capable of inducing competition among brands that are promoted

¹¹ The UJH *z*-statistics for all submarkets are highly significant. The K-M goodness-of-fit χ^2 statistics indicate disequilibrium conditions in some submarkets. The alternatives and the asymmetric switching pattern responsible for the disequilibrium are identified with an arrow in Figure 3.

even though they may not share similar product attributes, and eliminating such promotions would revert the market to the longer-term form based structure (as in the cracker market). On the other hand, promotional effects could be limited to within submarkets (as in the coffee market). Thus, any decision to eliminate promotions will have to be viewed from the perspective of how the competitive patterns are re-shaped rather than from the perspective of the brand alone. For example, with promotions all Nabisco brands are grouped in the same submarket. But once the promotional effects are partialled out, the submarket grouping is more on the basis of form - saltines, cheese/peanut flavor. Nabisco brands are then fragmented into groups facing competitors of the respective forms. Could this lead to a decrease in overall share? This is the question that the Nabisco brand manager has to know before he/she decides on eliminating promotions. Thus, identifying the stable, longer-term structure and understanding how promotions actually influence and shape the structure can enhance managers' ability to formulate effective marketing strategies.

A second implication is that care needs to be exercised in delineating submarket boundaries based solely on product attributes. Even though this is a very common method of defining market structure, there are inherent dangers in it as one could overlook the inter-category competition arising as a result of promotional activities (as in the cracker market). From an optimistic viewpoint however, our results do show that market structure need not always be viewed as a constraint on potential sales of a product. Just as advertising campaigns and consumer education can be used to capture a niche for a brand, similar tactics along with other promotional schemes may be used to break certain submarket barriers and help a brand appeal to a broader segment of consumers. Inter-category competition among product categories used in similar usage situations could develop as a result of extensive promotional activities in one category. Examples of some such product categories include ice cream and frozen yogurt; soft drinks, sodas, and fruit-based drinks; coffee, tea, and other beverages; etc. Managers can assess their opportunity to impact inter-category competition to their advantage by using the proposed systematic procedures.

Another important implication is that the stability of the structure depends on how well the products are differentiated on product attributes, the differential salience or utilities consumers have for those attributes, and the promotional practice adopted by different manufacturers. Products that

have followed a strategy of differentiation may find themselves in a better position to defend against inter-category attacks. However, our results also suggest that consumers have different utilities for different product attributes which determines to what extent promotions can distort the structure defined on their basis. For example, submarkets based on health-related attributes (low-salt and decaffeinated) are not affected by promotions while submarkets based on other attributes (saltine, brand name) are affected.

Finally, our study also highlights the importance of knowing which submarkets are stable and which submarkets are affected by promotions as it can be useful in deciding which product alternatives to promote (or not to promote) so as to maximize short-term revenues. For example, in the soft drinks market, the prevailing practice is that a firm promotes *all* its products, whether diet or caffeine-free or fruit-flavor or other types, simultaneously. If stable submarket boundaries are known (say diet submarket and non-diet submarket) then selective promotional campaigns for each submarket may turn out to be more effective and profitable for manufacturers and retailers.

Appendix A Identifying and Testing the Market Structure

We use one exploratory technique and two confirmatory procedures to determine the submarket structure. The exploratory technique applies cluster analysis on the inter-brand substitutability (similarity) measure derived from the brand switching matrix. We use two alternate estimates of this measure: index of interaction (NPD 1975) and proximity (Rao and Sabavala 1981). These two estimates capture different dimensions of the strength of competition between alternatives. The index of interaction compares the share of purchases of alternative j by alternative i 's buyers on occasions when they do not buy alternative i to the market share of alternative j when alternative i is absent from the market. The proximity measure is defined as the actual number of switches from alternative i to alternative j relative to the expected number of switches given the market shares of alternatives i and j .

The various submarket possibilities derived from the exploratory technique (using both estimates) are then subjected to two different confirmatory procedures to obtain convergent validity. The Multinomial-Dirichlet procedure of Kalwani and Morrison (1977) suggests that a group of alternatives form a competitive partition (submarket), if switching between alternatives within the partition is proportional to their shares *within* the partition. The observed switching levels within the submarket (derived from cluster analysis) are compared with the expected values predicted by the model to perform the confirmatory goodness-of-fit test (a χ^2 test). The K-M procedure operates under the assumption that the market is in equilibrium condition. The Urban, Johnson, and Hauser (UJH, 1984) procedure (adapted for the brand switching data) suggests that within a submarket, consumers switching out of an alternative are more likely to buy again in that submarket than would be predicted by the shares of those alternatives in the *overall* market. Thus, this confirmatory testing essentially involves comparing the actual switching levels within the submarket to the switching levels predicted by overall market shares using a one-tailed z -test. A significant z -statistic confirms the submarket¹².

¹² Readers interested in a detailed comparison of the above procedures in an application context can refer to Kalwani, Kannan, and Lim (1992).

Appendix B Testing for the Impact of Promotions

To identify the differential effects of marketing mix variables specific to each submarket, we systematically eliminate (partial out) the effect of each significant promotion variable. For example, to partial out the effect of “price cut” variable, we let the price variable for all alternatives in the model be their regular prices (price without any discounts) and set the price cut variable for all alternatives to zero. We then predict the brand switching matrix under this new scenario. To partial out the effect of display from the model, we change the instances of presence of display to absence of display to characterize the scenario under no display.

It is to be expected that by partialling out the effects of a significant variable from the model, the predicted switching probabilities of some (or all) alternatives are likely to be different from the original switching probabilities. However, we are more interested in the impact at the submarket level, namely: does the across-submarket switching change significantly when the effect of a promotional variable is partialled out? If the answer is affirmative, then there is a basis for the hypothesis that the promotional variable could impact or influence the submarket groupings. We use the following test for homogeneity based on the minimum discrimination information statistic (\hat{I}) developed by Kullback, Kupperman, and Ku (1962) to ascertain whether there has been a significant change in switching patterns at the submarket level when the effect of a promotional variable is partialled out.

We redefine the original brand switching matrix at the submarket level as follows. Let S be the total number of submarkets revealed by market structure identification procedures. Let f_{abc} represent the aggregate of all switches from alternatives in submarket b to alternatives in submarket c ($b, c = 1, \dots, S$) in the data set a , where $a = o, p$, depending on whether the data is the original brand switching matrix (o) or the predicted matrix (p), respectively. In particular, f_{obb} consists of the total number of repeat purchases as well as switches among alternatives within submarket b in the original data o . Thus, $\{f_{obe}\}$ represents the ($S \times S$) submarket switching matrix derived from the original brand switching data with conditional probability switching parameters $[\eta_{bc}]$. Let $\{f_{pbc}\}$ represent the corresponding submarket switching matrix p after partialling out the effect of the marketing mix

variable, with conditional probability switching parameters $[\nu_{bc}]$. The null hypothesis that the two sets of switching parameters are homogeneous, $H_0: [\eta_{bc}] = [\nu_{bc}]$ is tested using the minimum discrimination information statistic:

$$\hat{I} = \sum_{a=o,p} \sum_{b=1}^S \sum_{c=1}^S f_{abc} \ln \frac{f_{abc}}{\frac{f_{ab} \cdot f_{bc}}{f_{.b}}},$$

where f_{ab} represents $\sum_c f_{abc}$, f_{bc} represents $\sum_a f_{abc}$, and $f_{.b}$ represents $\sum_a \sum_c f_{abc}$. Under the null hypothesis, the information statistic \hat{I} asymptotically follows a χ^2 distribution with $S(S-1)$ degrees-of-freedom (Kullback, Kupperman, and Ku 1962). If the switching parameters are significantly different (especially if some ν_{bc} , $b \neq c$ are significantly greater than the corresponding η_{bc}), we can infer that the marketing mix variable could have a significant impact or influence in shaping the submarkets¹³. We, then, apply market structure identification procedures to the predicted brand switching data to reveal the specific changes in the grouping of the alternatives.

¹³ The original brand switching matrix and the predicted brand switching matrices after partialling out the marketing mix effects are not strictly independent samples as one is derived from the other. However, since the predicted matrix is the aggregate of individual level purchase probabilities summed over all consumers and over time, the dependency is not pronounced. Our simulation studies indicate that it does not affect the outcome of the test of homogeneity. The details are in a technical appendix available from authors.

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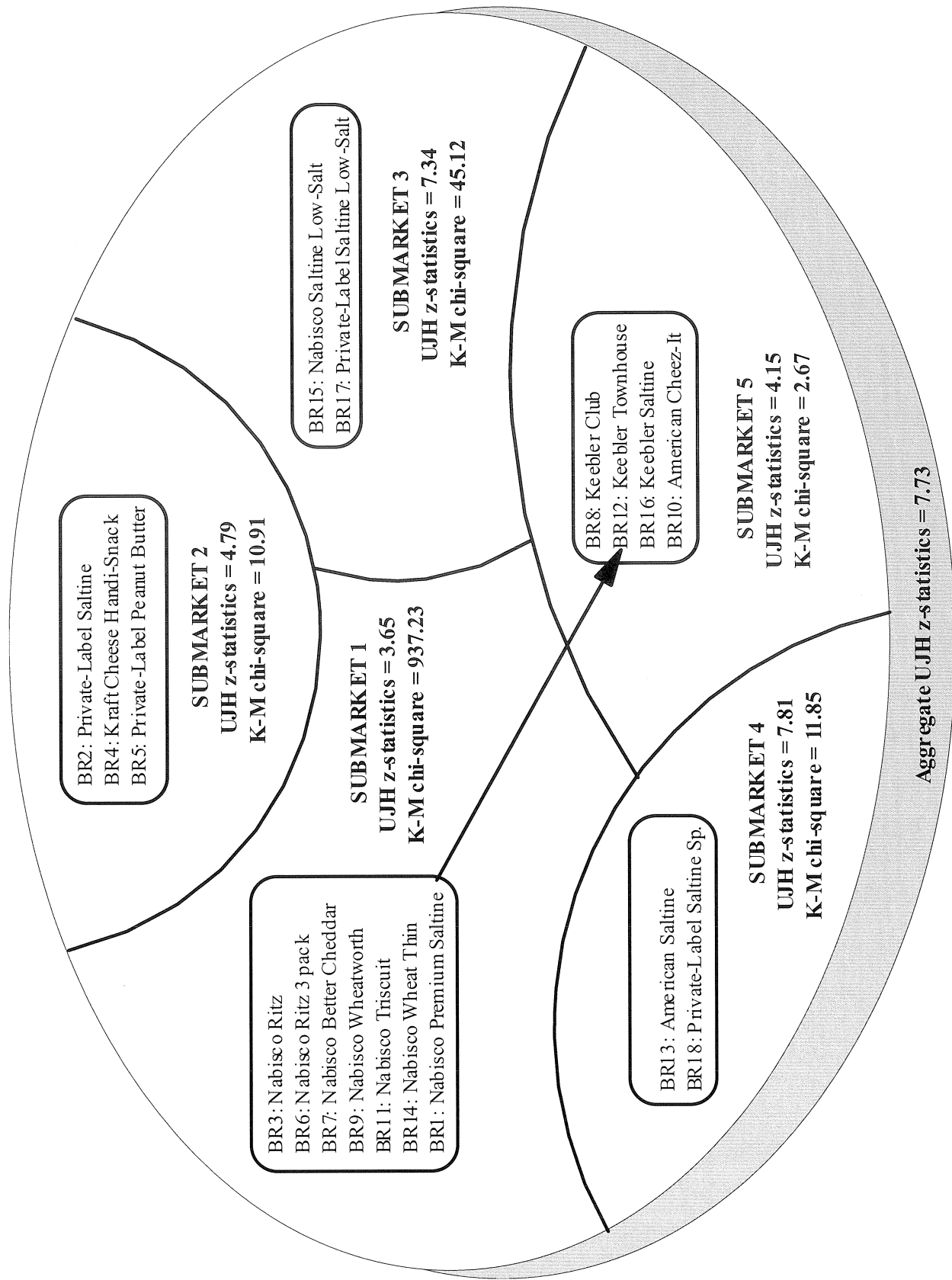


Figure 1: Cracker Market Structure with Promotional Effects - Period 1.

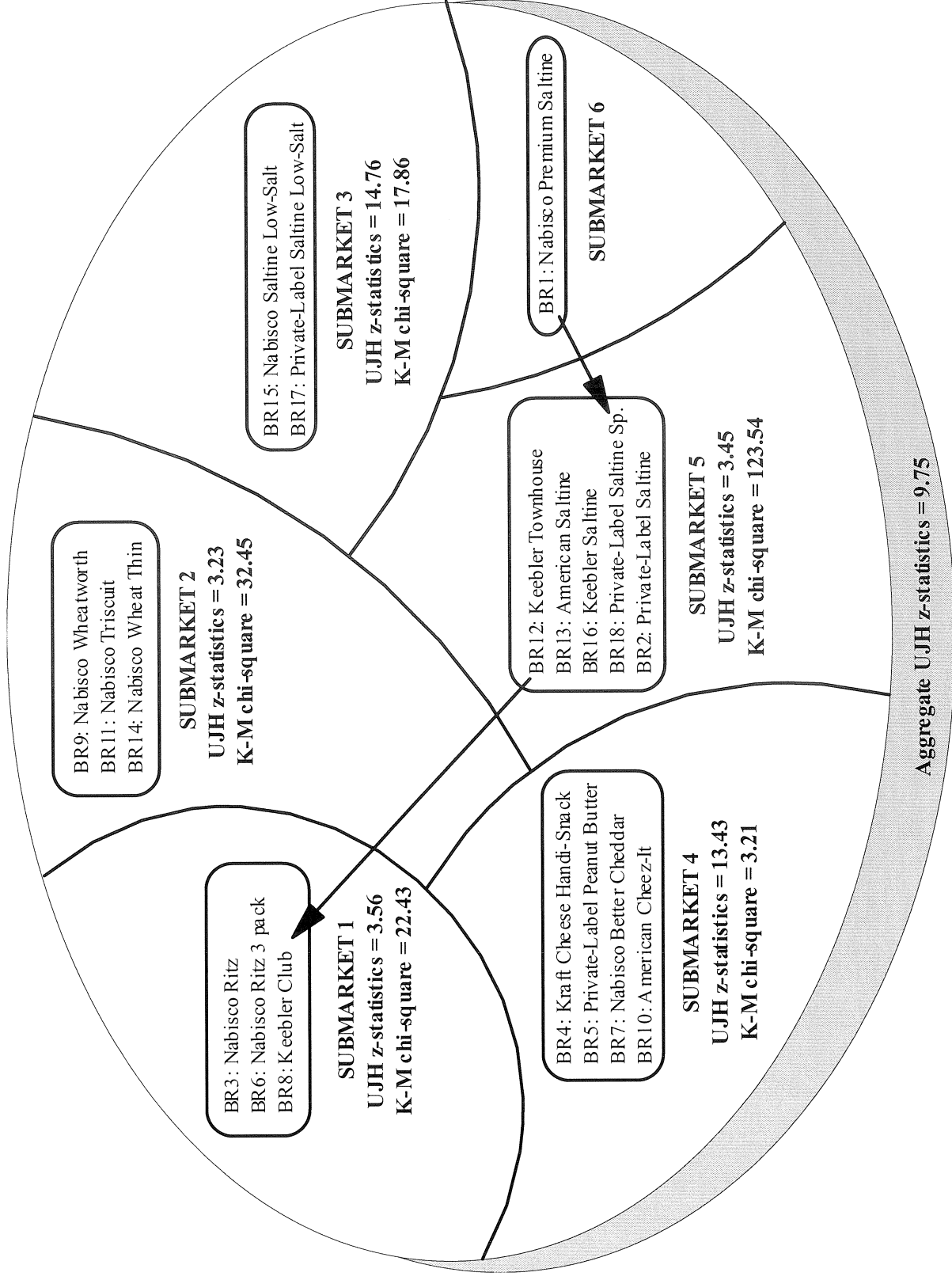


Figure 2: Cracker Market Structure with Effects of Display and Price Cut Removed - Period 1.

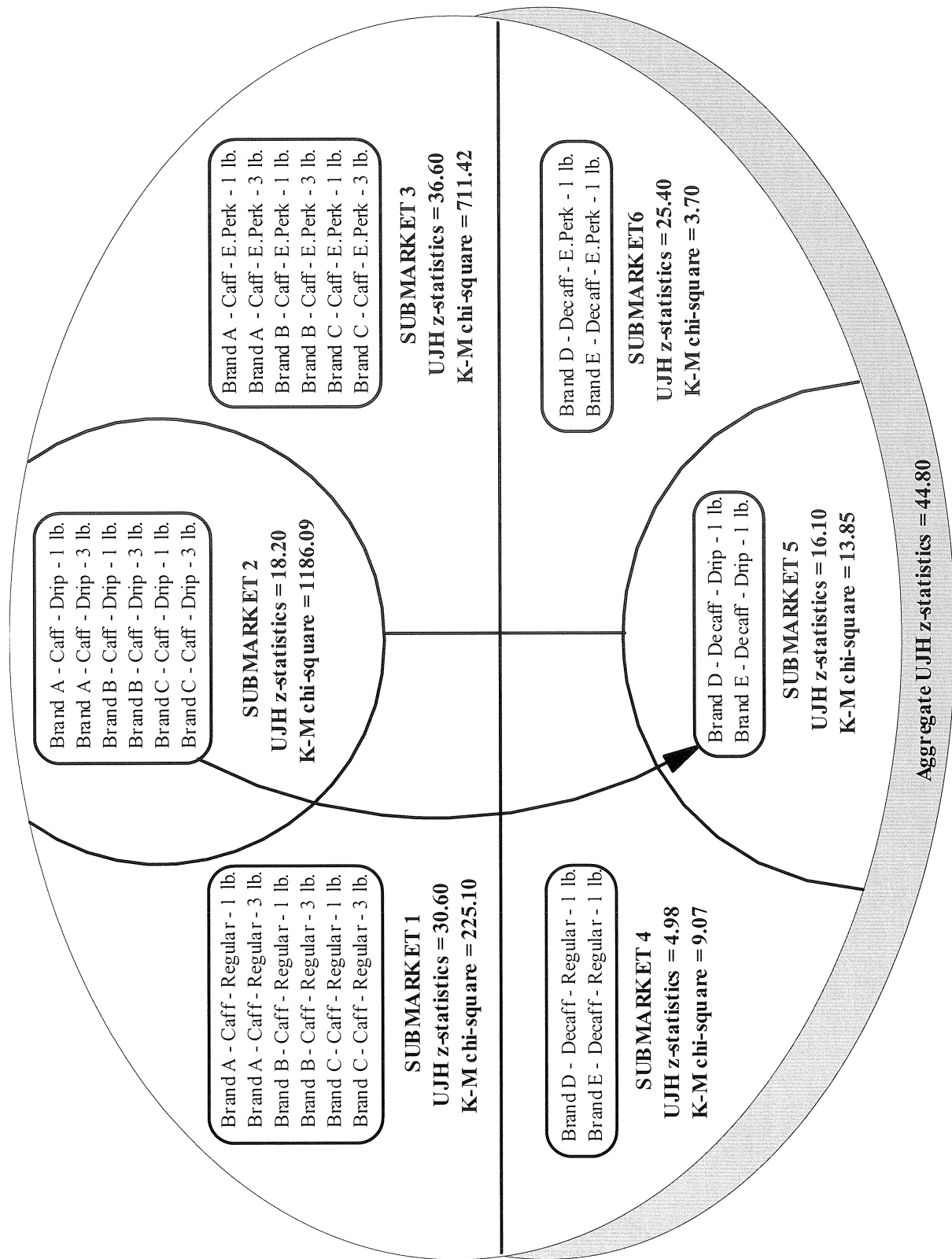


Figure 3: Ground Coffee Market Structure with Promotional Effects.

Table 1
Estimates from the Dogit Model of Brand Switching – Cracker Market (Period 1)

Variable	Parameter Estimate	p-value
Captivity Parameters (θ_1 through θ_{18})	0.000 to 0.094	
Alternative-Specific Constants (μ_1 through μ_{17})	-1.5472 to -0.0687	
BRNAME	0.6472	0.0000
SIZE	0.2174	0.0000
LSALT	1.6272	0.0000
CHEEZ	0.4967	0.0000
WHEAT	0.3964	0.0014
PRICE(I)G*	0.3624	0.0000
PRICE(I)L	-0.2742	0.0000
PRICE(II)G*	0.1822	0.0000
PRICE(II)L	-0.1629	0.0000
PRCUT(1)G	0.4872	0.0000
PRCUT(2)G	0.1231	0.3956
PRCUT(1)L	-0.4644	0.0000
PRCUT(2)L	-0.3245	0.1598
DISPLAY(1)G	0.5624	0.0000
DISPLAY(2)G	0.1832	0.2364
DISPLAY(1)L	-0.1842	0.0147
DISPLAY(2)L	-0.0567	0.6542
FEATURE(1)G	1.0249	0.0000
FEATURE(2)G	0.6502	0.1672
FEATURE(1)L	-0.8977	0.0000
FEATURE(2)L	-0.2921	0.2976

*Coefficient for PRICE(I) captures the effects for saltines, Nabisco Ritzs, and Keebler Townhouse, coefficient for PRICE(II) includes all other alternatives (specialty crackers). The index 1 and 2 for the other promotion variables refer to grouping of alternatives specific to each variable and are not the same across variables.

Summary of Calibrated Models

	LL	U ²	Adjusted U ²	BIC
Logit Model				
- Standard variables specified	-9787.24	0.526	0.525	-9907.05
Logit Model				
- Switching variables specified	-9746.47	0.528	0.527	-9888.46
Dogit Model				
- Standard variables specified	-9693.28	0.530	0.528	-9892.96
Dogit Model				
- Switching variables specified	-9633.14	0.533	0.531	-9855.00

Table 2
Differences in Response to Marketing Mix Between “Heavy Usage”
and “Light Usage” Consumers of Products in Submarket 2

Average Value of Price Paid and Display Purchases ^c	<u>“Heavy Usage”</u> <u>Consumers^a</u> (n = 128)	<u>“Light Usage”</u> <u>Consumers^b</u> (n = 1144)	<u>t-statistics</u>
Price Paid (cents/oz.)	8.099	9.115	2.256 ^e
Display (%)	20.330	13.994	-2.821 ^d

^a More than 70% of these consumers’ purchases of crackers are products in Submarket 2 (Private-Label Saltine, Kraft Cheese Handi-Snack, and Private-Label Peanut Butter).

^b At most 70% of these consumers’ purchases of crackers are the three products in Submarket 2.

^c The result for price paid (display) remains the same whether “heavy usage” consumers are defined as those consumers with more than 70% or 80% (50%, 60%, 70%, or 80%) of their total cracker purchases accounted for by the three products in Submarket 2.

^d Significant at $\alpha = .01$ (t-test).

^e Significant at $\alpha = .05$ (t-test).

Table 3
Estimates from the Dogit Model of Brand Switching (Ground Coffee Data)

Variable	Parameter Estimate	p-value
Captivity Parameters (θ_1 through θ_{24})	0.0000 to 0.1492	
Alternative-Specific Constants (μ_1 through μ_{23})	-1.2672 to 1.0242	
BRNAME	0.3621	0.0000
SIZE	0.4942	0.0000
TYPE	0.7973	0.0000
FORM	0.4262	0.0000
PRICE(I)G*	0.4762	0.0000
PRICE(I)L	-0.2817	0.0006
PRICE(II)G	0.2791	0.0172
PRICE(II)L	-0.1172	0.0362
PRICE(III)G	0.1726	0.0002
PRICE(III)L	-0.1496	0.0421
PRCUTG	0.0876	0.1062
PRCUTL	-0.2427	0.0000
FEATUREG	0.7647	0.0000
FEATUREL	-1.4211	0.0000

*Three set of significantly different price coefficients were estimated for three groups of brand-sizes of coffees.

Summary of Calibrated Models

	LL	U ²	Adjusted U ²	BIC
Logit Model				
- Standard variables specified	-13515.17	0.612	0.611	-13664.00
Logit Model				
- Switching variables specified	-13499.73	0.612	0.611	-13671.82
Dogit Model				
- Standard variables specified	-13406.96	0.615	0.614	-13639.51
Dogit Model				
- Switching variables specified	-13382.91	0.616	0.614	-13638.71