Assessing long-term promotional influences on market structure

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Abstract

The allocation of marketing budgets across advertising and sales promotions has changed over the past decade with a marked decrease in the percentage of budgets directed towards advertising. Moreover, there has been much speculation regarding how these changes have affected a brand's positioning vis-à-vis its competitors. In spite of this speculation, previous research has not examined the impact of changes in promotion and advertising on market structure. The purpose of this paper is therefore to ascertain how changes in promotional and advertising policy affect market structure over the long-term. The eight and one quarter years of scanner panel data used for our analysis indicate that brands in the analyzed product category tend to fall into premium/non-premium and attribute-based (mildness) tiers. Furthermore, the data suggest that the differentiation between non-premium and premium brands has diminished during the period of our study (1984–1992). The data also suggest that increases in price promotions and reductions in advertising have led to decreased differentiation between brands. These findings suggest that shifts in marketing dollars from advertising to promotions have made national brands more vulnerable to store brands' marketing activity.

Keywords: Market structure; Marketing mix; Promotion; Advertising; Econometric models

1. Introduction

1.1. Changing managerial tactics

A key brand management decision pertains to allocating promotional budgets across advertising, trade promotions and consumer promotions. Recently, brand management's disposition has lent itself toward trade promotions. According to Progressive Grocer (1995), 70% of manufacturers have increased promotions between 1990 and 1995. Indeed, manufacturers spend over $70 billion annually on trade promotions and a large portion of those trade promotions were passed through to consumers in the form of discounts. Recently, Nielsen found that price increases in 71 out of 100 categories have not matched inflation, in part due to discounting (Wall Street Journal, 1997).

The increasing levels of promotions have led managers to be increasingly concerned about the influence of these promotions on brand differentiation. While certain promotions (e.g. sampling) appear to have a positive effect on brand differentiation (Blattberg and Neslin, 1989; Gedenk and Neslin, 1997), others (e.g. discounting) may have negative long-term consequences for brands even though they can induce dramatic sales increases in the short-term. For example, Forbes (1991) suggests that an increase in trade promotional spending over a five year period

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led to a decline in share for the top three brands in categories ranging from popcorn to cat food. The Forbes (1991) article asserts that competition between premium and non-premium tiers of brands may have somehow increased over time as a result of an increase in promotions. Thus, the analysis of the long-term effects of promotions on competition and market structure has considerable interest to marketing managers. Yet much of the voluminous marketing research to date has focused on the short-term effect of these instruments.

Since Blattberg and Neslin (1989) and Gupta (1993) called for more research into the long-term effects of this increase in promotions, several studies have begun to appear. The literature on these effects has covered sales (Boulding et al., 1994; Dekimpe and Hanssens, 1995a,b), choice (Mela et al., 1997; Papatla and Krishnamurthi, 1996) and share (Lal and Padmanabhan, 1995). Dekimpe and Hanssens (1995b) and Lal and Padmanabhan (1995) both analyze how promotions impact brand market share over long periods of time (e.g. years). They conclude that, although promotions increase share in the short run, they have little impact on the long run share. Yet it is misleading to conclude from these studies that price promotions do not affect brand profits in the long-term. The positive short-term impact of one brand's promotions on brand share is likely to increase the retaliatory use of promotions by other brands. This, in turn, can increase brand switching and price sensitivity. In this scenario, even if the long run brand shares remain the same, consumer behavior and profitability can change significantly.

Some studies have begun to acknowledge this possibility. Boulding et al. (1994) find that higher levels of promotion tend to induce greater sales price sensitivity thereby reducing brand differentiation. Papatla and Krishnamurthi (1996) and Mela et al. (1997) find that price oriented promotions (e.g. coupons and temporary price reductions) induce higher price sensitivity. Mela et al. (1997) also find evidence that some types of non-price oriented promotions (e.g. displays), may benefit brands over time.

Many other studies have also suggested that advertising has an analogous, but opposite, effect to promotions by affecting price sensitivity over the long run even in the face of relatively constant market shares. Dekimpe and Hanssens (1995a) find that market shares are largely unaffected by advertising over the long-term. However, Kaul and Wittink (1995) and Mitra and Lynch (1995) overview the extensive literature regarding the effect of advertising on brands and conclude that unique, brand-oriented advertising in mature categories does tend to reduce sales price sensitivity. This type of advertising has the opposite long-term effect of price promotions and serves to better differentiate brands. Conversely, these studies suggest that advertising messages that do not stress unique features may expand consumers' consideration sets, lead to diminished brand differentiation and greater competition. Price oriented advertising is one such example of this.

Although this research is beginning to shed much light upon how promotions and advertising affect consumer choice, market share, brand sales, and price sensitivity in the long run, the long-term effect of promotions and advertising on market structure remains an unanswered question. The purpose of this paper is to fill that gap.

1.2. Dynamic market structure

Market structure (the representation of interrelationships of a set of products or brands in a way that reflects consumers' evaluations of the brands in the set) has been an area of extensive research since it is a critical component affecting brand planning and category strategy (for a complete review see Elrod, 1991; Elrod and Keane, 1995). The importance of market structure in brand management has been reflected in the more than 100 articles published in the area by 1987 (Grover and Srinivasan, 1987) and 99 published on the subject since then (Business Abstracts Database, 1997). Although both market structure and the long-term effects of promotion are important areas of research, virtually no research has been done at the confluence of these research streams. Most previous market structure research has focused on a static or 'snapshot' analysis (see Blattberg and Neslin, 1989; Bemmaor and Schmittlein, 1991; Gupta, 1993; Blattberg et al., 1995). Bemmaor and Schmittlein (1991) recently wrote, ''While there has been some investigation of longer-run effects and competitive market strategies, these latter issues have not been explored in as much depth (as opposed to shorter-run effects) to date.''

Moore and Winer (1987), in a pioneering study on dynamic market structure, used 'pick any' data to assess competitive maps over time. Their results suggest that advertising moves brands closer to ideal points. Erdem (1996) accommodates dynamics in the choice process when developing maps of market structure, yet the representation of market structure itself is fixed. Cooper (1988) used three-mode factor analysis to assess changes in competitive structure over a 52 week period. The Cooper (1988) work presages ours. Compared to these previous studies, our emphasis is on longer-term (many years of data) changes in market structure. In addition, our study explicitly examines the long-term effects of promotions and advertising on brand positions.

Day et al. (1979, p. 13) offer one explanation regarding why studying shifts in market structure may have remained an existing gap in the literature.

Behavioral measures (of market structure) suffer from an endemic weakness...actual switching is affected by current market factors such as...promotional message and expenditures.... If data are developed over long periods of time...sufficient variability may have taken place in the determinants of demand to reveal such potential substitutability.

With the advent of single source scanner data over ten years ago, data streams have recently become available that enable researchers to look over 'long periods of time' and erase the limits that Day et al. (1979) noted.

Given the importance of market structure and the paucity of research regarding how it develops and changes, this paper seeks to understand how advertising and promotions affect market structure over time. The paper is organized as follows. We first discuss our approach. Next, we describe our data and present our results. We conclude by outlining some managerial implications and some directions for future research. Our contribution is both substantive and methodological. Our substantive contribution is to ascertain the impact of many years of marketing activity on market structure. Our methodological

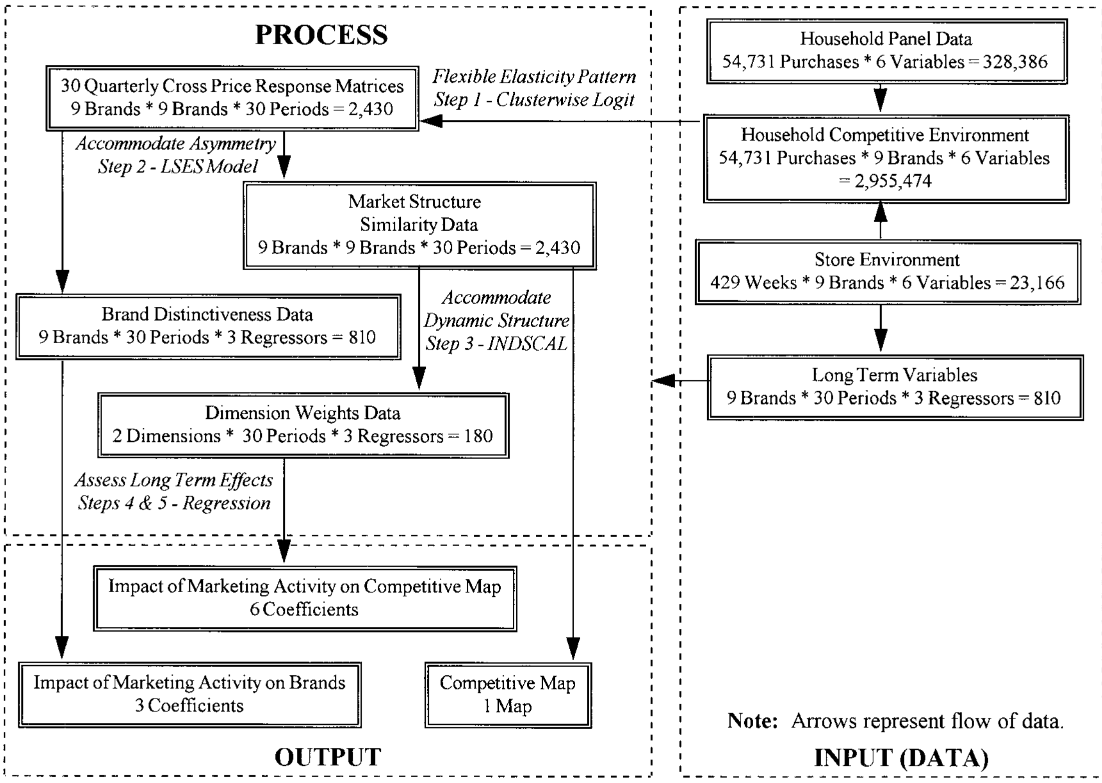

Fig. 1. Analytical procedure.

contribution is to provide a parsimonious and reliable approach to calibrating a dynamic model of market structure.

2. Analyzing changes in market structure

2.1. A longitudinal procedure for inferring market structure

We outline our procedure for inferring changes in market structure and creating a dynamic brand map in Fig. 1.

This procedure consists of five steps. These steps are overviewed below and are subsequently discussed in greater detail.

(1) Divide a long period of data into successive, discrete intervals (for example, quarters). Use short-term (weekly) marketing activities to assess own and cross price sensitivities for each quarter. These series of price sensitivities contain information about how competition among brands changes over time.

(2) Use the own and cross price sensitivity measures to partial out brand specific effects (the degree to which a brand is unique from the market as a whole) and brands' substitutability (the degree to which particular brand pairs are substitutable).

(3) Apply MDS techniques on the longitudinal series of brands' substitutability to construct a dynamic competitive map that portrays changes in substitutability over time.

(4) Assess how long-term changes in promotion and advertising affect brand specific effects.

(5) Assess how long-term changes in promotion and advertising affect brands' positions in the dynamic competitive map.

2.2. Step 1: Estimate similarity matrices

Shocker et al. (1990) suggest that own and cross price responses [1] are particularly well suited for the analysis of market structure as they offer a good measure of brand similarity as revealed by consumers' actual purchase behavior. We therefore measure changes in market structure via changes in cross price responses (see Elrod and Keane, 1995 for an extensive list of studies that use cross price matrices for analyzing market structure in time invariant settings).

Using disaggregate household-level purchase data, we fit the clusterwise logit model of brand choice (Kamakura and Russell, 1989) to each successive, discrete period of the data. The clusterwise logit model has two benefits. First, it accounts for heterogeneity in households' price sensitivities. Second, the clusterwise logit allows for a very general pattern of cross price response and is therefore especially well suited for capturing changes in market structure. Specifically, the probability, P_{qt}, of household h choosing brand i at time t during quarter q is given by [2]

$$P^h_{iqt} = \sum_{s=1}^{S} \pi_{sq} P^h_{isqt}; \quad \pi_{sq} \in [0, 1]; \ \sum_{s=1}^{S} \pi_{sq} = 1 \tag{1}$$

where s indexes the market segment and π_{sq} is the size of segment s in period q. The probability of household h in segment s choosing alternative i at time t is then given by the logit choice probability for that segment,

$$P^h_{isqt} = \frac{\exp\left(b_{0isq} + \beta_{sq}\mathbf{X}^h_{it}\right)}{\sum_{i=1}^{I}\exp\left(b_{0isq} + \beta_{sq}\mathbf{X}^h_{it}\right)} \tag{2}$$

Using the series of estimated price sensitivity parameters, β_{sq}, we then simulate the effect of a one unit

[1] Cross price responses are defined as the change in the share of brand j with respect to a change in the price of brand i. Own price response is defined as the change in share of brand i with respect to a change in its price.

[2] We use a quarterly measure for several reasons. First, the specification is consistent with Moore and Winer (1987) and the advice of sponsoring managers. Second, given the six week interpurchase times for this product, shorter periods (e.g. monthly or weekly) could indicate little meaningful change and longer periods (semi-annual or yearly) could fail to capture some of the dynamics. The Moore and Winer (1987) panel data based analysis indicated monthly, quarterly and eight-month windows yielded relatively stable results.

change in the price of a brand on its own share (Mela et al., 1997) as well as other brands' shares [3]. For i brands this procedure yields an $I \times I$ cross price response matrix for each quarter.

2.3. Step 2: Accommodating asymmetry

The market structure embedded in cross price response matrices has two components, substitutability and clout (Russell, 1992; Russell and Kamakura, 1994). Substitutability refers to the strength of competition between brand pairs or the degree to which their marketing actions influence one another. A set of brands that are highly substitutable form a submarket, brand-tier or market partition. An increase in substitutability therefore provides a symmetric measure of the influence on and susceptibility to competitors. Clout reflects the overall relative impact of a brands' marketing activity on its competitors. Substitution and clout yield different insights into how market structure is changing. Increases in brand clout suggest that a brand's marketing activity is having a greater unilateral impact on its competitors. Increases in substitutability suggest two brands or submarkets of brands are both becoming more competitive with one another (have higher cross price responses).

We employ the LSES (latent symmetric elasticity structures) model developed by Russell (1992) and applied in Russell and Kamakura (1994) to disentangle clout and substitutability effects in a cross price response matrix. The model decomposes the quarterly $I \times I$ cross price response matrix, $\boldsymbol{E}_q$, into three separate matrices: (i) a symmetric brand substitutability matrix, $\boldsymbol{S}_q$, (ii) a diagonal matrix of brand clout terms, $\boldsymbol{C}_q$ and (iii) a residual matrix, $\boldsymbol{R}_q$, that captures residual effects. The closer $\boldsymbol{R}_q$ is to the identity matrix, the better $\boldsymbol{S}_q$ and $\boldsymbol{C}_q$ capture the underlying cross response matrix. Algebraically, the LSES decomposition is given by

$$\boldsymbol{E}_q = \boldsymbol{S}_q \boldsymbol{C}_q \boldsymbol{R}_q \tag{3}$$

The following example illustrates the intuition behind the decomposition. The entries in Table 1 represent the percentage change in share of the row brand resulting from a 5% increase in the price of the column brand. For instance, if brand 3 increases its price by 5% the share of brand 1 will increase by 5%.

Table 1
Period 1 sample cross price response matrix

	Brand		
Brand	1	2	3
1	−40	20	5
2	20	−40	5
3	20	20	−10

Looking at the columns, note that brands 1 and 2 have greater cross price responses than brand 3 and therefore have a greater own price response (the columns sum to zero). The substitutability between brands is also apparent as the relative effect of brand 1's price change is evenly split between brands 2 and 3. Similarly, brands 2 and 3 draw share equally from each competing brand. Therefore, after controlling for brand specific effects, all the brands should be equally substitutable.

The LSES method decomposes the hypothetical cross price response matrix of Table 1 into a diagonal clout matrix, $\boldsymbol{C}$ and a symmetric substitutability matrix, $\boldsymbol{S}$. The clout measures estimated by the LSES method yield $4/9$ for brand 1, $4/9$ for brand 2 and $1/9$ for brand 3. As can be seen from these results, the LSES solution is consistent with our hypothetical data; the price sensitivity of brands 1 and 2 are equal and four times the price sensitivity of brand 3. The 3×3 substitutability matrix obtained from this procedure is presented in Table 2.

The LSES therefore captures the relative symmetry of the competition, suggesting that, controlling for brand specific effects, no brand draws or yields more share from one brand than another in response to a price change.

In sum, we estimate the LSES model in step 2 to obtain measures of clout and brand substitutability matrices for each consecutive period of cross price

[3] We use absolute changes in share in lieu of elasticities (percentage changes in share) to control for scaling artifacts introduced by elasticities (Russell et al., 1993). Absolute changes, when multiplied by the ratio (price/market share), yield elasticities. Thus, brands with higher prices and lower market share, by definition, have higher elasticities. Russell et al. argue that ''the often observed asymmetry of cross price elasticities is, in part, a scaling artifact introduced because base market shares and prices are unequal across brands (p. 11).''

Table 2
Estimated period 1 LSES substitutability matrix

	Brand		
Brand	1	2	3
1	−90	45	45
2	45	−90	45
3	45	45	−90

response matrices. In subsequent steps, we use changes in these measures of brand competition over time to infer the impact of marketing activity on competitive structure.

2.3.1. Is high 'clout' really good?

It is important to understand what clout really means. As higher clout suggests that a brand's price changes have a greater impact on its competitors than competitors' price changes have on it, many researchers have argued that clout is reflective of a brand's strength (Cooper, 1988; Blattberg and Wisniewski, 1989; Russell, 1992; Russell and Kamakura, 1994). As one might expect, large market share brands have higher clouts (Blattberg and Wisniewski, 1989; Russell, 1992) and these researchers have argued that this empirical observation further supports the notion that increases in clout are a good thing.

However, there is a flip side to this argument. Since market shares must sum to one, the sum of the brand's cross price response terms must equal the magnitude of the brand's own price response term [4]. Therefore, higher cross price responses (or higher clout) are indicative of a higher own price effect (see the example in Table 1). In this vein, there are at least two adverse effects of an increase in 'clout'. First, the increase in the own price effect can be directly linked to an increase in brand switching and a reduction in brand repeat purchase rates or loyalty (Russell et al., 1996). Second, Boulding et al. (1994) suggest that firms with higher own price effects are less differentiated, are less able to raise prices, and therefore forego the opportunity to earn higher margins and profits. For these reasons, we shall subsequently refer to an increase in 'clout' as a reduction in a brand's *distinctiveness*.

2.4. Step 3: Developing a dynamic map of market structure

The procedure detailed in step 2 yields Q periods of symmetric substitutability matrices, S_q ($q = 1, \dots, Q$). We treat the substitutability matrices as similarity matrices and use three way (time by brand by brand) Multidimensional scaling (MDS) to examine the changes in market structure over time. The MDS procedure uses the INDSCAL model (Carroll and Chang, 1970) expressed as

$$d_{ijq} = \sqrt{\sum_{m=1}^{M} w_{mq}(x_{im} - x_{jm})^2} \tag{4}$$

where d_{ijq} is the dissimilarity measure between brands i and j in period q, x_{im}, x_{jm}, are the respective positions of brand i and j on dimension m, and w_{mq} is the weight of dimension m in period q. d_{ijq} is inversely proportional to the substitutability, s_{ijq}, between brands i and j in period q. This model assumes that the number of dimensions, M, and brand positions, x, remain constant over time and that the changes in brand substitutability are captured through changes in the dimension weights, w_{mq}.

The MDS model yields brand coordinates in a M-dimensional space and dimension weights for each time period, q. Decreasing (increasing) weights over time are indicative of smaller (greater) distances and thus increased (decreased) substitutability between brands. Should a premium/ non-premium dimension exist, over time reduction in weights in this dimension would suggest that brand substitutability is in-

[4] Consider three brands with market shares m_1, m_2 and m_3. By definition, $m_1 + m_2 + m_3 = 1$. Differentiating both sides with respect to the price of brand 1, p_1, leads to $(\partial m_1/\partial p_1) + (\partial m_2/\partial p_1) + (\partial m_3/\partial p_1) = 0$ or $-\partial m_1/\partial p_1 = (\partial m_2/\partial p_1) + (\partial m_3/\partial / p_1)$, i.e. a brand's own price effect equals the sum of its cross price effects. Two other factors lend support to the link between clout and a brand's own price response. First, as defined by Russell (1992), a brand's own price elasticity, e_{jj}, is directly proportional to clout, $C(j)$, $e_{jj} = C(j)S(j, j)$ where $S(j, j)$ is a brand's substitution index. This relation implies price response increases with clout. Second, Table 1 of Russell (1992) shows that most previous studies have modeled the clout for a brand j as βm_j or $\beta m_j p_j$ where β is the price sensitivity parameter and p_j is the price of brand j. These definitions of clout imply that increases in a brand's price sensitivity increase a brand's clout. This relationship further confirms our argument that clout is directly related to a brand's own price response.

creasing between premium brands and non-premium brands.

2.5. Step 4: Assessing the long-term impact of promotions and advertising on brand distinctiveness

A *short-term effect* is the response to own and competitive price changes in a given week. These short-term effects are captured through the calibration of the clusterwise logit model in step 1. How these cross price response matrices change from quarter to quarter or year to year is the *long-term* issue. We posit that long-term changes in market structure are induced by long-term changes in marketing activities such as a substantial increase in the frequency of promotions used by brands

To assess whether brands' distinctiveness is changing over the long-term and if changes in advertising and promotions over the long-term are affecting these changes, we use a distributed lag model (Clarke, 1976; Jacobson, 1990). The brand distinctiveness, c_{iq}, for brand i in quarter q is modeled as

$$c_{iq} = \lambda_i c_{i(q-1)} + \sum_{k=1}^{K} \beta_{ki} z_{kiq} + e_{iq} \tag{5}$$

where K is the number of long-term variables, z_{kiq} (e.g. advertising) which can affect the distinctiveness [5] of brand i in period q.

The inclusion of the lagged term (similar to a Koyck specification) serves several purposes. The lagged term is included to capture the effect of previous periods' marketing activity as the longer term effects are likely to endure beyond a given period (Clarke, 1976; Leone, 1995). In this specification, more distant periods carry lower weights. Therefore, as λ increases, the more enduring the effect of the long-term marketing activity. Second, assuming the errors are not serially correlated, the inclusion of the lagged dependent variable serves to control for omitted variable bias (Jacobson, 1990). Such macroeconomic variables include household purchasing ability and fundamental shifts among consumers towards being 'value oriented'.

The specification in Eq. (5) assumes that the lag structure, λ, is common across variables. The ramification of this assumption is that the duration of advertising, promotion and income effects are all specified to be equal. This is a rather restrictive specification. We therefore test for the possibility of different lags for each variable using an approach outlined in Johnston (1984, p. 347).

Brand distinctiveness regressions are run at the brand level for two key reasons. First, brand level regressions allow for differences in brands' marketing effectiveness. Second, constraining parameters to be equal across brands is restrictive and may suffer from aggregation bias. We then treat the results from different brands as independent replications and use Fisher's pooling test [6] (Dutka, 1984; Fisher, 1948) to draw conclusions about whether or not advertising and promotions affect a brand's distinctiveness over the long run.

2.6. Step 5: Assessing the long-term impact of promotions and advertising on brand substitutability

As indicated in Section 2.4, a reduction in distance or, equivalently, an increase in substitutability of two brands arises from a decrease in the weights of the perceptual dimensions. To assess whether changes in advertising and promotion have a long-term impact on the M dimension weights, w_{mq}, we specify the following model

$$w_{mq} = \lambda_i w_{m(q-1)} + \sum_{l=1}^{L} \beta_l z_{lq} + e_{mq} \tag{6}$$

where the z_{lq} represent the L long-term market level variables that are hypothesized to affect the dimension weights. Since changes in dimension weights affect the position of all brands along a dimension,

[5] Note that elasticity based calculations of a brand's distinctiveness would be related to the brand's price (Russell, 1992), $c_j = f(p_j) = \beta m_j p_j$. Therefore, any changes in elasticity based brand distinctiveness would depend upon changes in causal factors such as price and promotions as well as household preferences and response to price (parameters of the choice model). Eq. (5) would therefore implicitly have price and promotions on both sides of the equation. However, our use of brand distinctiveness calculated from absolute changes in share (rather than elasticities) is not directly related to price and implies that changes in brand distinctiveness result from changes in households' preferences and responses to price.

[6] Pooling across brands is done to avoid type II error (Dutka, 1984; Fisher, 1948).

the long-term variables posited to affect the weights are calibrated at the market level. The specification of a lag term serves the same purpose as in Eq. (5). Once again, we test for the possibility of different lags for the z variables (Johnston, 1984).

2.7. Key model benefits

A dynamic market structure analysis presents the challenge of trying to simultaneously (i) define a measure of competition, (ii) control for short-term marketing activities, (iii) control for heterogeneity, (iv) allow for asymmetry in competition, (v) generate a competitive map, (vi) allow structures that evolve over time and (vii) link structure evolution to long-term marketing activity. Not only does our approach capture these variegated effects in a parsimonious framework, but it also uses reliable, well established techniques to do so.

The novel combination of these techniques enables managers to develop rich insights into changes in market structure over time that would not be available using simpler approaches. For example, it enables managers to delineate which brands become the greatest threats to them over time and why. Second, our method enables managers to infer which submarkets exist, how they are characterized, the degree of substitutability of products in own and competing submarkets and how the submarkets change over time. Such information may be helpful to reposition brands or to identify new market opportunities. Third, the approach offers insight into how advertising, price promotions and non-price promotions affect a brand substitutability and distinctiveness (operationalization of these variables will be discussed in the subsequent section). Fourth, it provides managers with two measures of differentiation (the substitutability and distinctiveness measures) to supplement the market level data. Central to developing such insights is a sufficient history of data from which to draw these inferences. We now describe the data we utilize to calibrate our model.

3. Data and variables

We use an eight and one-quarter year data set (1984–1992) of scanner panel and store environment data to calibrate the model. The data and managerial input for this study were provided by a major consumer packaged goods company and IRI. Although we cannot reveal the category due to confidentiality, we note that it is a non-food product, similar to soaps. The category consists of eight major brands with four sizes and various levels of mildness. A ninth brand was created by combining all remaining small brands. There is a great deal of switching among sizes; the two medium sizes represent about 3/4 market share and the smallest and largest account for about 1/8 each.

Brands 1–5 are large, higher quality, nationally known brands, brands 7 and 8 are less well known national brands and brand 9 is a compilation of all other brands, primarily private label and generic brands. Brand 8 is known for its ‘harshness’ while brands 2, 3 and 6 are known for their ‘mildness’ and white ‘color’. Brands 6, 7 and 9 are the least expensive (and lower quality) brands. Brand 7 also has a relatively high repeat purchase rate indicating it may, to a degree, be a niche brand.

The category has a median interpurchase time of 6 weeks and a mean interpurchase time of 12 weeks. The data incorporate the activity of 1590 panelists who purchased this category at least once every six months. In total there were 54,731 purchases. The use of the same 1590 panelists throughout the duration of the data enables us to accurately measure the panelists’ exposure to promotions and advertising. The demographics of the panel match closely the demographics of the United States, except that our panel had slightly higher incomes. About 92% of households purchased more than one brand during the duration of this study. In addition to the panel and store data, quarterly advertising expenditures for the market are available. The market consists of one medium size Midwestern city comprised of eleven stores. Within this product category there were no brand entries or exits during the time frame studied.

3.1. Short-term variables for step 1

As noted in Section 2, step 1 of our analysis generates cross price response matrices which become an input for steps 2 and 3. The short-term variables used in Eqs. (1) and (2) in Section 2.2 include price, temporary price reduction, feature, display, coupon and loyalty. The variables were operationalized as follows: price as the minimum price across brand sizes; feature and display as a 0/1 variable which assumed the value of 1 when any brand size was on feature; coupon as a 0/1 variable indicating whether mean redemptions for a brand exceeded one standard deviation above the mean level of redemptions for that brand and loyalty as a brand's share of the last four purchases [7]. The operationalization of the variables follows precisely those of Mela et al. (1997). As indicated earlier, the quarterly cross price response matrices were then generated by using the respective quarterly parameter estimates to simulate the changes in brand shares with respect to a unit change in brand prices.

3.2. Long-term variables for steps 4 and 5

Steps 2 and 3 provide the brand distinctiveness measures and the dynamic competitive maps that are related to long-term marketing activity in steps 4 and 5. To relate these measures and maps to long-term marketing activity, we first need to operationalize long-term variables that capture brands' attributes and marketing policy. The long-term variables included in our analysis are quarterly measures of advertising, price oriented promotions, non-price oriented promotions, disposable income, quality, and mildness. We note that the quarterly operationalization of the long-term variables does not mean their effects last one quarter. The duration of the effect is dependent upon the estimate for the lag term in Eq. (5).

3.2.1. Long-term advertising

Advertising is operationalized as a brand's quarterly, regional advertising spending (mostly television), obtained from the firm's advertising agency and deflated using the CPI. We assumed that increases in advertising spending in the market correlate with increases in households' exposure to advertising. This assumption is not without limitations; not all households see all advertisements. We note that this assumption has face validity and has previously been made by Boulding et al. (1994) and others.

3.2.2. Long-term promotions (price oriented and non-price oriented)

We accommodated the potentially different effects of promotions for two reasons. First, there is no reason to suspect that all promotions are intended to act as short-term financial incentives that are therefore 'bad' for brands [8]. In fact, certain promotions (e.g. frequent buyer programs) can be brand building (Blattberg and Neslin, 1989). Many non-price oriented promotions fall into this category. For example, displays, which often have a substantial advertising content, may be less likely to be perceived as a price oriented promotion, especially by low need for cognition individuals (Inman et al., 1990). Conversely, promotions such as coupons and temporary price reductions are always accompanied by price reductions and are therefore less likely to be image-building. We note that features are also usually accompanied by prominent pricing information and may also be thought of as a price oriented promotion.

We began by creating quarterly measures of coupons, feature, display and temporary price reduction. These were formed as frequency variables. Specifically, the quarterly feature, quarterly temporary price reduction, quarterly coupon and quarterly display variables were formed by calculating the percent of all store-weeks in a given quarter that a brand was on feature, temporary price reduction, coupon [9] and display, respectively. We then created the long-term (quarterly) *price promotion* (presumably brand deprecating) variable by averaging the quarterly coupon, quarterly temporary price reduc-

[7] The first two quarters were used to initialize the loyalty variable. As we had no advertising data for the last of the 33 quarters, we ultimately had 30 quarters of data to analyze.

[8] We are grateful to an anonymous reviewer for making this distinction and motivating the following discussion.

[9] Household's coupon exposure may be greater than our measure suggests. For example, consumers may have coupons in their possession that have not yet been redeemed. In this case, coupon redemptions may understate coupon exposure. To the extent that our measure underrepresents the effects of couponing, its use provides a conservative test of coupons' long-term effects and should bias our findings toward null results.

Table 3
Mean marketing activity (1984–1992)

	Brand 1	Brand 2	Brand 3	Brand 4	Brand 5	Brand 6	Brand 7	Brand 8	Brand 9
Feature[a]	0.051	0.034	0.022	0.031	0.020	0.010	0.002	0.009	0.010
Display[a]	0.098	0.150	0.065	0.124	0.065	0.023	0.010	0.018	0.036
TPR[a]	0.243	0.207	0.168	0.182	0.130	0.067	0.040	0.114	0.152
Price[b]	0.052	0.052	0.054	0.050	0.056	0.049	0.031	0.052	0.025
Advertising[c]	48.20	21.54	35.98	20.61	24.37	0.00	0.00	0.00	0.00
Quality[d]	1.50	1.50	1.40	1.50	1.40	0.82	0.17	1.33	0.00
Mildness	neutral	moderate	high	neutral	neutral	high	neutral	low	neutral
Market Share[e]	34.45	12.0	13.7	10.3	7.1	6.9	3.4	2.2	9.9

[a] Mean store weeks a given quarter with brand on deal divided by total store weeks.
[b] Mean brand price per ounce in dollars.
[c] Mean quarterly brand advertising in thousands of dollars.
[d] Consumer reports brand quality rating (zero is lowest quality).
[e] Mean quarterly brand share in percent.

tion, and quarterly feature variables. The long-term (quarterly) *non-price promotion* (presumably brand building) variable was then created from the quarterly display variable.

Last, similar to advertising, we assumed that there exists a correlation between promotional activity by retailers and a household's exposure to these promotions. This assumption also has face validity and is consistent with that made by Boulding et al. (1994).

3.2.3. Disposable income

In addition to the lag term, we controlled for economic effects via the inclusion of a quarterly household disposable income variable since spending power might impact the set of brands that a household considers. We chose to use this variable as a control for economic activity because it directly reflects the spending power of the household. Broader measures such as the GDP encompass additional economic activity that may be less directly related to household purchase behavior.

3.2.4. Quality and mildness

Quality ratings were obtained from *consumer reports*. The quality measure was scaled such that zero represents the lowest rated quality. The perceived mildness ratings were subjectively evaluated by the sponsoring organization.

Table 3 presents information regarding brand attributes and the quarterly marketing policies (the average of the quarterly prices in Table 3 was formed by using brands' mean quarterly prices across stores and weeks). The mean marketing activity reported in Table 3 represents the average levels of the quarterly variables over the entire quarterly data series.

3.2.5. Category level measures for step 5

As the dimension weights obtained in Section 2.4 are category level measures, the marketing activity posited to affect them is also at the category level (see Eq. (6)). We therefore created quarterly category level long-term variables by computing quarterly market share weighted averages of the brand level variables (price promotion, non-price promotion and advertising). Table 4 provides insight into category level advertising and price promotion activity across the duration of the data. In this category, total advertising spending decreases over time and

Table 4
Mean category marketing activity over time

	1984	1991
Non-price promotion[a]	0.02	0.11
Price promotion[a]	0.04	0.16
Price ($/ounce)[b]	0.049	0.052
Advertising[c]	295.5	64.5

[a] Mean store weeks in a given year with brand on deal divided by total store weeks.
[b] Mean brand price per ounce in dollars.
[c] Mean quarterly brand advertising in thousands of dollars.

Table 5
Mean cross price response (1984–1992)

	Brand 1	Brand 2	Brand 3	Brand 4	Brand 5	Brand 6	Brand 7	Brand 8	Brand 9
Brand 1	−2.30	0.41	0.35	0.40	0.24	0.25	0.06	0.09	0.31
Brand 2	0.44	−1.25	0.16	0.21	0.11	0.13	0.03	0.04	0.16
Brand 3	0.37	0.16	−1.09	0.15	0.10	0.11	0.03	0.04	0.14
Brand 4	0.43	0.21	0.15	−1.22	0.11	0.12	0.03	0.04	0.15
Brand 5	0.27	0.11	0.11	0.11	−0.77	0.07	0.02	0.03	0.10
Brand 6	0.27	0.13	0.11	0.12	0.06	−0.85	0.02	0.03	0.12
Brand 7	0.07	0.03	0.04	0.03	0.02	0.02	−0.24	0.01	0.03
Brand 8	0.11	0.04	0.04	0.04	0.03	0.03	0.01	−0.31	0.04
Brand 9	0.34	0.16	0.14	0.15	0.09	0.11	0.03	0.04	−1.04

Entries to be read change in share of row brand with unit change in price of column brand.

the average percent of time brands are promoted is increasing.

4. Results and discussion

4.1. Step 1: Obtaining cross price response matrices

Step 1 yields a quarterly series of cross price response matrices which become the input for step 2. Table 5 portrays the *mean* of the thirty quarterly cross price response estimates (see footnote 7).

We note that the cross price response matrix in Table 5 is fairly symmetric. This matrix corresponds to the core matrix in Russell et al. (1993). They show the core matrix to be more symmetric than cross price elasticity matrices due to the scaling artifacts inherent in cross price elasticities (which we wish to avoid). Therefore, our use of cross price response matrices rather than elasticities results in much smaller asymmetries and therefore lesser disparities in brand distinctiveness measures. As a result, the differences in brand distinctiveness that we obtain will be smaller than those of Russell (1992) and Russell and Kamakura (1994) who use price elasticities.

4.2. Step 2: Obtaining brand distinctiveness and substitutability measures

The LSES model decomposition provides a good representation of the cross price response matrices as the mean residual matrix, ***R***, across all quarters is close to identity (see Table 6).

Further, the average value of the fitting function which minimizes the differences between observed and estimated cross price responses is less than 0.0001, indicating a good fit (Russell, 1992).

The LSES model estimates brand distinctiveness and brand substitutability for each quarter. The *means* of these quarterly series are provided in Table 7. Due to the symmetry of the cross price response matrices,

Table 6
Average residual (***R***) matrix (1984–1992)

	Brand 1	Brand 2	Brand 3	Brand 4	Brand 5	Brand 6	Brand 7	Brand 8	Brand 9
Brand 1	0.97	0.02	0.00	−0.03	0.00	−0.01	0.01	−0.01	0.00
Brand 2	0.03	0.91	0.03	0.03	0.01	−0.01	0.02	0.01	−0.01
Brand 3	0.00	0.02	0.95	0.00	0.00	−0.01	0.02	0.00	0.00
Brand 4	−0.02	0.02	0.01	0.92	0.03	0.01	0.01	−0.02	0.00
Brand 5	0.01	0.00	−0.01	0.02	0.94	−0.01	0.02	−0.01	−0.01
Brand 6	0.00	−0.02	−0.01	0.01	−0.01	0.97	0.05	0.00	−0.01
Brand 7	0.02	0.02	0.03	0.02	0.02	0.05	0.78	0.03	0.03
Brand 8	0.01	0.01	0.00	0.02	0.02	0.01	0.04	0.92	0.01
Brand 9	0.00	−0.01	0.00	0.00	−0.01	−0.01	0.02	0.01	0.99

Identity matrix implies good fit.

Table 7
Mean brand distinctiveness and brand substitutability matrix (1984–1992)

	Brand 1	Brand 2	Brand 3	Brand 4	Brand 5	Brand 6	Brand 7	Brand 8	Brand 9
Brand substitutability									
Brand 1	−21.24	3.90	3.19	3.94	2.30	2.37	0.56	0.93	2.89
Brand 2	3.90	−10.60	1.44	1.81	1.05	1.30	0.24	0.37	1.43
Brand 3	3.19	1.44	−8.80	1.23	0.93	1.01	0.25	0.32	1.17
Brand 4	3.94	1.81	1.23	−9.61	0.89	1.01	0.20	0.41	1.27
Brand 5	2.30	1.05	0.93	0.89	−6.25	0.62	0.17	0.29	0.85
Brand 6	2.37	1.30	1.01	1.01	0.62	−6.89	0.15	0.25	1.03
Brand 7	0.56	0.24	0.25	0.20	0.17	0.15	−1.21	0.09	0.23
Brand 8	0.93	0.37	0.32	0.41	0.29	0.25	0.09	−2.17	0.32
Brand 9	2.89	1.43	1.17	1.27	0.85	1.03	0.23	0.32	−8.69
Brand distinctiveness									
	0.1184	0.1126	0.1116	0.1121	0.1086	0.1105	0.1109	0.1044	0.1109

The brand distinctiveness terms must be normalized to sum to one in order for the model to be identified (Russell, 1992).

the brand distinctiveness estimates in Table 7 do not show dramatic differences across brands. However, the *average* brand distinctiveness estimates obscure some interesting dynamics. For example, regressions of brand distinctiveness on time indicate that four of the nine brands have had statistically significant ($p < 0.05$) changes in brand distinctiveness over time. We further investigate the impact of advertising and promotions on these changes in step 4.

4.3. Step 3: Developing a dynamic map of market structure

Using the series of quarterly brand substitutability matrices as input, we derived multi-dimensional brand maps using the INDSCAL procedure. The squared correlation between the input data and the estimated brand distances were 0.76, 0.90 and 0.96 for the one-, two- and three-dimension solution, respectively. The three dimensional solution provided a marginal increase in fit over the two dimensional solution but failed to provide additional insights in spite of the added complexity. Therefore, we chose a two-dimensional map to represent brand substitutability in this product category. Fig. 2 portrays the derived two dimensional map of brand positions.

Based upon the brand characteristics, we label the two dimensions as mild and premium, respectively. Brand positions along the mild dimension correlated the highest with the mildness attribute (0.51). Brand positions along the premium dimension correlated highly with consumer reports quality ratings (0.73) and correlated with higher price (0.58). These results are consistent with previous studies which suggest that analyses of competitive structure may include attribute based submarkets (e.g. Grover and Srinivasan, 1987; Allenby, 1989) and high price/quality based submarkets (Blattberg and Wisniewski, 1989). Our research uncovers both partitionings in this

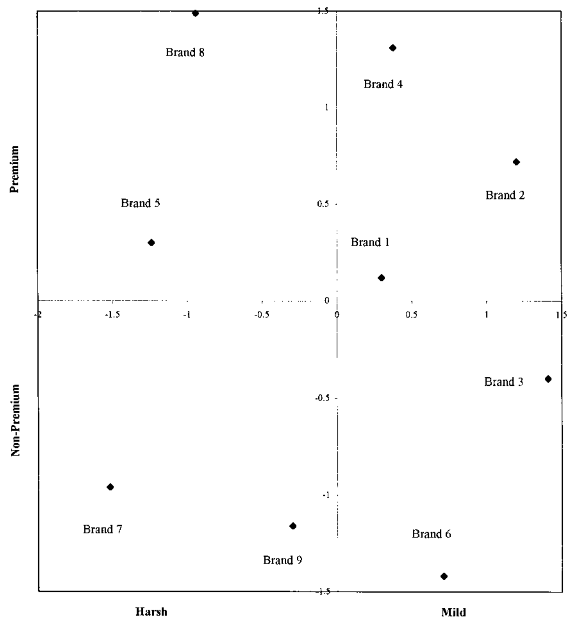

Fig. 2. Brand positions (x).

product category. Overall, the interpretation of the brand space appears to align with objective information as well as the managers' expectations.

It is also possible to portray the changes in brand positions on a map. Since the distance between two brands along a given dimension is given by $d_{ijmq} = \sqrt{w_{mq}(x_{im} - x_{jm})^2}$, we can compute brand i's coordinate along dimension m in period q by $d_{i0mq} = \sqrt{w_{mq}}\, x_{im}$. Fig. 3 presents such a map for two periods and two brands. Only two brands and two periods are plotted in order to keep the map from becoming cluttered (similar insights were obtained by plotting other brand pairs or periods).

We plot the market leader (brand 1) and the off-price, low quality brand (brand 7). Fig. 3 highlights the finding that, from 1984 to 1991, premium and off-price brands have moved closer together.

The map in Fig. 3 underscores the point that brand substitutability is changing. To formalize this result we regressed the dimension weights on time. The regressions yield some interesting results. The weight of the mild dimension (mean $= 4.81$) decreases by 0.0096 ($t = -2.50$, $p < 0.05$) per quarter and the weight of the premium dimension (mean $=$ 4.69) decreases by 0.0232 ($t = -4.72$, $p < 0.001$) per quarter. Thus, brand substitutability has increased over the eight year duration of this data suggesting that premium and non-premium brands are becoming more substitutable. Similarly, mild and harsh brands are perceived as being more substitutable. This suggests that, in the eyes of consumers, extrinsic cues such as price are becomingly increasingly important relative to intrinsic cues such as mildness. However, the substitutability along the premium dimension has decreased at over twice the rate of the decrease along the mild dimension. Next, we assess the impact of long-term shifts in advertising and promotions on these changes in market structure.

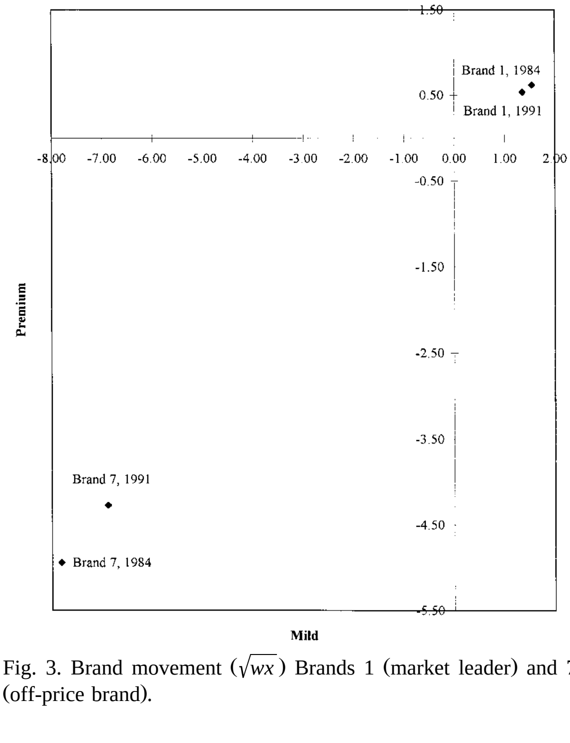

Fig. 3. Brand movement ($\sqrt{wx}$) Brands 1 (market leader) and 7 (off-price brand).

4.4. Steps 4 and 5: Assessing the long-term impact of promotions and advertising on brand distinctiveness and substitutability

In Table 8 we present (i) the long-term effect of brand level marketing activity on the brand distinctiveness measures obtained in step 2 and (ii) the long-term effect of category level marketing activity on dimension weights obtained in step 3. To conserve space, we report the parameter means of the 9 brand distinctiveness regressions. For the same reason, the reported significance levels are based on pooled Fisher tests of the 9 regression parameters. Our a priori expectations (discussed below) for the results are also reported in Table 8.

In addition to controlling for omitted variable effects via the use of the lagged dependent variable (Jacobson, 1990) [10], we included disposable income in our analysis. We find that this control variable has little effect on brand distinctiveness in this category. Finally, using the Johnston (1984) test for equal lags, we could not reject a null hypothesis of equal lag parameters in any of the three regressions. The lag term for the premium dimension weight is highly significant indicating a highly enduring effect of

[10] Our estimation model is equivalent to the state dependency, or persistence model (Jacobson, 1990). Jacobson (1990) notes that this model is a popular means for controlling for unobservable effects.

Table 8
The long-term impact of promotions and advertising on market structure

Variable	Brand distinctiveness[a], c_{it}	Weights along mild dimension[b], w_{1t}	Weights along premium dimension, w_{2t}
Hypothesized effect			
Advertising	increase	increase	increase
Price promotion	decrease	decrease	decrease
Non-price promotion	increase	increase	increase
Disposable income	control variable	control variable	control variable
Estimated values			
Lag	0.0017	0.27	0.70^{**}
Advertising	0.00014^{*}	0.0045^{*}	0.0060^{*}
Price promotion	-0.17^{**}	-0.21	0.23
Non-price promotion	0.10	0.04	0.37
Disposable income	0.00025	-0.0004	-0.0002
R^2	0.35	0.61	0.82

[a] Brand distinctiveness regressions are mean estimates across brand level regressions. Overall significance of pooled results are obtained using Fisher's pooling test. R^2 is mean R^2 across brand level regressions.
[b] Increasing weights represent increased distance in the brand space. Therefore a positive sign indicates increased distance and therefore lower substitutability.
$^{*}p < 0.05$.
$^{**}p < 0.01$.

marketing activity on consumers' perceptions of brands along this dimension. We shall now detail our findings with respect to each of the variables hypothesized to impact competitive structure.

4.4.1. Advertising

Prior to hypothesizing the effect of advertising on market structure, it is important to differentiate between price oriented and non-price oriented advertising. Kaul and Wittink (1995) and Boulding et al. (1994) argue that price oriented advertising is likely to increase consumers' emphasis on price while non-price oriented advertising is likely to decrease the emphasis on price (especially in mature product categories (Mitra and Lynch, 1995)). According to the sponsoring firm, our advertising data are national brand advertising comprised largely of non-price oriented brand differentiating messages. We therefore expect reductions in advertising to both reduce a brand's distinctiveness and lead to a lesser partitioning of brands [11].

Advertising has diminished dramatically over the duration of the data with the advertising expenditures of the leading brands declining from $442,000 in this market in Q2, 1984 to $44,000 in Q2, 1991, a decrease of some 90%. Since the advertising of national brands we analyzed conveyed a message of quality, the higher levels of national advertising in the early to mid 1980's may have helped to reduce the likelihood that lower quality, non-advertising brands serve as substitutes for premium brands. Consistent with our expectations, our results suggest that reductions in advertising did have this effect. Table 8 shows that advertising significantly increases the mild and premium dimension weights in the brand substitutability map. As dimension weights and substitutability are inversely related, this result implies that reductions in advertising made brands more substitutable (closer) on both the premium and mild dimensions. Decreases in national advertising spending has therefore affected brand positions by making brands more substitutable and by reducing their brand distinctiveness.

4.4.2. Price promotions

Unlike increases in advertising, we suspect that increases in price promotions are likely to reduce brand distinctiveness in the long run. Several cognitive mechanisms may underlie the specific long-term effect of price dealing on market structure and brand distinctiveness. First, price dealing leads to lower

[11] It is also possible for changes in advertising message to affect substitutability and distinctiveness. In our data, category managers felt there were no such repositionings during the years of analysis.

reference prices. Both the price-quality literature (Curry and Reisz, 1988) and object-perception theory suggest a linkage between lower perceived prices and lower perceived quality. Second, self-perception theory (Dodson et al., 1978) also predicts that price promotions reduce the distinctiveness of premium brands as households ascribe their perceived purchase motivation to the deal rather than the intrinsic attributes of the brand (Blattberg and Neslin, 1989). Thus, deals cause brands to be increasingly seen as commodities purchased on price, with their distinctiveness subsequently diminished. Econometrically, several studies supported the hypothesis that increases in price promotional spending can affect brand positions by making consumers more price sensitive (Boulding et al., 1994; Papatla and Krishnamurthi, 1996; Mela et al., 1997).

Consistent with our hypotheses, our results indicate that an increase in the long-term price promotion variable has an opposite long-term effect to that of advertising. As shown in Table 8, price promotions decrease brand distinctiveness over the long run. This finding implies that price may be becoming a more salient attribute for brands attempting to attract consumers from other brands. The increase in salience of the price cue may actually result in further increases in dealing on the part of brand managers, resulting in yet less distinctiveness and more dealing in the future. In other words, price promotions may show substantial short-term gains while hurting the brand in the long run. Discussions with brand managers echo our result that they cannot seem to escape this trap. The increased relative importance of price for brands suggests the declining importance of many of the other standard quality cues that are often associated with brands (e.g. packaging, advertising, mildness and quality), to the benefit of non-premium brands and to the detriment of higher quality brands.

4.4.3. Non-price promotions

Conversely, brand building promotions (such as loyalty rewards) may actually help brands maintain their competitive edge. For example, Gedenk and Neslin (1997) find that product sampling has positive ramification for brand loyalty. To the extent non-price oriented promotions contain brand message and serve to build brand awareness in the absence of any pricing cues, we expect non-price activity to function more like advertising than price cutting.

However, we find that none of the effects for the long-term non-price promotion variable are significant. We do note, however, that the signs are all consistent with the advertising effect as hypothesized. Nonetheless, we conclude that non-price promotions serve neither to increase nor reduce brand distinctiveness or to change the overall pattern of brand substitutability. As displays typically contain less brand quality information than national advertising we speculate that this result may have risen from the less persuasive nature of this marketing mechanism.

4.5. Managerial implications

As noted in Section 1, market structure has a number of managerial implications for brand strategy, marketing tactics and the behavior of the marketing channel.

4.5.1. Strategic implications

As the differential advantage of brands has eroded, competitive barriers have been removed and brands within partitions have become increasingly vulnerable to attack from brands in other market partitions. For example, in our market, both premium and mild submarkets of brands should be considering low price, low quality brands a greater threat than they had been in the past. Recognizing threats early is one of the key steps in pre-empting competitive battles. The maps produced by our analysis can be an effective tool in this area.

Second, category planners with multiple brands need to make decisions regarding the allocation of marketing resources across brands. Redundant brands can waste resources as well as cannibalize one another's sales. Therefore product line managers need to be aware how their brands compete with one another and whether this unintended competition is engendered by their tactical decisions regarding advertising and sales promotions. As brands become less differentiated, managers may wish to replace them with better differentiated, perhaps higher price alternatives.

Third, the procedure we have developed can provide a useful diagnostic for managers wishing to assess the overall health of their brands. Increased differentiation or loyalty can be desirable for a brand and our procedure provides a dynamic view of these factors. Should management keep longer term records of brands, such information can be used to assess brand managers themselves. A long-term perspective considers that positive short-term gains arising from dealing can be weighed against the deleterious longer term effects of deals.

Last, the resulting maps of brand movement not only have the ability to confirm managerial judgment about what has historically occurred in the market place, but also afford managers the ability to extrapolate trends into the future, enabling them to know what changes are occurring and how quickly they are likely to occur. The ability to make such projections is instrumental in category planning.

4.5.2. Tactical implications

Profits depend, in part, upon a brand's differentiatial advantage over other brands in the market. As distinctiveness decreases and substitutability increases, it becomes exceedingly difficult to raise prices. Oddly, models correlating market share to promotions may not observe such changes; if all brands simultaneously increase their discounting over the years, their shares may remain relatively constant even in the face of this increase.

Our analysis shows that decreases in advertising and increases in price promotions have affected brand abilities to successfully differentiate themselves and thereby command higher margins. However, retraction of deals at this point appears problematic given consumers have become conditioned to react to them in this market. Introductions of new, non-discounted differentiated brands (as currently is occurring in frozen pizzas and other categories) into heavily discounted categories may help. Further, the benefit of increased advertising may offset the harmful effect of deal retractions in the long run.

4.5.3. Channel implications

Retailers face at least two strategic concerns impacted by market structure. The first concern lies in the growing importance of store brands to retailers trying to maintain their profit margins. Retailers desire to know whether their brands are effective at siphoning demands from manufacturers' brands. The decrease in brand distinctiveness arising from the use of price promotions helps store brands to compete with national brands, raise their prices without a significant change in share and enhance store profits. Such a conflict between the desires of retailers and manufacturers should further trouble manufacturers when retailers demand trade promotions; the resultant price cuts at the retail level exacerbate the weakness in the manufacturers' competitive posture relative to the stores' brands.

The second concern pertains to the sizable increase in the number of brands vying for their limited shelf space (Messinger and Narasimhan, 1995). Like manufacturers, retailers may wish to avoid redundancy and increase efficiency by paring down their SKUs. By knowing which brands are more similar they can make better informed decisions about which items to eliminate.

4.5.4. Analytical implications

In addition, we sought to present a means of reviewing longitudinal competition and of analyzing asymmetric data. Toward that end we extended the Russell (1992) LSES approach to estimate changes in competition over time. The method allows managers to infer market partitions and to accommodate changes in brand positions over time. The data reduction resulting from this technique further benefits brand managers by reducing a long series of large cross price response matrices into a coherent pattern. This reduction can be impressive. We began with a set of 30 quarters of $9*9$ cross price response matrices and a set of 30 quarters of 4 independent variables, a total of 2,430 numbers for a brand manager to analyze. We ended with 12 parameters to review. In the process this approach has accommodated heterogeneity, dynamic and asymmetric competition and disentangled long and short-term effects. Moreover, there is no need for managers to pre-specify competitive partitions or dimensions: the data determine the partitions.

5. Conclusions and future research

In this paper we sought to answer several questions regarding long-term changes in competitive structure. First, we ascertained if the competitive gap between premium and non-premium brands exists. Our map of brand substitutability indicates that such a partition does exist and that a partition based upon intrinsic product characteristics exists as well. Second, we sought to answer whether market structure changes over long periods of time. Results of regressions of brand distinctiveness and brand substitutability on time indicate that market structure is changing over time in this category and that premium brands are losing their differential advantage. It appears that, over the long run, reductions in advertising have induced a decrease in the favorable positioning held by premium brands. Concurrently, increases in price promotions have reduced brands' distinctiveness over the years. As price promotions primarily impact brand distinctiveness, we suggest that deals decrease the loyalty and increase the price sensitivity of the promoting brand more than they affect other brands. Last, our approach also addressed ancillary questions such as (i) which brands provide the greatest threats to managers and how those threats change over time and (ii) what other market partitions (other than premium) exist and how do the partitions change over time.

In order to obtain these insights, we developed a reliable and parsimonious model of dynamic market structure that allows for competitive asymmetry and generates a dynamic competitive map. We feel this approach can easily be applied to any case where asymmetric matrices are to be analyzed over time (such as perceived similarity judgment matrices).

Our findings have several ramifications for managers. First, an unintended consequence of their dealing has been greater competition from off-price and store brands. Subsequent strategic planning should consider these threats. Our competitive maps provide rich managerial insights into which brands are emerging as threats and how those threats change over time. Second, managers have made it difficult to extricate themselves from increasingly competitive markets. To increase their brand's distinctiveness and reduce its substitutability, managers may wish to consider new brand introductions supplemented with advertising. Third, retailers benefit from the increased substitutability of their products in categories with frequent discounting. Therefore, retailers would be well advised to consider this point when cooperating with manufacturers in initiatives such as EDLP and efficient consumer response. Finally, we argue that tracking shifts in brand performance over years, instead of quarters is a better measure of brand manager performance, short-term gains from discounting may be offset by deleterious long-term effects in market behavior. While collectively these implications are straightforward, our analysis is among the first to offer empirical substantiation of these speculations.

5.1. Limitations

One limitation of this study is its correlational nature. We cannot make definitive claims regarding the exogeneity of the various promotional and advertising effects. Although other studies of long-term effects (Boulding et al., 1994; Dekimpe and Hanssens, 1995a,b) have also assumed that marketing activity leads to response rather than the reverse direction, we have attempted to control for concerns regarding exogeneity. First, we can make a case for the temporal precedence of the independent variables. The independent variables measure past marketing activity up to the current period. The dependent variable is measured in the current period. It is not conceptually likely that current periods of structure impact past advertising. Second, we sought to control for omitted variable bias by incorporating a macroeconomic variable (disposable personal income) and a lagged dependent variable in the regressors. Third, we ran simultaneous equation causal tests. We modeled (i) brand distinctiveness on lagged brand distinctiveness and marketing activity and (ii) marketing activity on lagged marketing activity and brand distinctiveness. The linear simultaneous system of equations was estimated via two stage least squares for each brand and then pooled via Fisher's procedure. A similar system of equations was estimated for the dimension weights. The results suggest that the effects we found are cyclical; not only does activity impact structure, but structure impacts activity. The causal test result has two key implications. First, based upon the forgoing procedure, one cannot rule out the possibility that marketing activity affects market structure. Second, brands' shifts to dealing have led to a 'vicious cycle'. As dealing reduces brand distinctiveness managers may be forced to rely more upon dealing. The dealing would, in turn, reduce differentiation. The cycle could then repeat itself, leading to a highly price sensitive and undifferentiated market. An additional limitation in our manuscript arises from our results being based upon one product category in one geographical market over one (albeit long) interval. Such a limitation is not unique to this study (see also Inman and McAlister, 1994; Russell and Kamakura, 1994; Elrod and Keane, 1995) and is partly due to the difficulty in obtaining multiple data sets.

5.2. Extensions

Our analysis provides one of the first tests of protracted changes in market structure arising from a budgetary shift from advertising to promotions. We feel that replicating and extending this study across categories may yield important insights. As we feel the research into the long-term effects of promotions is fairly new, there are a number of additional issues yet to research. For example, how does the shift affect brand equity? Are brands less likely to be chosen by households as a result of this shift? Are consumers changing their primary demand? Are they buying less, more often? If these changes exist, what are the underlying cognitive mechanisms that affect them? Given an understanding of the long-term effects, how are optimal levels of advertising and promotional spending affected? Is competitive response to marketing activity affected in the long run? With enormous expenditures of consumer packaged goods firms in these areas and the considerable concern of brand managers regarding these effects, we hope our analyses will inspire further exploration into some of these issues regarding the long-term effects of advertising and promotions.

Acknowledgements

The authors would like to thank two anonymous IJRM reviewers and the editor for their helpful comments. The authors would also like to thank Information Resources and an anonymous consumer packaged goods corporation for providing the data.

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