THE IMPACT OF COMPETITIVE CONTEXT ON THE ALLOCATION OF MARKETING MIX RESOURCES

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Abstract

While evidence exists that the efficiency of marketing instruments changes over time, there have been few attempts to develop and test theory as to the causes of these changes. In this study, we investigate differences in the effectiveness of a brand's marketing mix decision variables over time that may be caused by changes in competitive context due to brand entry, brand exit, and/or changes in feature offerings of brands. We test for asymmetries in market response over time due to differences in competitive context using data from two durables categories. A market share attraction model is developed where the parameters vary as a function of competitive context and of non-observable effects. Hence, we generalize varying parameter models to attraction models. Results show that competitive context is an important source of variation in elasticities over time, with evidence that the greater the competitive density, the greater the market share sensitivity to price and distribution, and the smaller advertising effectiveness, *ceteris paribus*. Consequently, these results offer an explanation as to why managers should adopt different allocations of resources across marketing mix instruments over time.

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Introduction

Understanding how marketing mix elasticities vary with market conditions is an essential ingredient in developing successful marketing strategies (Russell and Bolton 1988). For example, Parker (1992a) derives the optimal price of an innovation over time under different patterns of price elasticity dynamics. A better understanding of why elasticities vary can help managers to predict which marketing mix instruments are most effective. Indeed, a change in elasticity may suggest a reallocation of marketing mix resources (Dorfman and Steiner 1954). Hence, the ability to predict changes in elasticity caused by changes in market conditions can improve the planning of a firm's own marketing actions, and can facilitate a speedier response to the actions of competitors.

While there have been attempts to study and document changes in price elasticity (Hackl and Westlund 1996, Parker 1992b, Liu and Hanssens 1981, Simon 1979) and advertising elasticity (Arora 1979, Parsons 1975) over time, there is little theory as to the causes of these changes (Gatignon and Robertson 1991). In this paper, we examine a plausible explanation for why the effectiveness of a brand's marketing mix efforts vary over time. Over time, new brands may enter a market, others may exit, and existing brands may be modified causing changes in the relative positioning of competitors. Our goal is to test whether changes in competitive context explain differences in the effectiveness of marketing instruments over time. Following Huber, Holbrook and Kahn (1986), we define competitive context as the relative position of a brand in comparison to those with which it competes.

The paper proceeds as follows. In the next section, we briefly describe marketing theory which suggests that managers vary the allocation of resources across marketing mix instruments over time. We then elaborate on our basic premise that competitive context influences the effectiveness of marketing instruments. We develop a model to test our hypotheses where the effectiveness of a marketing mix instrument is allowed to systematically vary with the competitive context for a brand. The model is based on the market share attraction model (multiplicative competitive interaction) which

has been used previously in the literature to model sources of asymmetries and to explore their strategic implications (Bowman and Gatignon 1996, Carpenter, *et al.* 1988, Cooper and Nakanishi 1988). Hence, we generalize varying parameter models to attraction models. Following the model development, we discuss our data and then present the results of our empirical analysis. We conclude with a discussion of the implications of our findings and suggest some directions for future research.

Changes in Marketing Mix Elasticities Over Time: Theory and Evidence

In a general discussion of marketing decision variables, Parsons (1975 p.476) states that "[I]n general, the absolute magnitudes of these elasticities exhibit a nonlinear decline over time". Parson's study, like this one, focuses on the **systematic** changes in marketing elasticities over time. He goes on to argue that different starting points and differential rates of decline over time mean that the relative importance of each marketing decision variable changes over time.

The dominant framework used to explain changes in elasticities over time is the product life cycle (Lilien and Yoon 1988, Parsons 1975, Mickwitz 1959). Advertising elasticity for example is thought to be highest during introduction due to the need to create awareness (Mahajan, Bretschneider, and Bradford 1980) and during growth because of its role in encouraging repurchase (Parsons 1975). Advertising elasticities would then be lowest during the later stages of the life cycle, i.e., the maturity stage (Tellis and Fornell 1988). Conversely, price elasticity is thought to be highest during this maturity stage, although it may decrease in the decline stage (Mickwitz 1959). Parsons (1975) provides the rationale that new customers come only from price conscious segments at maturity and customers become insensitive to price changes.

While a number of hypothesized trends in elasticity have been suggested over the years, empirical evidence that supports or contradicts these conjectures is limited. Hanssens, Parsons and Schultz (1990) observe that empirical evidence on changes in the efficiency of various marketing instruments at different stages of the product life cycle is sparse. After reviewing the literature on the dynamic behavior of price elasticity, Lilien, Kotler, and Moorthy (1992 p.196) conclude, "while we

should expect significant variations in elasticity over the product life cycle, the direction and magnitude of those variations have not been definitively determined by research to date."

By allowing response parameters to vary over time, researchers have sought to provide empirical evidence that assuming a stable response is too restrictive, and have attempted to characterize the direction of marketing mix elasticity changes over time. Table 1 summarizes studies that provide evidence of changing price and advertising elasticity over time. Explanations associated with simple trends over time do not seem to generalize across different data sets. While the product categories analyzed display a broad spectrum, it appears difficult to distinguish any pattern, even by product category (Parker 1992b). Although some studies use category sales as the dependent variable and other studies analyze brand sales, the same inconsistency in the elasticity variation over time is observed. The majority of the studies indicate a decrease in price elasticity in the first part of the life cycle, although Liu and Hanssens (1981) find that demand for an inexpensive gift becomes more price sensitive over time. Similarly, Winer's (1979) study of the Lydia Pynkham data is not consistent with Arora's study of another pharmaceutical product (Arora 1979), although the period covered is relatively short in the latter case (22 months as opposed to 52 years for the Lydia Pynkham study). Parker and Neelamegham (1997) studied thirteen categories of consumer durables over periods ranging from 11 years to 50 years and found five different patterns of category price elasticity dynamics. The most frequent pattern was decreasing, then increasing; however, they also found patterns of no change (2 categories), strictly decreasing (3 categories), increasing, then decreasing (2 categories) and strictly increasing (1 category) elasticities.

In all the studies reviewed, the emphasis is on sales (either category sales or brand sales) rather than market share. Category sales are the most directly linked to the product life cycle and, therefore, the trends associated with the evolution of a product class (e.g., intensification of competition) should help us to understand the evolving nature of marketing mix elasticities. At the same time, a better understanding could be provided by a disaggregate analysis at the brand level (Simon 1979), as

explanations such as new product awareness development may apply differently to product category sales and to the sales of specific brands where brands introduced at a later stage of the product life cycle may exhibit a much faster awareness development process than earlier brands. This suggests that a separate analysis be made for primary demand and market share elasticities.[1] This study is concerned with the evolution of the impact of marketing mix on market share over time, in contrast with prior studies which have focused on sales (for the most part on category sales).

Another concern which arises from the literature review is that with one exception, each study focused on a single marketing mix variable over time. While it may be that for some products a single marketing mix variable dominates the way marketing is conducted, in general, the marketing literature confirms the necessity to consider marketing mix coordination.

Conceptual Development

The premise in this paper is that differences in the effects of marketing mix on market share over time are caused in large part by differences in competitive context. At any point in time, a brand's competitive context is defined by its relative positioning in an attribute space vis-à-vis the current competitors. Changes in the relative positioning of a brand therefore, may be due to i) brand entry(s) into the market, ii) brand exit(s), iii) and changes in the feature offerings of any of the available brands.

Our approach complements prior efforts to link market structure or positioning with market response estimation in order to gain insights into the dynamic behavior of markets. Moore and Winer (1987) and Winer and Moore (1989) explain market share using a measure of a brand's relative positioning. In addition to a market share response function, they define a second equation that models changes in relative positioning as being affected by marketing decision variables (price and advertising in their application):

$$\text{Share}_{it} = f(\text{relative positioning}_{it}) + u_{it}^{1}$$

$$\text{Relative positioning}_{it} = g(\text{price}_{it}, \text{advertising}_{it}) + u_{it}^{2}$$

where u_{it}^1 and u_{it}^2 represent stochastic components.

This recursive system represents the interaction between a brand's perceptual positioning and the other marketing mix variables. While we also consider these marketing decision variables as significant determinants of a brand's market share, our model considers the relative competitive structure position in terms of the physical characteristics or features of the brands available in the market in addition to the other marketing mix variables rather than as an intermediary variable. Our focus is on understanding changes in the effectiveness of the marketing decision variables over time, and especially as they may be explained by changes in a brand's relative positioning:

$$\text{Share}_{it} = f(\text{marketing decision variables}_{it}, \mu_{it})$$

$$\text{Effectiveness of marketing decision variables}_{it} = g(\text{relative positioning}_{it}, \varepsilon_{it})$$

where μ_{it} and ε_{it} represent the stochastic elements of the relationships.

Defining Competitive Context

Like Huber, Holbrook and Kahn (1986 p.250), we define competitive context as the relative position of a brand in comparison to those with which it competes. A construct which is derived from competitive context is the competitive density of a brand. The competitive density of a brand captures the extent to which substitute brands can be found in the market. Therefore, this construct represents not only the number of brands competing with a given brand (or the number of brands in the market), but also their relative positions.

It is important to note that the construct is defined relative to a specific brand as opposed to being a characteristic of the market. This is best illustrated by considering a single product dimension on which three brands may be available with three different levels. The brand with the lowest (highest) value of this unique dimension is relatively similar to the bracketed brand and relatively dissimilar to the highest (lowest) valued brand on this dimension. However, the bracketed brand is itself relatively similar to the other two brands located on each side of this unique dimension (assuming they are equidistant for ease of exposition). Therefore, the competitive density concept is specific to a brand and

not to market as a whole.

The competitive density of a brand depends on the position of that brand relative to the others. More precisely, competitive density should present the following desirable properties:

1. Holding the relative positions of existing competitors fixed in a competitive space, the measure should increase (decrease) with new brand entry (brand exit), and
2. For a fixed number of competitors, the measure should increase (decrease) as one or more competitors becomes a closer substitute (less close) in competitive space due to a change in feature offering.

Below we outline how changes in competitive context (and density) caused by changes in market conditions can explain variations in the response to marketing mix variables.

Competitive Context and Price Elasticity

Increasing competitive reactivity heightens price sensitivity (Gatignon 1984). The experimental results of Huber, Holbrook and Kahn (1986) support this view. They found that competitive context (relative positioning) moderates price sensitivity. In a forced choice experiment, they asked subjects to select one of three non-dominated brands defined by two attributes (price and quality) from each of six categories of consumer products. The experimental manipulation varied whether the experimental brand was the high price/high quality offering or whether the experimental brand was bracketed by the two other competitors. They found that estimated price elasticity was smaller (less negative) when the experimental brand was a boundary brand (high price/high quality) than when it was bracketed. Huber, Holbrook and Kahn (1986) offer two possible explanations for their finding. The first is that making a price-quality evaluation is more difficult and has less justification in the bracketed versus in the boundary condition. The second is that bracketing increases substitutability.

Normative results also support this view. Gruca *et al.* (1992) show that the optimal response to entry is to reduce price; increased rivalry among brands pushes prices down (Eliashberg and Jeuland

1986). Indeed, Parker and Gatignon (1996) find that price elasticity tends to be higher when there are more competitors. However, this result is only mildly significant and appears to vary by brand (Parker and Gatignon 1994). Furthermore, in an empirical study of eighteen brands of pharmaceutical drugs facing competition from generics, Grabowski and Vernon (1992) found that, in most cases, incumbents continued to increase their prices at the same rate as prior to the entry of a generic. Hence, the number of competitors alone may not be sufficient to explain a change in price elasticities. It should be complemented by the relative positions of the brands in the market. As mentioned, this includes both the number of competitors in the category and the relative positions of these brands.

Tellis (1988), using a product life cycle framework, also suggests that price elasticities should increase with increases in competitive context. He notes that in the early stages, few competitive substitutes exist and consumers may be ill-informed of competitive alternatives. Consequently, price elasticity should be low.

In general, brand i's price sensitivity at time t, $\beta_p(it)$, will be moderated by the brand's competitive density at that time. We suggest Hypothesis 1, that a brand's price sensitivity is an increasing function (more negative) of its density as shown below in equation **(1)**.

$$\beta_p(it) = f_p(\text{Density}_{it}) + \varepsilon_p(it) \quad ; \quad \left|\frac{\partial f_p}{\partial \text{Density}_{it}}\right| > 0 \qquad \textbf{(1)}$$

Competitive Context and Response to Quality

The characteristics of brands have often been used in econometric models of brand shares to represent the "quality" of the brands (Lambin 1970a, b). However, another dimension of product quality, prominent in the economics literature, concerns the reliability of the product (Bowman and Gatignon 1996). We refer to this last aspect when we refer to product quality and to product features otherwise.

While product quality is an important concern to consumers, its saliency depends on the competitive set or context. Product quality is evaluated relative to the features of the product which differentiate brands at a given point in time, as well as over time. As the competitive density increases

due to more brands with similar features entering the market, the saliency of product quality increases. This phenomenon could occur over the product life cycle, as competition is typically thought to be less intense in early versus mature markets (Kotler 1965). This is partly due to the fewer brand alternatives that are available. This could also follow from the fact the differentiation among brands may decrease as successful brands are imitated with new me-too brands entering the market (Schnaars 1994). Consumer learning over time about the product category and the specific brands available in the market makes consumers more focused on the differentiating product attributes, especially product quality (Sujan 1985, Maheswaran and Sternthal 1990). This results in a greater sensitivity to changes in product quality. Consequently, we suggest Hypothesis 2, that a brand's sensitivity to changes in quality is an increasing function (more positive) of its competitive density, as shown below in equation **(2)**.

$$\beta_q(\mathrm{it}) = f_q(\mathrm{Density}_{it}) + \varepsilon_q(\mathrm{it}) \quad ; \quad \left|\frac{\partial f_q}{\partial \mathrm{Density}_{it}}\right| > 0 \qquad \textbf{(2)}$$

Competitive Context and Advertising Effectiveness

As markets become crowded with competitors and/or more close substitutes emerge, it becomes increasingly difficult for a brand to have its message heard through advertising clutter (Webb and Ray 1979, Brown and Rothschild 1993). This suggests that response to advertising should be greater when competing with fewer similar brands. This is consistent with Parker and Gatignon (1996)'s finding that advertising elasticity decreases as the number of competitors increases. Therefore, we expect that the effectiveness of brand i's advertising expenditures on its market share at time t , β_a(it), should be moderated by its competitive density at that time. In particular, we propose Hypothesis 3, that advertising effectiveness on market share decreases with competitive density as shown below in equation **(3)**.

$$\beta_a(\mathrm{it}) = f_a(\mathrm{Density}_{it}) + \varepsilon_a(\mathrm{it}) \quad ; \quad \left|\frac{\partial f_a}{\partial \mathrm{Density}_{it}}\right| < 0 \qquad \textbf{(3)}$$

Competitive Context and Distribution Effectiveness

When few competitive substitutes exist, as is often the case during the early stages of the product life cycle, availability in the distribution channels is critical to developing demand. Achieving distribution provides an opportunity for consumers to check out the product and its features and to obtain information about its performance.

With many suitable alternatives however, comparison is more difficult and the role of distribution is heightened as a source of information for consumers to compare alternatives. In addition, consumers are likely to have been exposed to information about alternative brands and therefore are less willing to seek out any particular brand on their own. Consequently, distribution becomes even more critical in order to ensure that a given brand is considered by customers. Similarly, when brands are more similar, other dimensions associated with distribution such as the service that they provide becomes a differentiating factor which makes distribution more critical.

In general, we suggest Hypothesis 4, that brand i's response to distribution efforts at time t, $\beta_d(it)$, is an increasing function (more positive) of its competitive density, as shown below in equation **(4)**

$$\beta_d(it) = f_d(\text{Density}_{it}) + \varepsilon_d(it) \;\; ; \;\; \left|\frac{\partial f_d}{\partial \text{Density}_{it}}\right| > 0 \qquad \textbf{(4)}$$

Methodology

Operational Measure for Competitive Context

As indicated above, our basic premise is that changes in competitive context of a brand over time cause changes in the effectiveness of marketing mix instruments. In order to investigate this issue, we require an operational measure for a brand's competitive context which possesses the desirable characteristics described earlier.

A spatial density measure for brands in a dimensionally-organized metric space was proposed by Krumhansl (1978). This measure, introduced to the marketing literature by DeSarbo and Manrai (1992), satisfies these criteria. For k=1,..,K dimensions, the Euclidean distance between brand i and

brand j is,

$$d_{ij}^2 = \sum_{k=1}^{K} \left(X_{ik} - X_{jk}\right)^2 \tag{5}$$

The density of brand i is then defined in relation to the concentration of surrounding brands as,

$$\text{Density}(i) = \sum_{\substack{j=1 \\ j \neq i}}^{I} \frac{1}{d_{ij}^2} \tag{6}$$

where Density(i) $\in \left]0, \infty\right[$.

For fixed X_{ik} and X_{jk}, the introduction (exit) of a brand will result in a greater (lower) density for brand i satisfying the first criterion listed above. For a given set of brands organized in a metric space, any changes in the feature offerings of brand i which positions it closer to brand j will increase the density of both brands, hence satisfying the second criterion listed above. Therefore, greater competitive density is represented by larger values of the density measure in equation (6)

Model Development

The multiplicative competitive interaction (MCI) model (Nakanishi and Cooper 1974, 1982) is often used in studies of the effectiveness of marketing instruments across brands (e.g., Bowman and Gatignon 1996, Carpenter *et al.* 1988). If $Attr_{it}$ is the attraction of brand i at time t (i=1,2,..,I) and MS_{it} is its market share, then the market share of brand i is simply the ratio of the attraction of brand i to the sum of the attraction of all the competitors in the industry:

$$MS_{it} = \frac{Attr_{it}}{\sum_{j=1}^{I} Attr_{jt}} \tag{7}$$

The attraction of a brand is a function of its marketing efforts. A multiplicative form is specified for each competitor's attraction as a function of the marketing mix variables. We have identified four marketing mix variables - price (P), product quality (Q), advertising expenditures for the brand (A), and distribution outlets (D) whose effectiveness may be influenced by a brand's competitive context. When both cross-sectional and time series data are available, the market share for brand i at

time t is given by:

$$MS_{it} = \frac{e^{\beta_0(i)} P_{it}^{\beta_p(it)} Q_{it}^{\beta_q(it)} A_{it}^{\beta_a(it)} D_{it}^{\beta_d(it)} e^{\mu_{it}}}{\sum_{j=1}^{I} e^{\beta_0(j)} P_{jt}^{\beta_p(jt)} Q_{jt}^{\beta_q(jt)} A_{jt}^{\beta_a(jt)} D_{jt}^{\beta_d(jt)} e^{\mu_{jt}}} \tag{8}$$

where $\beta_0(i)$ is the constant term, $\beta_p(it)$ is the price sensitivity of brand i, $\beta_q(it)$ is the market response to quality, $\beta_a(it)$ is the advertising effectiveness of brand i, and $\beta_d(it)$ is the market response to distribution. We have hypothesized that, for a particular brand, the effectiveness of each of its marketing mix variables (k) at time t is influenced by its density.

$$\beta_k(it) = f_k(\text{Density}_{it}) + \varepsilon_k(it) \qquad \forall k \in \{p,q,a,d\} \tag{9}$$

An MCI model is a special case of a log-linear model and can be estimated using log-linear regression techniques. With appropriate dummy variables defined below, the ordinary least squares estimator is BLUE (best linear unbiased) (Cooper and Nakanishi 1988, Nakanishi and Cooper 1982). Ordinary least squares estimation assumes that the process functions are completely specified, $\varepsilon_k(it)=0$ for all k, which is a testable restriction. However, in addition to systematic variations in marketing mix sensitivities due to competitive density, some randomness of the process may exist, in part due to the lack of complete specification of the process function because of unobservable factors. Our model can be expressed as a varying parameter model with response function,

$$\ln MS_{it} = \beta_0(i) + \beta_p(it) \times \ln P_{it} + \beta_q(it) \times \ln Q_{it} + \beta_a(it) \times \ln A_{it} + \beta_d(it) \times \ln D_{it} + \sum \delta_t + \mu_{it} \tag{10}$$

where, δ_t are time specific constants.

We specify the process function with a brand specific constant to control for across brand differences, which are not related to the competitive density explanation (which varies over time). For simplicity and in the absence of theory concerning the functional form of the relationship, we assume a linear functional form for the density term as follows,

$$\beta_k(it) = \beta_{k0}(i) + \beta_{k1} \times \text{Density}_{it} + \varepsilon_k(it) \tag{11}$$

While each brand's marketing mix may have a different effect (which represents asymmetric competition as in Carpenter *et al.*, 1988), our hypotheses concern changes in these sensitivities over

time and we do not explain the basic differences across brands which arise due to, for example, order of entry (e.g., Bowman and Gatignon 1996).

Substituting the process functions into the response function yields the following model,

$$\begin{aligned}\ln MS_{it} = {} & \beta_0(i) + \beta_{p0}(i) \times \ln P_{it} + \beta_{p1} \times \ln P_{it} \times Density_{it} + \\ & \beta_{q0}(i) \times \ln Q_{it} + \beta_{q1} \times \ln Q_{it} \times Density_{it} + \\ & \beta_{a0}(i) \times \ln A_{it} + \beta_{a1} \times \ln A_{it} \times Density_{it} + \\ & \beta_{d0}(i) \times \ln D_{it} + \beta_{d1} \times \ln D_{it} \times Density_{it} + \\ & \sum \delta_t + \varepsilon_p(it) \times \ln P_{it} + \varepsilon_q(it) \times \ln Q_{it} + \varepsilon_a(it) \times \ln A_{it} + \varepsilon_d(it) \times \ln D_{it} + \mu_{it}\end{aligned} \tag{12}$$

The error structure ($V\left[\varepsilon_k(it)^2\right] = \alpha_k; \quad E\left[\varepsilon_k(it)\varepsilon_{k'}(it)\right] = 0$) suggests an heteroskedasticity specification for Equation **(12)** which models the variance as a linear function of exogenous variables. Hence, we specify the equation of interest as,

$$\begin{aligned}\ln MS_{it} = {} & \beta_0(i) + \beta_{p0}(i) \times \ln P_{it} + \beta_{p1} \times \ln P_{it} \times Density_{it} + \\ & \beta_{q0}(i) \times \ln Q_{it} + \beta_{q1} \times \ln Q_{it} \times Density_{it} + \\ & \beta_{a0}(i) \times \ln A_{it} + \beta_{a1} \times \ln A_{it} \times Density_{it} + \\ & \beta_{d0}(i) \times \ln D_{it} + \beta_{d1} \times \ln D_{it} \times Density_{it} + \\ & \sum \delta_t + e_{it} \\ = {} & X_{it}' \beta + e_{it}\end{aligned} \tag{13}$$

where

$$E\left[e_{it}\right] = 0 \quad ; \quad E\left[e_{it} e_{js}\right] = 0 \tag{14}$$

and the variances are

$$\begin{aligned}E\left[e_{it}^2\right] &= \sigma_{it}^2 \\ &= \alpha_0 + \alpha_p (\ln P_{it})^2 + \alpha_q (\ln Q_{it})^2 + \alpha_a (\ln A_{it})^2 + \alpha_d (\ln D_{it})^2 \\ &= z_{it}' \alpha\end{aligned} \tag{15}$$

The GLS estimator for β is

$$\hat{\beta} = \left(X'\Phi^{-1}X\right)^{-1} X'\Phi^{-1}y$$
$$\text{where: } \Phi = \text{diag}\left\{z_{it}'\alpha\right\} \tag{16}$$

A number of possible estimators have been suggested for α to give an EGLS estimator for β. Define e as the vector of residuals from a least squares analysis of Equation **(13)** with each of its elements squared, and $\dot{M}$ as the matrix $I-X(X'X)^{-1}X'$ with each of its elements squared. One option is to apply least squares directly to Equation **(15)** (Goldfeld and Quant 1972), which yields

$$\hat{\alpha} = (Z'Z)^{-1} Z'\hat{e} \tag{17}$$

This estimator, however, is biased and inefficient since $E\left[\hat{e}\right] = \dot{M}Z\alpha$ and hence,

$E\left[\hat{\alpha}\right] = (Z'Z)^{-1} Z'\dot{M}Z\alpha$. This suggests that an unbiased estimator can be obtained by applying least squares to the expected value of the matrix of residuals from a least squared analysis of Equation **(13)** with each of its elements squared (Hildreth and Houck 1968). The application of least squares to

$$\hat{e} = \dot{M}Z\alpha + w \quad ; \quad E[w] = 0 \tag{18}$$

yields

$$\hat{\alpha} = \left(Z'\dot{M}\dot{M}Z\right)^{-1} Z'\dot{M}\hat{e} \tag{19}$$

which is then used in Equation **(16)** for the estimation of β. This option is preferred due to the absence of bias.

Empirical Analysis

Data

We examine two categories of (automobile) durables, minivans and sport utility vehicles, over the period 1983-94. Our hope is that convergent results from a twelve year observation period for two categories, each at different stages of the product life cycle, will provide support for our premise that changes in competitive context explain changes in elasticities over time. The minivan category was

established in 1983 with the introduction of the Chrysler Caravan, Plymouth Voyager, and Toyota Van brands. During the period 1983-94, eighteen brands entered, and three brands exited. Although the product category for sport utility vehicles was well established when our observation period began in 1983 with nine brands competing (three of which were line extensions), seventeen new brands entered, and seven withdrew during the twelve year period 1983-94 under study.

Market Share Data

Ward's Automotive collects monthly unit sales data for all brands of automobiles and trucks sold in the United States. The market share for each brand in any particular month was calculated as the sales for the brand during the month divided by the total sales of all the brands in the category during the month. The list of brands to include in the analysis was taken from the category definitions in *Ward's* 1991 and 1993 Yearbooks.

Engineering Features Data

For this study, we used the engineering features data reported in *Ward's Automotive*. Feature data available for the minivans were indicators of size (small, middle) and drive-train (front wheel drive, rear wheel drive, four wheel drive). Features data available for the sport utility vehicles were indicators of size (small, middle, large), drive-train (rear wheel drive, four wheel drive) and body style (two door, four door).[2]

Correspondence analysis using the engineering features data was used to position the brands in metric space. A separate correspondence analysis was run for each category. An observation was defined for each unique feature combination for each brand. Hence, one observation was used for brands that did not change their feature offerings over the observation period, and multiple observations were included for brands that changed their features over the observation period. The feature indicators as well as brand dummies were used in this analysis. Brand dummies ensure that the distance between any two brands with identical features is non-zero (since the reciprocal of the spatial distance measure is used in the density measure). This accounts for brand/model names which represent a specific

feature reflected in the density measure. Figure 1 illustrates the evolution of this competitive density measure for selected sport utility vehicles over the period. It is clear from the Figure that the density typically heightens for all the brands as the number of products offered increases. However, decreases in the measures occur as well. In addition, the impact of these entries and departures is different for each brand. Similarly, changes occur over time as the features offered in a given brand evolve. Therefore, our measure of competitive density represents a construct distinct from the simple competitive structure of the market defined as the number of competitors in that market.

Price Data

For each model year, *Ward's Automotive* publishes the suggested base price of each vehicle. Customers seldom pay exactly this price because of the wide variety of optional equipment and the proliferation of manufacturer and dealer pricing incentives. However, since chosen equipment options vary across customers, prices would not be comparable. In practice, it is impossible to control for the variety of optional equipment ordered across customers and the specific price packages offered to individual customers. Therefore, the base price is typically used in aggregate econometric models (e.g., Lambin and Dor 1989, Wildt 1974, Lambin 1972, 1970a, b). The price of a brand for a particular model year was taken as the base price.[3]

Advertising Data

The LNA/Mediawatch Multimedia Service of *Competitive Media Reporting* provides total advertising expenditures from ten classes of media. For print media including magazines and newspapers, all major and most minor newspapers and magazines are scanned for advertisements. Based on the size of the advertisement and its format (color or black-and-white), advertising rate cards supplied by publishers are used to estimate expenditures for each brand. For broadcast media including local spot television, national network television, cable television, and radio, estimates of advertising expenditures are based on the time of day an advertisement is aired, its duration, the broadcast station, and the audience covered (local or national). Because quarterly data was available, a uniform monthly

distribution within each quarter is used.

There are three line extensions in the sport utility vehicle category - Bronco II (Bronco), Blazer-S (Blazer), and Jimmy-S (Jimmy). For these brands, in addition to advertising for the brand under study, we also included a measure to capture the influence of advertising expenditures for the related, earlier entrant.

Distribution Data

Automotive News publishes the number of retail truck outlets by manufacturer as of January 1 of each year. Retail outlets include dealerships, distributorships, and factory-owned outlets. Because the number of outlets is relatively stable over the observation period, we used the simple two point average as an estimate of the number of retail outlets for each manufacturer throughout a calendar year. We assumed that when a manufacturer such as Ford produced multiple brands, all the brands were available at all Ford outlets.

Quality Data

For this study, we examine product quality based on data reported in *Consumer Reports*. *Consumer Reports* data has been used previously in research as a measure of product quality (e.g., Curry and Faulds 1986, Lichtenstein and Burton 1989). *Consumer Reports* publishes quality ratings of automotive products on 17 items. Each item is rated on a 5 point scale. The ratings represent frequency of repair estimates based on a survey of their readers. These measures reflect product quality information available to consumers. We use the most recently published ratings on the newest model. Hence, we assume that product quality perceptions are influenced by published ratings of the prior year's model.

A separate factor analysis was done for sport utility vehicles and for minivans. In each market, the factor associated with the largest eigenvalue was dominant. This factor is similar in both markets: a measure of body/engine quality.

Results

Table 2 provides the basic descriptive statistics of the data for both markets. The variances were first estimated using Equation **(18)** based on the residuals obtained from estimating Equation **(13)**. Negative estimates were changed to zero (Judge *et al.* 1980). If the error terms e_{it} are normally distributed, a test for homoscedasticity can be constructed (Judge *et al.* 1985). If $\alpha'=(\alpha_1, \alpha^{*\prime})$, then under the null hypothesis $\alpha^{*\prime}=0$, the test statistic

$$g = \frac{\hat{\alpha}^{*\prime} D^{-1} \hat{\alpha}^{*}}{2\hat{\sigma}^4} \qquad \textbf{(20)}$$

is distributed χ^2(df=s-1, where s is the number of columns of Z). In Equation **(20)**, $\hat{\sigma}^2 = \hat{e}'\hat{e} / N$ (where N is the number of observations) and D is the matrix $(Z'Z)^{-1}$ with the first row and first column deleted. We reject homoscedasticity for both the minivan category (χ^2=514.5; df=3; p<.01) and the sport utility vehicle category (χ^2=311.9; df=4; p<.01). Therefore, it is critical to use the estimated generalized least squares estimator as expressed in Equations **(16)** and **(19)** which considers unobservable components of the process function. Table 3 presents the results for both product categories. Only the coefficients showing the interaction effect of competitive density on the marketing mix sensitivity parameters are shown because they are the focus of the study and the large number of other coefficients (as can be seen from Equation **(13)**, there are as many intercepts as they are brands in the response function, i.e., $\beta_0(i)$, as well as in each process function, i.e., $\beta_{p0}(i)$, $\beta_{q0}(i)$, $\beta_{a0}(i)$ and $\beta_{d0}(i)$, in addition to the time dummy variables).

The results generally support our thesis that competitive density provides an explanation for the fact that marketing mix elasticities vary over time. As indicated above, prior studies investigating marketing mix elasticity dynamics have modeled these dynamics with a time variable, even though time in itself does not explain **why** elasticities may vary. We analyzed whether time *per se* adds significantly to our theoretical explanation. Therefore, a model with time introduced in a linear as well as quadratic and logarithmic functional forms were added in the process Equations **(11)**. The difference

in the sum of squared residuals from the nested models was insignificant for both product categories. While time itself could be used as a surrogate for modeling marketing mix elasticity dynamics, our results suggest that competitive density provides an explanation for why elasticities vary over time.

We also compared our measure of competitive density with a simple measure of competitive structure, i.e., the number of competitors, which has been used in a few prior studies (Bowman and Gatignon 1996, Parker and Gatignon 1996, 1994). Competitive density appears to perform slightly better than simply the number of competitors; the R squared obtained from OLS estimation is higher when using competitive density and the number of competitors does not add significantly to the explained variance of the competitive density.[4]

We hypothesized that the relationship between market response, $|\beta_k(it)|$, and competitive density would be increasing for price, quality, and distribution, and decreasing for advertising. The data generally support the hypotheses.

Consistent with Hypothesis 1, price sensitivity increases (becomes more negative) with density for both the minivan category ($p<.01$) and the sport utility vehicle category ($p<.05$). This result confirms the argument that by providing more choices to the consumers, they tend to become more price sensitive.

Hypothesis 2 is not supported in either market where response to product quality is not significantly affected by competitive density. In fact, although insignificant, the coefficients are of the opposite sign than was expected in both markets. It is possible that when a number of similar brands are available in the market, reliability is used by consumers to discriminate between the brands. When there are few similar brands available, reliability is not used to the same degree. It may be that consumers have less confidence in the reliability measures of dissimilar brands since the basis of comparison is somewhat different. It could also be that the choice is more based on features of the product and less on the reliability. In other words, some consumers are so eager for the features that they are willing to sacrifice some reliability.

Sensitivity to advertising expenditures is significant and decreases with density for both the minivan category ($p<.05$) and the sport utility vehicle category ($p<.01$). Therefore, these results generally provide supporting evidence for Hypothesis 3, that competitive density decreases advertising effectiveness. We also included, for line extensions, advertising expenditures associated with related brands in the sport utility vehicle category. Competitive density influences positively the effectiveness of advertising expenditures associated with related brands ($p<.01$). Therefore, the advertising of the earlier related entry has a larger effect on the associated brands when these brands are competing with other similar brands.

Consistent with Hypothesis 4, sensitivity to the number of distribution outlets increases with competitive density in both markets ($p<.01$). This result brings support to the more critical role of distribution in competitively dense markets, in part due to the increase importance of the location of the distributor when features do not strongly differentiate the brands available in the market.

These results generally support our thesis that competitive density provides an explanation for the fact that marketing mix elasticities vary over time. These findings have important managerial implications, as discussed in the introduction, because they enable us to estimate the influence competitive context has on the implied elasticities.

Discussion

We have investigated why managers should vary their marketing mix efforts over time. Using data from two categories of durables, we find general support for our hypotheses that differences in the effectiveness of marketing mix efforts across brands is systematically related to competitive context. Competitive context which changes over time due to brand entry, brand exit, and changes in product features, therefore, provides an explanation for changes in the effectiveness of marketing mix variables over time.[5] As a consequence, changes in the effectiveness of marketing mix variables cannot be predicted by a smooth function of time. Adjusting the allocation of marketing resources to the various mix variables depending purely on time in the market fails to recognize the causes which explain why

this allocation must be changed. Our results show that management must consider the competitive context as a major reason for reallocation decisions.

Consistent with marketing theory, we find that market response to price is larger for higher competitive density. Close substitutes compete on price. Further, as a market gets increasingly crowded, the importance of price is heightened.

Market response to a brand's advertising efforts is lower for higher competitive density. It becomes increasingly difficult to have your brand's message received as the number of close substitutes increases.

Market response to distribution is higher for high competitive density. With many suitable alternative brands, consumers are less willing to "seek out" any particular brand on their own and distribution's role is more critical. Hence, the importance of having extensive distribution coverage increases.

We have studied why the effectiveness of marketing mix instruments should vary over time. In addition to changes in the competitive situation facing a brand caused by brand entry, brand exit, and new features, there are other factors which may cause changes in elasticities over time. Unobservable factors such as changes in the distribution of marketing mix elasticities in the population over time, and learning requirements and processes that evolve over time also influence elasticities over time. Changes in elasticities over time may also be associated with exogenous factors, and with possible effects due to saturation of the market (Gatignon and Robertson 1991). Our estimation procedure controls for these unobservable effects.

We add to the growing literature which empirically investigates the effects of competition on marketing strategy. Mahajan, Sharma, and Buzzell (1993) have recently shown how competitive entry can influence market expansion and incumbent sales. We show how competitive entry can alter market response to a brand's marketing decision variables through changes in the relative positioning of the competitors.

Although we examined two categories of (automotive) durable products for which the results converge, future research could examine non-durable products, services, or other durable categories. This would further generalize these results.

This research represents a first step towards empirically measuring ***why*** the effectiveness of marketing mix instruments changes over time. Understanding why marketing mix elasticities change over time has important implications for management who can then control more effectively the allocation of marketing resources.

Endnotes

[1] Market share is chosen in this study over brand sales to capture the competitive dynamics in a manner which is both parsimonious and conform to state-of-the-art competitive models (Cooper and Nakanishi 1988).

[2] Perceptual information could also be used, as commonly done in positioning studies. However, time-series data on perceptions of key dimensions (either directly measured or derived from, for example, multidimensional studies) with constant methodologies are typically not available.

[3] The strategic pricing differences between domestic and imported models where options are typically included in the base price may lead to a bias. Dummy variables for imported vehicles were not significant and are, therefore, not included in the reported results.

[4] While the reverse is also true, because the residual sum of squares is smaller when using competitive density, this indicates a slight superiority of this model specification.

[5] It is theoretically possible that changes in the effectiveness of marketing mix variables are driving the decisions by firms to enter or exit the market. However, the directions of the changes in the elasticities as a function of density differ across the marketing mix variables. For example, greater density leads to heightened price elasticity but to lower advertising elasticity. Consequently, it would be difficult to infer a pattern of entry or exit; margins may become lower with greater density which would induce exit, but advertising may become less of a barrier.

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Figure 1: Measures of Density over Time for Selected Sport Utility Vehicles

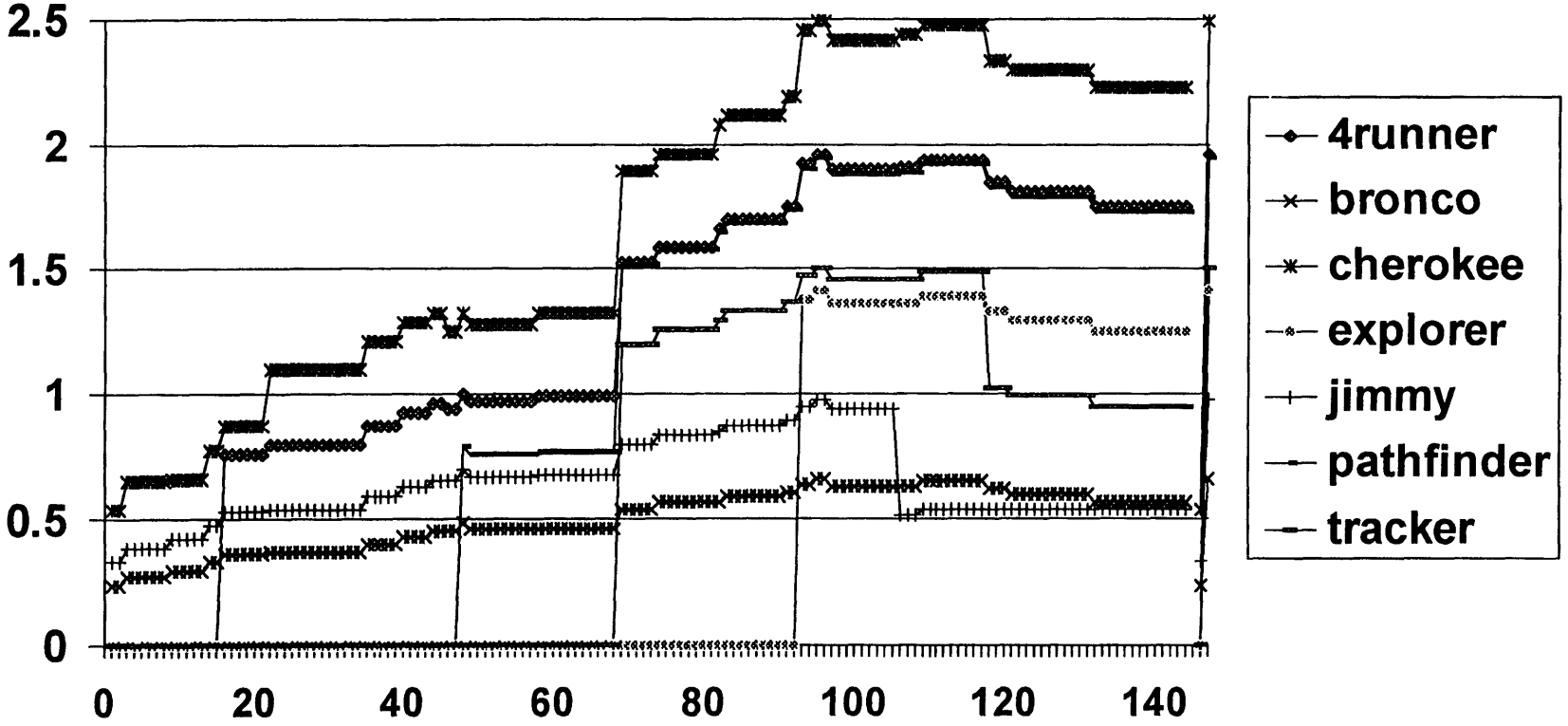

Table 1: Empirical Evidence That Elasticities Change Over Time

Decision Variable	Study	Product	Elasticity Trend	Length of Time Series	Dependent Process	Other Mkt'g Vars in Model
Price	Wildt (1976)	unidentified consumer	decr.	30 mo.	category sales	advertising
	Simon (1979)	pharmaceuticals	decr., then stable	6 yrs	brand sales	none
		cleansers	decr., then incr.	7 mo.	brand sales	none
	Liu and Hanssens (1981)	inexpensive gift	incr.	19 wks	category sales[a]	none
	Lilien and Yoon (1988)	industrial chemicals	stable, then decr.	11 to 37 yrs	category sales	NA
	Parker and Neelamegham	color TVs	stable	27 yrs	category sales	none
	(1997)/Parker (1992)	room a/c's	stable	31 yrs	category sales	none
		freezers	decr.	31 yrs	category sales	none
		refrigerators	decr.	48 yrs	category sales	none
		steam irons	decr.	31 yrs	category sales	none
		bed covers	decr., then incr.	32 yrs	category sales	none
		B&W TVs	decr., then incr.	20 yrs	category sales	none
		blenders	decr., then incr.	31 yrs	category sales	none
		ironers	decr., then incr.	23 yrs	category sales	none
		ranges	decr., then incr.	48 yrs	category sales	none
		bed covers	incr., then decr.	32 yrs	category sales	none
		dishwashers	incr., then decr.	31 yrs	category sales	none
		disposers	incr.	31 yrs	category sales	none
	Parker and Gatignon (1996)	frequently purchased cosmetic product	Incr.		brand sales	advertising
Advertising	Parsons (1975)	cleanser	decr.	16 yrs.	category sales[a]	none
	Arora (1979)	pharmaceutical	Decr.	22 mo.	brand sales	none
	Winer (1979)	L.Pynkham	Incr.	52 yrs	category sales[a]	none
	Parker and Gatignon (1996)	frequently purchased cosmetic product	Decr.		brand sales	price

NA= Not Available
[a] Single brand in category

Table 2a
Descriptive Statistics for Minivans

Raw Data Variable[1]	n	Mean	Min.	Max.	Model Variable[2]	Mean	Min.	Max.	1.	2.	3.	4.	5.
Mkt share$_{it}$	1,284	0.106	<.001	1.000	1. log(Mkt share$_{it}$)	-3.053	-11.34	0					
Density$_{it}$	1,284	0.892	0.00	1.72	2. Density$_{it}$	0.892	0.00	1.72	.12				
Price$_{it}$	1,273	16,456	8,998	26,896	3. log(Price$_{it}$)	9.608	0	10.20	-.09	.27			
Quality$_{it}$	965	1.106	0.430	2.911	4. log(Quality$_{it}$)	0.019	-0.84	1.07	.06	.23	.06		
Advertising$_{it}$	1,000	1,391	2	11,142	5. log(Advertising$_{it}$)	2.969	-9.21	9.32	.54	.21	-.06	.12	
Distribution$_{it}$	1,284	2,738	115	5,138	6. log(Distribution$_{it}$)	7.728	4.74	8.54	.53	.19	-.08	-.16	.39

Table 2b
Descriptive Statistics for Sport Utility Vehicles

Raw Data Variable[1]	n	Mean	Min.	Max.	Model Variable[3]	Mean	Min.	Max.	1.	2.	3.	4.	5.	6.
Mkt share$_{it}$	2,456	0.058	<.001	0.714	1. log(Mkt share$_{it}$)	-3.530	-11.48	-0.34						
Density$_{it}$	2,456	1.084	0.24	2.50	2. Density$_{it}$	1.084	0.24	2.50	.11					
Price$_{it}$	2,456	15,233	6,860	26,496	3. log(Price$_{it}$)	9.600	8.83	10.18	-.01	.13				
Quality$_{it}$	1,636	1.074	0.400	3.447	4. log(Quality$_{it}$)	-0.004	-0.92	1.24	.04	.31	.03			
Advertising$_{it}$	1,779	888	1	12,163	5. log(Advertising$_{it}$)	1.861	-9.21	9.41	.40	.19	.12	-.03		
Related Adv$_{it}$	78	865	1	3,779	6. log(Rel. Adv$_{it}$)	-1.045	-9.21	8.24	-.32	-.01	.14	.07	-.14	
Distribution$_{it}$	2,456	2,262	50	5,155	7. log(Distribution$_{it}$)	7.322	3.91	8.55	.46	-.29	.30	-.16	.09	-.27

[1] Raw quality data was not available for all brands in all time periods. Descriptive statistics for raw advertising data are reported only for periods where advertising was greater than zero.

[2] n=1,284 for all variables. Zero advertising was coded as 0.001 before log transformation. Descriptive statistics for the quality model variable are for the product of log(Quality)×Indicator the quality data was available.

[3] n=2,456 for all variables. Zero advertising was coded as 0.001 before log transformation. Zero related advertising was coded as 0.001 only for those brands that are master brands or line extensions. Descriptive statistics for the quality model variable are for the product of log(Quality)×Indicator the quality data was available. Descriptive statistics for the related advertising model variable are for the product of log(Rel. Adv)×Indicator the brand was a master brand or line extension.

Table 3:
The Influence of Competitive Context on Marketing Mix Effectiveness*

Variable	Exp. Sign	Minivans	Sport Utility Vehicles
$\ln(Price_{it}) \times Density_{it}$	-	-2.443 (2.7)***	-0.179 (2.1)**
$\ln(Quality_{it}) \times Density_{it}$	+	-0.249 (0.5)	-0.188 (1.4)
$\ln(Advertising_{it}) \times Density_{it}$	-	-0.040 (1.8)**	-0.053 (6.0)***
$\ln(Related\ Adv_{it}) \times Density_{it}$	-	Not Applicable	0.042 (2.3)***
$\ln(Distribution_{it}) \times Density_{it}$	+	0.314 (6.5)***	0.381 (3.2)***
R-squared(OLS)		.92	.87
No. of observations		1,284	2,456

* Time specific constants and brand specific constants not shown.
t-statistics in parentheses.
** Significant at .05 level.
*** Significant at .01 level.