Implications of Market Structure for Elasticity Structure

Understanding how marketing mix elasticities vary with market conditions is a key element in developing successful marketing strategies. For example, by anticipating the likely evolution of price elasticities over the product life cycle, managers can choose rationally between skim and penetration pricing policies (see, e.g., Simon 1979). However, relating elasticities to market characteristics remains a challenging task. Though the economic theory of demand is well elaborated (Wold and Jureen 1964), the abstractness of the theory makes it difficult to forecast how a brand's marketing mix elasticities will be affected by changing competitive conditions.

Marketers have responded to this challenge in two ways. The more traditional stream of research seeks to establish empirically valid generalizations by obtaining estimates of elasticities across product classes under a variety of conditions. Though some studies only offer "ballpark" estimates (e.g., Houthakker and Taylor 1970; Lambin 1976), more recent work provides direct evidence of systematic relationships between market characteristics and the magnitudes of elasticities (Bolton 1988; Farley, Lehmann, and Ryan 1982; Ghosh, Neslin, and Shoemake 1983; Hagerty, Carman, and Russell 1988). A major criticism of this work is that the findings tend to be highly idiosyncratic. For example, an early study by Telser (1962) found that the market share price elasticities of low priced brands of frozen orange juice were greater than those of high priced brands. However, the opposite relationship held for the other categories in Telser's study (regular coffee, instant coffee, and margarine).

The second (and newer) stream of research builds models that explicitly link the magnitudes of own- and cross-brand elasticities to the competitive structure of the market (e.g., Clarke 1978, Elrod 1988; Shugan 1987). These models typically calibrate a perceptual space of brand attributes and infer a distribution of consumer preferences. A good example of this work is the "price map" methodology of Shugan (1987). Adopting the Lancastrian choice framework of the DEFENDER model (Hauser and Shugan 1983), Shugan expresses elasticities as a function of a brand's position along the efficient frontier for an entire set of brands. By observing how changes in positioning and pricing affect the efficient frontier, the model is able to predict the most likely elasticity pattern. Though specific elements of the model are...
open to criticism, the general approach is attractive because aggregate consumer price sensitivity is linked to a theory of consumer choice.

We build on this work by showing how the magnitudes of marketing mix elasticities can be predicted by using knowledge of market structure. Specifically, we develop a model that explains how elasticity structure, a distinctive patterning of own- and cross-brand elasticities, is induced by aggregate consumer tendencies to switch within and across submarkets. Instead of calibrating a complete model of consumer choice (i.e., brand positions and consumer preferences), we assume that consumer perceptions of brand substitutability allow the market to be divided into brand groupings within which market share is described by an aggregate version of the Luce (1959) choice model. Using these proportional-draw submarkets, we develop a parsimonious description of elasticity structure that relates market share and marketing mix variables (e.g., price) to brand elasticities. The result is a useful decomposition of observed elasticities into two components: generalized consumer reactions to price changes and structural characteristics of the market.

In the following sections, we develop the model both theoretically and empirically. First we derive an elasticity structure, which we call the "aggregate constant ratio elasticity pattern" (ACREP). We then assess the model's performance by examining the price elasticity patterns of several product markets. Our analysis shows that observed elasticities conform reasonably well to the ACREP theory. Moreover, the model's underlying switching parameters accurately reflect market conditions. Finally, we discuss the implications of the ACREP model for managerial decisions.

A MODEL FOR MARKET SHARE ELASTICITIES

One of the most interesting recent developments in the marketing literature is research that seeks to decompose product markets into managerially useful partitions. In this research, a product market partition generally is considered to be a group of products that are perceived to be substitutes by a particular group of customers for specific occasions. A partition can be defined on the basis of either consumer perceptions and judgment or behavioral measures of interbrand substitution (Day, Shocker, and Srivastava 1979). Our approach builds on the latter measures.

Two commonly used behavioral approaches to defining market partitions are assessments of cross-elasticities of demand and the analysis of brand switching behavior. According to the standard economic approach, two brands are considered to be in the same market if their cross-elasticities of demand (with respect to some marketing activity, usually price) are large. Recently, marketers have applied this approach in the development of maps of brands' competitive proximity (e.g., Cooper 1988; Shugan 1987). In brand switching approaches, the matrix of brand switching probabilities is broken down into competitive markets, such as in the Hendry system. A major distinction between these two approaches is that the first relies on aggregate data and the second uses individual-level data. The model developed here bridges these two behavioral approaches by positing a functional relationship between marketing mix elasticities and underlying determinants of aggregate brand switching propensities. It leads to a parsimonious description of brand elasticity structure.

The Aggregate Constant Ratio Model

Following Urban, Johnson, and Hauser (1984), we define a market partition as a set of brands whose market shares conform to a proportional-draw mechanism. That is, if brand $j$ is not available for purchase, the shares of all other brands are given by the relation

$$MS^*_j = MS_j/(1 - MS_j)$$

where $MS_j$ is the usual market share of brand $i$ and $MS^*_j$ is the revised share. This relation implies that the within-partition market share of a brand is given by

$$MS_j = A_i \left( \sum_{s=1}^{N} A_s \right)$$

where $A_i$ is the ratio-scaled attraction of brand $i$ and $N$ is number of brands in the partition. Because this "us versus (us + them)" structure is formally equivalent to the Luce (1959) choice model, Urban, Johnson, and Hauser (1984) have defined equation 2 as the aggregate constant ratio model (ACRM).

The ACRM is fundamentally an aggregate model that does not make strong assumptions about underlying consumer choice rules. Accordingly, the model must be interpreted cautiously. Though the ACRM describes the expected equilibrium market shares, it does not necessarily imply that individual consumers follow the Luce choice axiom. Moreover, it does not necessarily imply that the market collectively behaves as an aggregate zero-order consumer. (For example, in most markets, the proportion of consumers repeat-buying brand $i$ on adjacent purchase occasions will be larger than $MS_i^2$.) Rather, the ACRM simply states that when the equilibrium market share of a given brand increases, the share increase will be drawn proportionally from the remaining brands in the partition.

For two reasons, one can expect the ACRM to be a suitable representation for many markets. Jeuland, Bass, and Wright (1980) have shown that if brand choice and purchase timing are independent, the ACRM describes the market shares of a population of zero-order consumers with heterogeneous, Dirichlet-distributed purchase probabilities. More generally, Givon and Horsky (1978) have argued that gravitational-type attraction models like the ACRM provide a good approximation to the market shares of any population of zero-order consumers. As Bass et al. (1984) show that the majority of consumers in a variety of nondurable product classes fol-
low stationary zero-order choice processes, it seems reasonable to expect market partitions satisfying ACRM criteria. In fact, applications of the PRODEYG methodology (Urban, Johnson, and Hauser 1984) indicate that ACRM partitions do exist.

Additional evidence for the existence of such markets can be found in the brand switching literature. Under the same conditions described by Jeuland, Bass, and Wright (1980), the fraction of the market switching between brands \( i \) and \( j \) on adjacent occasions will be proportional to the product \( MS_iMS_j \). This relationship is one of the key features of the Hendry system (Kalwani and Morrison 1977) and has been demonstrated to hold empirically in a variety of product classes. Because both the Hendry system and the ACRM can be derived as aggregate manifestations of the same underlying consumer choice model, the empirical success of the Hendry system is encouraging. Though the two models are not equivalent (i.e., the ACRM is not a consequence of the Hendry system), we expect that ACRM partitions often will correspond to partitions derived by using the Hendry system. Hence, market structure derived by using Hendry criteria is apt to be a useful guide to ACRM submarkets.

Next we derive elasticity patterns for ACRM partitions. Because there are good reasons for believing that many market partitions meet ACRM criteria, the elasticity structure proposed here should be commonly observed.

**The ACREP Model**

To extend the ACRM to a structure for marketing mix elasticities, we must specify the way in which the \( A_i \) vary with elements of the marketing mix. Following the well-established tradition of logit modeling (e.g., Guadagni and Little 1983), define \( A_i = \exp(U_i) \) where

\[
U_i = \mu + \sum_{k=1}^{r} \beta_k x_{ik}
\]

depends on \( x_{ik} \), the set of marketing mix variables (i.e., price, advertising, etc.) for brand \( i \). Here \( \mu \) represents the overall market preference for the brand. The \( \beta_k \) can be regarded as within-partition switching parameters that measure the aggregate consumer response to the \( x_{ik} \).

Notice that the \( \beta_k \) are identical for all brands, implying that a given change in any element of the marketing mix (e.g., a 10-cent price increase) affects the attraction of each brand by the same absolute amount (10\( \beta \)). However, on a percentage basis, brands are differentially affected. Those with a larger overall preference value \( \mu \) will have smaller percentage changes in attraction.

Consequently, this formulation does not imply that the resulting marketing mix elasticities will be the same across brands. The market share elasticity, \( \eta_{i}^{(ms)} \), for any variable \( x_{ik} \) is defined as

\[
\eta_{i}^{(ms)} = d(\log MS_i)/d(\log x_{ik})
\]

Substituting equation 3 into the ACRM and solving,\(^1\) we have

\[
\eta_{i}^{(ms)} = \beta_i (1 - MS_i)x_{ik}
\]

\[
\eta_{ij}^{(ms)} = -\beta_j MS_i x_{jk}, \quad i \neq j.
\]

Note that these equations are a completely general description of all marketing mix elasticities: price elasticities, advertising elasticities, and so on. Though the rest of our discussion is in the context of price elasticities, it applies with equal force to any element of the marketing mix.

Rewriting the expressions to characterize the market share price elasticities (i.e., selecting \( k \) so that \( x_{ik} = p_i \)), we obtain

\[
\eta_{i}^{(ms)} = \beta(1 - MS_i)p_i
\]

\[
\eta_{ij}^{(ms)} = -\beta_j MS_i p_{ij}, \quad i \neq j,
\]

where \( \eta_{i}^{(ms)} \) is the percentage change in market share of brand \( i \) with a 1% change in the price of brand \( j \) and \( \beta \) is the common price sensitivity parameter for the submarket. Hereafter, we sometimes refer to \( \beta \) as the within-partition switching parameter for price.

For convenience, this structure (equations 7 and 8) is defined as the aggregate constant ratio elasticity pattern (ACREP). It implies that own elasticities are inversely proportional to market share and cross elasticities are directly proportional to market share and asymmetric. The behavior of the cross elasticities is particularly interesting because it embodies the idea of market power. Larger market share competitors (i.e., brands with larger values of \( MS_i \)) will have a larger proportional impact on the sales of any given brand (see equation 8). In this way, the proportional draw characteristic of the ACRM influences the structure of the elasticities.

**Evidence from Previous Research**

Obtaining empirical support for ACREP structures from previous studies of market share elasticities is difficult because brand characteristics (i.e., share and price) seldom are reported. However, Telser (1962) reports sufficient information to calibrate the ACREP model for own-price market share elasticities of national brands in four different categories. On the basis of the structure of equation 7, we estimated \( \beta \) by regressing Telser's estimates of own market share elasticities on \((1 - MS_i)p_i\). (Consistent with equation 7, these regressions did not include an intercept.) The ACREP model yields statistically significant \( \beta \) coefficients (\( p < .15 \)) in three of the categories: regular coffee (\( \beta = -0.0669 \)), instant coffee (\( \beta = -0.5004 \)), and stick margarine (\( \beta = -0.592 \)). As expected, all \( \beta \) estimates are negative. The fourth cat-

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\(^1\)In equation 3, we impose a specific functional form on the market share model. By changing equation 3, we can generate elasticity patterns that are different from the one presented here. See Cooper (1988) for a detailed discussion.
category, frozen orange juice, is not described well by the ACREP model, primarily because lower priced brands appear to be more elastic.2

Further evidence supporting the ACREP model can be found in a recent study of market share price elasticities for 29 ready-to-eat breakfast cereals. Ghosh, Neslin, and Shoemaker (1983) observed that brands with higher relative prices were more price elastic whereas those with higher market shares were less price elastic. Both relationships are consistent with the ACREP formula for own market share price elasticity (equation 7).

In the preceding discussion, the ACREP model is assumed to describe brand market share elasticities within an ACRM submarket. However, the ACREP model also could describe elasticities at the submarket level—if changes in a submarket’s share of the entire market also reflect the proportional-draw principle. For example, the ACREP model could describe elasticities for different types of soft drinks (cola, noncola) if equilibrium share adjustments of colas and noncolas were described by the ACRM. In general, the ACREP structure holds at the level of product market aggregation for which the ACRM provides a good approximation to changes in share.

**EXTENSIONS TO SALES ELASTICITIES**

In practice, the elasticity of most interest to managers is the sales elasticity. Because brand sales equal submarket sales (i.e., total sales of all brands in the partition) multiplied by the brand’s market share, the brand sales elasticity can be decomposed as the sum of a submarket expansion elasticity and a market share elasticity (see, e.g., Clarke 1973). That is

$$\eta_i = \eta_i^{(s)} + \eta_i^{(m)}$$

(9)

where $\eta_i$ is the percentage change in the sales of brand $i$ with respect to the price of brand $j$ and $\eta_i^{(s)}$ is the brand-specific submarket elasticity that measures the extent to which the price of brand $j$ affects the total sales for all brands in the partition. Note that this expression characterizes short-term sales elasticities. Long-term sales elasticities, which represent an expansion of equation 9 to adjust for likely competitive reaction, are beyond the scope of our study (see, e.g., Hanssens 1980; Lambin, Naert, and Bultez 1975).

**The Submarket ACREP Model**

The preceding decomposition suggests an extended model that we term the “submarket ACREP.” Substituting the ACREP definitions of market share elasticities into equation 9, we see that the sales elasticities become

$$\eta_i = \eta_i^{(s)} + \beta (1 - MS_i)p_i$$

(10)

Here, as assumed before, brands $i$ and $j$ are members of the same ACRM partition. Though we should expect $\eta_i^{(s)}$ to have the same sign as $\beta$ (i.e., $\beta < 0$ implies $\eta_i^{(s)} < 0$), no other restrictions are necessary. However, if we assume that the $\eta_i^{(s)}$ are relatively stable across observed price levels, it is evident that the submarket ACREP model is parsimonious. On the basis of knowledge of market shares and prices, we can reconstruct all $N^2$ price elasticities for a submarket of $N$ brands using only $(N + 1)$ parameters: $N$ values of $\eta_i^{(s)}$ and $\beta$.

**The Generalized ACREP Model**

A remarkably simple generalization of the ACREP model is possible if specific restrictions are placed on the submarket elasticities $\eta_i^{(s)}$. Suppose consumers, taken in the aggregate, first choose a submarket, then choose a brand. Let $MS_{sub}$, the market share of brand $j$’s submarket, be determined by a second ACRM structure in which submarket attraction $A_{sub} = \exp[U_{sub}]$ is defined as

$$U_{sub} = \mu_{sub} + \beta_{sub} P_{sub}$$

(12)

where $P_{sub} = \sum_{i=1}^{N} MS_i p_i$ is the submarket’s weighted average price. Then, because $\eta_i^{(s)} = d(log MS_{sub})/d(log P_j)$, it follows immediately that

$$\eta_j^{(s)} = \beta_{sub}(1 - MS_{sub})p_{sub} d(log p_{sub})/d(log P_j)$$

(13)

Assuming that the market is stable in the sense that market shares do not change radically in response to price, we obtain the approximation

$$\eta_j^{(s)} = \beta_{sub}(1 - MS_{sub})MS_j p_j$$

(14)

Because $\beta_{sub}$ and $MS_{sub}$ do not depend on which brand $j$ is selected, this approximation can also be written as

$$\eta_j^{(s)} = \alpha MS_j p_j$$

(15)

Here, $\alpha$ takes the same sign as $\beta_{sub}$ (and $\beta$).

If equation 15 is used as the definition for $\eta_j^{(sub)}$, the submarket ACREP model becomes the two-parameter structure

$$\eta_i = \alpha MS_i p_i + \beta (1 - MS_i)p_i$$

(16)

$$\eta_i = \alpha MS_i p_i - \beta MS_i p_i$$

(17)

Simplifying,

$$\eta_i = \beta^*(\alpha^* - MS_i)p_i$$

(18)

3This approximation is exact if aggregate switching behavior conforms to the generalized extreme value (GEV) choice model (see, e.g., Domenech and McFadden 1975). Because we do not impose the restrictions of the GEV in defining the two-tier ACRM structure, we regard equation 14 as simply a testable proposition.

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2This finding could be explained if the frozen orange juice brands were grouped into several ACRM partitions with different $\beta$'s. Because Telsar does not provide estimates of cross elasticities, we are unable to investigate this finding further.
\[ \eta_{ij} = -\beta^*MS_{ij} \rho, \quad i \neq j, \]

where:

\[ \beta^* = (\beta - \alpha) \]
\[ \alpha^* = \beta / (\beta - \alpha). \]

To ensure the correct signs on the elasticities, we must assume that \( |\alpha| < |\beta|. \) This assumption is consistent with the general finding that category elasticities are smaller than brand sales elasticities (Neslin and Shoemaker 1983). Hence, \( \beta^* \) is expected to have the same sign as \( \beta \) and \( \alpha^* \) cannot be smaller than one.

The elasticity pattern in equations 18 and 19 is called the "generalized ACREP model." It is important to understand that the generalized ACREP parameters (\( \beta^* \) and \( \alpha^* \)) are derived from the underlying switching parameters \( \beta \) and \( \alpha. \) As discussed before, \( \beta \) represents consumer sensitivity to price for brands within the ACRM submarket. In contrast, \( \alpha \) reflects the tendency for consumers to cross market partitions in response to price. Hence, \( \beta^* \) and \( \alpha^* \) capture these same two switching propensities.

The generalized ACREP predicts that cross elasticities will be very small when submarket expansion effects are large, which can be demonstrated in the following way. Submarket expansion effects reach a maximum when \( \alpha = \beta. \) Notice that as \( \alpha \) approaches \( \beta, \) \( \beta^* \) approaches zero and \( \alpha^* \) approaches infinity. Making the substitution into equations 18 and 19, we have

\[ \eta_{ii} = \beta \rho, \quad i \neq j \]
\[ \eta_{ij} = 0, \quad i \neq j \]

That is, when submarket expansion effects are sufficiently large, cross elasticities approach zero and own elasticities are independent of market share. This is a possible explanation for the fact that a relationship between market share and price elasticities is not evident in certain product classes (Ghosh, Neslin, and Shoemaker 1983).

Conversely, when submarket expansion effects are negligible, \( \alpha \) approaches zero implying both \( \beta^* = \beta \) and \( \alpha^* = 1. \) Under these conditions, the sales elasticity pattern in equations 18 and 19 is identical to the market share elasticity pattern derived before. As one would expect, the simple ACREP is a special case of the generalized ACREP.

In summary, the generalized ACREP model implies that market structure has implications for elasticity structure. The model postulates that own and cross elasticities are driven by the underlying switching behavior of consumers (as measured by \( \alpha \) and \( \beta). \) However, the magnitudes of the elasticities also depend on the distribution of market shares and the variability in the levels of the marketing variables. Thus, large differences in these characteristics can translate into large differences in the magnitudes of elasticities.

AN EMPIRICAL INVESTIGATION OF THE ACREP MODELS

The analysis in the preceding two sections demonstrates that marketing mix elasticity patterns similar to ACREP ought to be observed in ACRM submarkets. As noted before, there is some evidence that such ACRM submarkets exist. However, the prevalence of elasticity patterns consistent with the ACREP models is an empirical question.

Here, we examine the price elasticity patterns of national brands in four nondurable product categories to gain some appreciation for the descriptive value of the ACREP structure. The analysis is conducted in two steps. First, we obtain estimates of the own- and cross-price elasticities for a set of brands. Second, we use these estimates to infer the underlying ACREP parameters. Because we are interested in testing the validity of ACREP, the estimates of price elasticities obtained in the first step are not constrained to follow the ACREP pattern. The fit of the ACREP structure to these unconstrained estimates and the interpretability of the recovered ACREP parameters form the basis for our conclusions.

Estimating Unconstrained Own- and Cross-Price Elasticities

The four product categories examined are bleach, bathroom tissue, ketchup, and stick margarine. In each case, aggregate sales and marketing mix data were used to estimate a matrix of average own- and cross-price elasticities for a set of national brands. Details of the estimation of the sales equations and derivation of the price elasticities for the first three categories are reported by Bolton (1988). Details of the fourth category are reported by Blattberg and Wisniewski (1985). We summarize these studies.

The database for bleach, bathroom tissue, and ketchup was optical scanner data supplemented with field survey data. It described weekly sales and marketing activity for the major brands in the category at each of 12 stores for a period of 75 weeks. For each brand in these categories, sales were postulated to be a function of the pricing, advertising, and promotional activities of the brand and its major competitors; in addition, sales were allowed to vary with seasonality and the amount of store traffic. After several alternate functional forms (primarily linear, exponential, and multiplicative) were tested, the multiplicative model was selected as most appropriate. Model fit was remarkably good for all brands at all stores; the average \( R^2 \) was about 77%.

The database for the fourth category, stick margarine, was also optical scanner data supplemented with field survey data. However, it described weekly sales and marketing activity for the major brands in the category for 26 stores of one supermarket chain over a period of 48 weeks. The sales response equation selected by Blattberg and Wisniewski (1985) makes no allowance for individual store effects; all data were aggregated to the chain via
level before analysis. For each brand, sales were pos-
tulated to be a function of price and in-store displays for
the brand and its competitors. Adjustments were made
for seasonality. After testing various functional forms,
Blattberg and Wisniewski (1985) also selected a multi-
licative sales response equation. The average $R^2$ of
these regressions was 92%.

In each category, price effects were estimated by re-
grressing the logarithm of sales on the logarithms of
the other variables. Because of the multiplicative func-
tional form of all sales equations, the price coefficients of
these models can be interpreted as estimates of the aver-
age own- and cross-price elasticities for the particular set
of brands. Moreover, because these equations contain ad-
ditional marketing mix and seasonal variables, these
elasticity estimates represent the net effects of price after
controlling for other sales influences. Consistent with
the theoretical development of the ACREP models, the
recovered own and cross elasticities reflect only the short-
run impact of price changes.

A major methodological difference between the two
studies affects the interpretation of our results. The price
elasticities for brands in bleach, bathroom tissue, and
ketchup were measured at each of 12 stores. That is,
potentially 12 independent estimates of each elasticity
(and cross elasticity) were available for analysis. (If a
particular brand was not sold at all 12 stores, there was
a smaller number of estimates for each elasticity.) In
contrast, the price elasticities for brands of stick mar-
garine represent a pooling of data from 26 stores of one
supermarket chain. In effect, only mean elasticity esti-
mates were available in this case. As we see shortly, the
difference in level of data aggregation has a substantial
impact on the fit of the ACREP models.

Within each category, national brands (usually sold at
premium prices) were assumed to constitute an ACRM
submarket. For example, the two major brands of bleach
were assumed to compose an ACRM submarket; private
label and regional brands of bleach were excluded. This
assumption is consistent with the idea that consumers
use price tiers as one criterion in identifying sets of brands
that they regard as equally substitutable (Blattberg and
Wisniewski 1985, 1986). Because national brands in a
product category also can be divided into a number of
submarkets (Grover and Srinivasan 1987), we attempted
to select sets of national brands with relatively homo-
geous attributes. For example, the margarine data ex-
clude soft-textured national brands in tub form. Ob-
viously, the fit of the ACREP model depends on the
accuracy of this prior specification of the ACRM sub-
markets.

Descriptive statistics for the brands in the four cate-
gories are reported in Table 1. The number of brands in
each ACRM submarket ranges from two to five. The
number of (own and cross) price elasticities for each
category ranges from 25 to 102, depending on the number
of brands and the level of data aggregation.

<table>
<thead>
<tr>
<th></th>
<th>Observations*</th>
<th>Price*</th>
<th>Market share</th>
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<tbody>
<tr>
<td>Bleach</td>
<td></td>
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<tr>
<td>Brand 1</td>
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<td>11.87</td>
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<tr>
<td>Brand 2</td>
<td>19</td>
<td>9.43</td>
<td>15</td>
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<td>Bathroom tissue</td>
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<td></td>
<td></td>
</tr>
<tr>
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<td>34</td>
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<td>54</td>
</tr>
<tr>
<td>Brand 2</td>
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<td>27.23</td>
<td>32</td>
</tr>
<tr>
<td>Brand 3</td>
<td>34</td>
<td>22.07</td>
<td>14</td>
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<td>5</td>
<td>64.00</td>
<td>.08</td>
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</table>

*The number of observations shown indicates the number of own-
and cross-price elasticities for each brand. This number varies across
brands in the same category because all stores did not stock all brands.

For stick margarine, price given is package price. For all other
categories, price is unit price (e.g., cents per 10 ounces).

Estimating the ACREP Models

Assuming that the national brands in each of these cat-
egories constitute an ACRM partition, we expect that the
own- and cross-price elasticities for the brands will have
a structure consistent with the ACREP models. To in-
vestigate this issue, we analyzed the unconstrained es-
timates of price elasticities to recover the parameters of
the submarket ACREP (equations 10 and 11) and the
generalized ACREP (equations 16 and 17). That is, we
attempted to predict the estimated matrices of average
own- and cross-price elasticities using the known aver-
age prices and market shares.

The calibration of the ACREP models was carried out
by “unpacking” each $N \times N$ matrix of estimated own
elasticities $\eta_{ij}$ and cross elasticities $\eta_{ij}$ into a vector
of size $N^2 \times 1$. Define the variables $x^{(1)}_{i} = (1 - MS_i) p_i$,
$x^{(2)}_{ij} = -MS_j p_i$, and let $D_{ij}$ be the Kronecker delta (i.e.,
$D_{ij} = 1$ if $i = j$; otherwise, $D_{ij} = 0$). In the case of
the submarket ACREP, we analyzed the $N^2$ system of equa-
tions

$$\hat{\eta}_{ij} = \sum_{x=1}^{N} \eta_{ij}^{(x)} D_{ij} + \beta x^{(1)}_{i} + \epsilon_{ij},$$

$$\hat{\eta}_{ij} = \sum_{x=1}^{N} \eta_{ij}^{(x)} D_{ij} + \beta x^{(2)}_{ij} + \epsilon_{ij}, \quad i \neq j,$$

where $\epsilon_{ij}$ denotes a normally distributed random error.
In the case of the generalized ACREP, we analyzed the
$N^2$ system of equations

$$\hat{\eta}_{ij} = (\alpha - \beta) x^{(2)}_{ij} + \beta p_i + \epsilon_{ij},$$
We then inferred estimates of $\alpha^*$ and $\beta^*$ by inserting the estimates of $\alpha$ and $\beta$ into equations 20 and 21.

Because both systems are linear, the ACREP parameters were estimated by applying ordinary least squares (OLS) with the appropriate cross-equation parameter constraints. (In each system, a single elasticity estimate was used as the dependent variable for each of the $N^2$ equations.) For bleach, bathroom tissue, and ketchup, independent estimates of the price elasticity matrix were available for each of 12 stores. The analysis defined the independent variables ($x_{ij}^{(1)}, x_{ij}^{(2)},$ and $p_j$) using store-level data, generated a system of equations for each store, then "stacked" these equation systems into one grand regression. This procedure involves the implicit assumption that the ACREP parameters are identical across stores. For stick margarine, only the single aggregate chainwide elasticity matrix could be analyzed. Because of the structure of these systems of equations and our use of OLS, the ACREP parameter estimates are unbiased but not necessarily efficient.

**Overall Results**

Results of the analysis are reported in Tables 2 and 3. The submarket ACREP and generalized ACREP models reproduce the estimated brand sales elasticities very well. The models provide the best fit for stick margarine, both explaining about 97% of the observed variation. They provide a good fit for bleach and ketchup (explaining, on average, about 37% of the observed variation), and a relatively poor fit for bathroom tissue. We discuss the fit of bathroom tissue in more detail subsequently.

Notice that the explanatory power of both models is lower for the first three categories than for margarine. This result occurs because the price elasticities for stick margarine are chainwide averages, whereas the price elasticities in the other categories describe brands at each of 12 stores. Brand price elasticities differ across stores because stores differ in their clientele, positioning, and marketing activities. However, the analysis does not capture this difference, except to the extent that it is reflected in store prices and market shares. In the absence of store-specific ACREP parameters, some across-store variation in the price elasticities of the first three categories will be unexplained by the models.

**Submarket ACREP versus Generalized ACREP**

In a performance comparison of the submarket ACREP model and the generalized ACREP model, the generalized ACREP model receives strong support. Recall that the difference between these two models is that the generalized ACREP model constrains the brand-specific submarket elasticities $\eta_{ij}^{(sub)}$ to be equal to $\alpha MS_j p_j$, where $\alpha < 0$. Because the brands in all categories are arranged in order of decreasing market share and the high market share brands typically have higher prices (see Table 1), Table 2 should show negative brand-specific category elasticities that decline in absolute value down each column. Bleach and stick margarine provide the best support for this prediction; the patterns for bathroom tissue and ketchup are contrary to theory. However, bleach, bathroom tissue, and ketchup have a relatively high degree of measurement error. The most accurate $\eta_{ij}^{(sub)}$ estimates, those for stick margarine, are closely approximated by the formula $(.03) MS_j p_j$.

### Table 3
**GENERALIZED ACREP MODEL RESULTS**

<table>
<thead>
<tr>
<th></th>
<th>Bleach</th>
<th>Bathroom tissue</th>
<th>Ketchup</th>
<th>Stick margarine</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Basic switching parameters</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\alpha$</td>
<td>-1560**</td>
<td>-0290</td>
<td>-0304**</td>
<td>-0306**</td>
</tr>
<tr>
<td>(0.0411)</td>
<td>(0.0424)</td>
<td>(0.0086)</td>
<td>(0.0042)</td>
<td></td>
</tr>
<tr>
<td>$\beta$*</td>
<td>2.58</td>
<td>1.23</td>
<td>2.42</td>
<td>2.21</td>
</tr>
<tr>
<td>(0.508)</td>
<td>(0.0341)</td>
<td>(0.0075)</td>
<td>(0.0019)</td>
<td></td>
</tr>
<tr>
<td><strong>Derived switching parameters</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\alpha^*$</td>
<td>2.58</td>
<td>1.23</td>
<td>2.42</td>
<td>2.21</td>
</tr>
<tr>
<td>(0.508)</td>
<td>(0.0341)</td>
<td>(0.0075)</td>
<td>(0.0019)</td>
<td></td>
</tr>
<tr>
<td><strong>Measure of fit</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$R^2$</td>
<td>37.5**</td>
<td>16.5**</td>
<td>36.5**</td>
<td>97.5**</td>
</tr>
<tr>
<td>Degrees of freedom</td>
<td>2.37</td>
<td>2.100</td>
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<td>2.23</td>
</tr>
</tbody>
</table>

*Standard errors are in parentheses
*Values of $\alpha^*$ and $\beta^*$ are inferred by inserting estimates of $\alpha$ and $\beta$ into equations 20 and 21

* $p < .05$
** $p < .01$

### Table 2
**SUBMARKET ACREP MODEL RESULTS**

<table>
<thead>
<tr>
<th></th>
<th>Bleach</th>
<th>Bathroom tissue</th>
<th>Ketchup</th>
<th>Stick margarine</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Brand-specific submarket elasticities</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Brand 1</td>
<td>$-1.5693**$</td>
<td>$-6839$</td>
<td>$-8952**$</td>
<td>$-9340**$</td>
</tr>
<tr>
<td>(4493)</td>
<td>(7688)</td>
<td>(3274)</td>
<td>(1540)</td>
<td></td>
</tr>
<tr>
<td>Brand 2</td>
<td>$-0.566$</td>
<td>$0.2428$</td>
<td>$-1.750$</td>
<td>$-6.180*$</td>
</tr>
<tr>
<td>(4537)</td>
<td>(4783)</td>
<td>(3766)</td>
<td>(1530)</td>
<td></td>
</tr>
<tr>
<td>Brand 3</td>
<td>NA</td>
<td>$-8.845$</td>
<td>$-5762*$</td>
<td>$-6.340*$</td>
</tr>
<tr>
<td>(7567)</td>
<td>(3299)</td>
<td>(1530)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Brand 4</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>$-1.760$</td>
</tr>
<tr>
<td>(1530)</td>
<td></td>
<td></td>
<td></td>
<td>(1530)</td>
</tr>
<tr>
<td>Brand 5</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>$-1.760$</td>
</tr>
<tr>
<td>(1530)</td>
<td></td>
<td></td>
<td></td>
<td>(1530)</td>
</tr>
<tr>
<td><strong>Wahl-submarket switching parameter</strong></td>
<td>$-2.588**$</td>
<td>$-1.532**$</td>
<td>$-0.490**$</td>
<td>$-0.561**$</td>
</tr>
<tr>
<td>(0.0563)</td>
<td>(0.0350)</td>
<td>(0.0080)</td>
<td>(0.0021)</td>
<td></td>
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<tr>
<td><strong>Measure of fit</strong></td>
<td>$38.5**$</td>
<td>$18.5**$</td>
<td>$36.5**$</td>
<td>$97.5**$</td>
</tr>
<tr>
<td>Degrees of freedom</td>
<td>3.36</td>
<td>4.98</td>
<td>4.75</td>
<td>6.19</td>
</tr>
</tbody>
</table>

*Standard errors of all parameters are in parentheses
Brands are numbered to correspond with Table 1. NA (not applicable) indicates that the ACRM submarket contained less than five brands

* $p < .05$
** $p < .01$
If the constraints imposed by the generalized ACREP are valid, we should expect the submarket ACREP and generalized ACREP to describe the elasticity patterns equally well and to yield comparable parameter estimates. A comparison of Tables 2 and 3 shows that these expectations are met. In terms of $R^2$, the predictive power of the two-parameter generalized ACREP model is virtually the same as that of the submarket ACREP model in all categories. The estimates of $\beta$, the within-partition switching constant, are statistically significant and remarkably consistent between Tables 2 and 3. This finding is strong evidence for the validity of the generalized ACREP. That is, the tendency for consumers to switch across submarkets in response to price is well captured by a hierarchy of ACRM mechanisms.

**Predicted Elasticities**

Further insight into the relative performance of the two models can be obtained by examining Table 4. Here, the predictions of the submarket ACREP and generalized ACREP models are compared with the unconstrained brand elasticity estimates obtained from regressions on the sales data. For bleach, bathroom tissue, and ketchup, these unconstrained estimates are means over stores carrying the brand. For stick margarine, the unconstrained estimates are the single chain average.

Clearly, a major problem with the unconstrained estimates is the common occurrence of cross-price elasticities that are large and have negative (rather than the theoretically correct positive) signs. A calculation of the standard deviations of the elasticity estimates across stores (not shown) indicates that this problem is particularly pronounced for bathroom tissue. “Noisy” price elasticities of this sort often are obtained when sales equations are estimated with optical scanner data characterized by multicollinearity among prices and promotional variables (see, e.g., Ghosh, Neslin, and Shoemaker 1983).

The impact of the two ACREP models is to progressively smooth the elasticity pattern. The submarket ACREP tends to shrink the cross elasticities, but does not necessarily ensure a positive sign. The generalized ACREP allows empirical analyses of the underlying switching parameters ($\alpha$ and $\beta$) with theoretically specified constraints. The evident face validity of the generalized ACREP predictions is due to the fact that these constraints are satisfied. As shown in Table 3, the absolute value of $\alpha$, the across-partition switching constant, is always smaller than the absolute value of $\beta$, and all parameter estimates are negative. This finding is significant because the procedure we used to estimate the ACREP parameters does not impose these constraints.

Overall, the performance of the ACREP models on the

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*Because of averaging across stores, the predicted $\eta_{i,j}$ is not always identical to the predicted $\eta_{i,k}$ ($k \neq i \neq j$) for bleach, bathroom tissue, and ketchup. For stick margarine, the relation is exact because only one chain average elasticity matrix is used in the analysis.

**Table 4**

<table>
<thead>
<tr>
<th>Elasticity*</th>
<th>Observations</th>
<th>Actual</th>
<th>Submarket ACREP</th>
<th>Generalized ACREP</th>
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<tr>
<td><strong>Bleach</strong></td>
<td></td>
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</tr>
<tr>
<td>$\eta_{(1,1)}$</td>
<td>12</td>
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<td>$\eta_{(1,2)}$</td>
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<td>1.06</td>
<td>0.93</td>
<td>95</td>
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<td>8</td>
<td>-2.22</td>
<td>-2.14</td>
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<tr>
<td><strong>Bathroom tissue</strong></td>
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<td></td>
<td></td>
<td></td>
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<tr>
<td>$\eta_{(1,1)}$</td>
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<td>-2.39</td>
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<td>-2.63</td>
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<td><strong>Ketchup</strong></td>
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<td>11</td>
<td>-2.70</td>
<td>-2.58</td>
<td>-2.43</td>
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<tr>
<td><strong>Stick margarine</strong></td>
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<td>$\eta_{(1,1)}$</td>
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<td>-4.32</td>
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<tr>
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<td>.13</td>
<td>57</td>
<td>53</td>
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<td>$\eta_{(1,3)}$</td>
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<td>49</td>
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<td>$\eta_{(1,4)}$</td>
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<td>41</td>
<td>26</td>
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<td>01</td>
<td>16</td>
<td>12</td>
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<td>41</td>
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<td>-4.09</td>
<td>-3.43</td>
<td>-3.45</td>
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</tbody>
</table>

*The notation $\eta_{(i,j)}$ denotes the elasticity of brand $i$'s sales with respect to brand $j$'s price. Because of averaging across stores, the predicted $\eta_{(i,j)}$ may not be exactly equal to the predicted $\eta_{(k,j)}$. This relation is exact for stick margarine because only one chainwide average is used in the analysis.
four categories is encouraging. The observed elasticity estimates suggest that the brand elasticity structure is driven by market share and is asymmetric. Cross elasticities are small in relation to own elasticities and brand-specific category elasticities vary directly with both market share and price. Though the noisiness of our data depresses the absolute value of $R^2$, the ACREP structure appears to capture fundamental underlying regularities in the price elasticity pattern. Moreover, it does so parsimoniously.

APPLICATIONS OF THE GENERALIZED ACREP

Another way of assessing the validity of the elasticity pattern generated by the ACREP models is to use the theory to analyze the price elasticities of specific market structures. If the ACREP theory is valid, the underlying ACREP parameters ought to be related systematically to known characteristics of the market. Here, we examine price elasticity patterns at two levels of aggregation: the brand elasticities within national and private label partitions of the stick margarine market and the submarket elasticities of the ready-to-eat cereal market. In both cases, the generalized ACREP parameters provide a logically consistent link between the observed elasticities and the structure of the market.

National Brand Versus Private Label Elasticities

Marketing theory suggests that consumers of private label brands are more price sensitive than consumers of national brands. In fact, the estimated stick margarine price elasticities of Blattberg and Wisniewski (1985) show that private label brands are less price elastic. This paradox can be explained easily by using the generalized ACREP model.

Table 5 compares the elasticity structures of the five national brands examined before and two additional private label margarine brands. Both general statistics about the observed elasticities and estimated generalized ACREP parameters are listed. By analyzing national and private label brands separately, we are implicitly assuming that each set of brand elasticities can be modeled by the generalized ACREP. Because the price levels are very different and national brands have a higher quality image, national brands and private labels are unlikely to occupy the same ACRM partition.

Several interesting patterns are evident. Though private label consumers generally are assumed to be more price sensitive, the average private label price elasticity is actually lower than the average for national brands ($-2.65$ vs. $-4.04$). The generalized ACREP model explains this paradox in two ways. First, the average price level of the private labels is 34 cents lower. Because the generalized ACREP predicts that the absolute value of any elasticity is correlated positively with price, the price differential alone explains most of the variation in the magnitude of the elasticities. Notice that the ratios of average prices (1.68) and average elasticities (1.52) are similar.

Second, comparing the $\alpha^*$ estimates shows clearly that private labels have a larger submarket expansion effect. That is, private label consumers have a greater tendency to switch across market partitions in response to price changes. Because the theory does not specify which other partitions are involved in the switching, this finding can also be interpreted as evidence that these consumers are more willing to accelerate or postpone purchases in response to price changes. Either interpretation implies that the private label buyers have greater price sensitivity.

It is interesting to note that the underlying within-partition switching parameter $\beta$ is nearly the same for national brands and private labels. This finding means that all differences in elasticities can be characterized in terms of differences in price level and the submarket expansion parameters. The observed price elasticities are misleading because they confound the two effects. In this case, one can argue that private label buyers are more price sensitive, though the observed price elasticities suggest the opposite conclusion.

Cross-Partition Elasticities

As discussed before, the ACREP models are not only models of brand sales elasticities. They also represent the elasticity structure of any market in which the shares of market entities obey the proportional-draw principle. Support for this proposition can be found in a recent study.

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5Standard results from microeconomics indicate that the magnitude of price elasticity is typically a function of price level. Even if one consumer segment is more price sensitive than another, it does not necessarily follow that the price sensitive segment will appear more price elastic. The generalized ACREP can be regarded as an elaboration of the relevant microeconomic theory.
by Neslin and Shoemaker (1983). Their results indicate that the elasticity structure of the ready-to-eat (RTE) cereal market—consisting of presweetened, low sugar, and granola cereal market partitions—conforms to the generalized ACREP model.

The objective of the study by Neslin and Shoemaker (referred to hereafter as N&S) was to estimate the price elasticity for presweetened cereal sales using data derived from a "natural price experiment"; a large increase in the prices of presweetened cereal due to the sugar shortage of 1974. The authors postulate a model of RTE cereal sales and models of the relative market shares of presweetened, low sugar, and granola cereals. On the basis of these models, they derive an expression for the own-price elasticity of presweetened cereal and calculate its average value.

N&S's expression for own-price elasticity is remarkably similar to the generalized ACREP model (equation 16). Defining \( P_C \) as the market-share-weighted price of the cereal category and \( p_s \) as the price of presweetened cereals,

\[
\eta = \beta_1 MS_s P_s / P_C + \beta_4 MS_L + \beta_6 MS_G
\]  

where \( MS_s \), \( MS_L \), and \( MS_G \) are the shares of presweetened (S), low sugar (L), and granola (G) cereals. This expression has two parameters (\( \beta_4 \) and \( \beta_6 \)) that reflect the effects of switching from presweetened cereals to low sugar and granola cereals and a single parameter (\( \beta_1 \)) that can be interpreted as the average price elasticity of the RTE cereal category.

Simple algebraic manipulation shows that the generalized ACREP is a special case of N&S's model. The two models are equivalent when

\[
\beta_1 = \alpha P_C
\]

and

\[
\beta_s = \beta p_s
\]

where \( \alpha \) and \( \beta \) are the generalized ACREP parameters.

This conclusion can be verified by noting that equations 28–30 reduce to equation 16, the generalized ACREP formula for own elasticity.) In words, the category elasticity must be proportional to category price and the submarket switching parameters must be equal.

Both conditions are reasonable. Though the first condition is difficult to verify with the N&S data, the assumption is equivalent to the generalized ACREP requirement that brand-specific submarket elasticities must be proportional to market share and price. Moreover, consistent with equation 30, N&S show that the partition-switching parameters are very similar in both the calibration sample (\( \beta_4 = 2.57 \) and \( \beta_6 = 2.92 \)) and the holdout sample (\( \beta_4 = 2.26 \) and \( \beta_6 = 2.24 \)).

Using N&S's data and equations 29 through 30, we can infer the parameters of the generalized ACREP model for the RTE cereal market. The switching parameter (\( \beta \)) equals -0.0791 and the submarket expansion parameter (\( \alpha \)) equals -0.0108. As theoretically expected, \( |\alpha| < |\beta| \). Hence, \( \beta^* = -0.0683 \) and \( \alpha^* = 1.16 \).

At this level of aggregation, we regard the RTE cereal category as an ACRM partition within the market of all breakfast foods. Thus, when \( \alpha^* = 1 \), consumers do not switch away from RTE cereals in response to price changes. Consequently, the estimated ACREP parameters imply that price changes induce switching among cereal types (i.e., presweetened, low sugar, and granola), but do not induce much switching away from the RTE cereal category per se. N&S's interpretation of the data is similar. They conclude that consumers responded to the rise in the price of presweetened cereals primarily by shifting from presweetened to low sugar cereals.

**DISCUSSION**

We applied the ACREP models to nine markets. In each case, we generated estimates of the underlying generalized ACREP parameters and argued that they are consistent with an elasticity pattern driven by differences in market share and price. However, it is useful to consider whether the magnitudes of these parameters are reasonable.

As noted before, the ACREP parameters reflect aggregate consumer switching in response to price and ought to be related to differences in consumer behavior across markets. Unfortunately, cross-market analysis is complicated by the fact that the generalized ACREP parameters are not necessarily comparable in different contexts. We next use some reasonable scaling conventions to develop a coherent picture of intercategory differences in elasticity structure.

**Switching Across ACRM Partitions**

In the generalized ACREP model, both \( \alpha \) and \( \alpha^* \) measure the amount of switching across submarkets. The values of \( \alpha^* \), however, are particularly useful because they are scaleless quantities. Recall that the simple ACREP prediction of a market share cross elasticity is \( \eta^m_{ij} = -\beta MS_i p_j \), whereas the generalized ACREP prediction of a sales cross elasticity is \( \eta_{ij} = -\beta^* MS_i p_j \). By taking the ratio of these quantities, we obtain

\[
\frac{\eta^m_{ij}}{\eta_{ij}} = \beta / \beta^* = \alpha^*.
\]

Because equation 31 is a ratio of elasticities and does not depend on the brand pair (i, j) chosen, \( \alpha^* \) can be compared readily across markets. As expected, when \( \alpha^* \) is unity, sales cross elasticities are identical to market share cross elasticities. This is another way of saying that \( \alpha^* = 1 \) implies that all price-induced switching is confined within the partition.

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4The sum of all brand-specific submarket elasticities within any market partition—not necessarily an ACRM partition—is equal to the total elasticity for the partition. Hence, the total elasticity (i.e., the category elasticity) for the RTE market implied by the generalized ACREP is \( \sum \alpha MS_i p_j = \alpha P_C \).
Switching Within ACRM Partitions

Both \( \beta \) and \( \beta^* \) can be used to assess the amount of within-partition switching in response to changes in price. Of the two measures, \( \beta \) is more interpretable because it adjusts for differences in submarket expansion effects (i.e., differences in \( \alpha^* \)). However, both parameters are difficult to compare across markets because they reflect the scale of the price units used in the analysis. Moreover, they measure the absolute change in a brand’s attraction when prices are altered. Cross-category comparisons are more understandable when stated in terms of relative (i.e., percentage) measures.

One way to address these issues is to scale \( \beta \) to take into account intermarket differences in the distributions of market shares and price market shares. Again, recall that the generalized ACREP market share cross-elasticity \( \eta_{ij} \) is equal to \( -\beta_1 M_{ij} \). Because this expression does not depend on which brand \( i \) is chosen, all of brand \( j \)'s competitors will have the same percentage sales decline when brand \( j \)'s price is lowered. Thus, there are only \( N \) unique cross elasticities, one corresponding to each brand. The market share weighted average of these unique cross elasticities is

\[
\sum_j M_{ij} (-\beta_1 M_{ij} p_j) = -\beta \left( \sum_j M_{ij}^2 \right)
\]

where the summation runs over all brands in the partition. We refer to this quantity as a “scaled \( \beta \)” and use it to measure the relative price sensitivity within each ACRM partition.

Cross-Market Comparison

In Table 6, we summarize \( \alpha^* \) and scaled \( \beta \) for the RTE cereal partitions and the eight brand submarkets discussed before. A pattern quickly becomes apparent when these parameters are used to generate a “price elasticity map” for the various markets (Figure 1).

In general, the food categories and nonfood categories are ordered along the scaled \( \beta \) axis. That is, consumers are relatively more sensitive to price differences among brands of nonfood items. One explanation for this finding is that consumers do not perceive significant differences in the physical composition of nonfood brands; in contrast, they are apt to perceive interbrand differences in taste for food products. The only exception is private label margarine, a submarket of food brands in which consumers apparently value low price more highly than taste.

On the \( \alpha^* \) axis, the product categories split into three basic groups. Bathroom tissue is at the low end of this scale; private label soft margarine is at the high end. National brands of bleach, margarine, and ketchup are in the midrange. (Telser’s 1962 data cannot be plotted because no information is available about \( \alpha^* \).) On the basis of these positions, bathroom tissue is the only one of the four national brand categories without ready substitutes in other markets or submarkets. Certainly, this finding is in accord with intuition. Consistent with the ACREP theory, the \( \alpha^* \) axis is related plausibly to consumer perception of product substitutability.

Notice that the location of the RTE cereal submarkets is at the low end of both axes. The map position suggests a market with few meaningful substitutes and with relatively strong attribute differentiation. Both propositions are reasonable. Given that the N&S data describe switching among submarkets (not brands) in the RTE cereal market, substitutability ought to be smaller than for most brand groups (e.g., margarine, ketchup, and bleach). Moreover, because the attributes of the three cereal submarkets are distinct, the RTE cereal market ought to be on the low end of the scaled \( \beta \) axis (i.e., relatively low price sensitivity).

Figure 1 clearly shows an intimate connection between the observed elasticity pattern and structural market characteristics. The potential of the ACREP model lies in this ability to separate the transitory effects of marketing activities from stable components of consumer behavior.

### Table 6

<table>
<thead>
<tr>
<th>Product category</th>
<th>Across partition</th>
<th>Within partition</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( \alpha^* )</td>
<td>( \beta )</td>
</tr>
<tr>
<td>Nestlé and Shoemaker's (1983) data</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RTE cereal submarkets</td>
<td>1 16</td>
<td>-0.791</td>
</tr>
<tr>
<td>Telser's (1962) data*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Regular coffee</td>
<td>NA</td>
<td>-0.669</td>
</tr>
<tr>
<td>Instant coffee</td>
<td>NA</td>
<td>-0.504</td>
</tr>
<tr>
<td>Stock margarine (N)</td>
<td>NA</td>
<td>-0.592</td>
</tr>
<tr>
<td>Summary of Tables 3 and 5</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bleach</td>
<td>2.58</td>
<td>-2.547</td>
</tr>
<tr>
<td>Stock margarine (PL)</td>
<td>8.81</td>
<td>-0.936</td>
</tr>
<tr>
<td>Bathroom tissue</td>
<td>1.23</td>
<td>-1.566</td>
</tr>
<tr>
<td>Ketchup</td>
<td>2.42</td>
<td>-0.517</td>
</tr>
<tr>
<td>Stock margarine (N)</td>
<td>2.21</td>
<td>-0.538</td>
</tr>
</tbody>
</table>

*Estimates of \( \alpha^* \) are not available (NA) for Telser’s (1962) data because only market share price elasticities are provided. For stock margarine, N denotes national brands and PL denotes private labels.

### CONCLUSIONS

ACREP is a parsimonious model of elasticity structure that describes the elasticity pattern of submarkets characterized by a proportional-draw market share mechanism. Two basic arguments justify the model. First, the ACRM structure underlying ACREP can arise under the same conditions as the often-observed Hendry switching pattern. Second, an investigation of observed price elasticities in several product classes shows reasonable correspondence with the ACREP predictions. In particular, the generalized ACREP model emerges as an empirically valid representation of sales elasticities.

Though our research does not demonstrate that ACREP is a general structure obeyed by all marketing mixelas-
From a managerial perspective, the most important aspect of our research may be the parametric structure of the generalized ACREP. If the structure of a particular market is known, the ACREP model provides a method of pooling information across brands to improve the accuracy of elasticity estimates. In the longer term, research firms may be able to develop norms (analogous to the generalized ACREP $\alpha^*$ and $\beta^*$) corresponding to the underlying consumer sensitivity parameters for a partition. Using these norms, one could forecast the elasticities characterizing a new product on the basis of the planned marketing mix and expected long-run market share. Hence, simple parametric representations of elasticity structure would enable new product managers to tailor marketing plans to the particular submarket in which the product is expected to compete.

The key limitation of our research is the prior assumption of the composition of ACRM submarkets. In practice, two different approaches could be used to ver-
ify submarket membership. The most obvious approach is to fit the ACREP model only to submarkets that have the Hendry property of aggregate brand switching in proportion to market share. Though a Hendry submarket is not necessarily an ACRM submarket, there is good reason to believe that the two models often will be observed in the same brand sets. A second approach is to develop a submarket classification by analyzing the unconstrained cross elasticities. Though Allenby (1986) has recently proposed such a procedure, the approach is susceptible to measurement problems (such as multicollinearity) that affect scanner data. Additional research is needed to resolve the issue.

The ACREP model developed here should be viewed as a theory of elasticity behavior under idealized conditions. However, given the widespread availability of optical scanner data, models of this sort hold considerable promise for advancing the state of the art in marketing mix model construction.

REFERENCES


